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Healthcare Expenditures for the Young-Old Population

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Declaration of Authorship and Co-Authorship Disclaimer

This thesis, titled 'Healthcare Expenditures for the Young-Old population', is submitted as completion of the Ph.D. Program in Economics - DEFAP at the University of Milano-Bicocca.

Chapter 1 and 2 are joint works with Professor Lucifora Claudio, Università Cattolica del Sacro Cuore, and Dr. Antonio Russo, Epidemiology Unit, Agency for the Health Protection of the Province of Milan. I, Irene Torrini, am the first co-author.

I, Irene Torrini, declare, under my responsibility, that:

- The thesis was done entirely while in candidature for the mentioned Ph.D Program.
- The thesis was never submitted, in part or in full, for a degree at any other university.
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Abstract

In this thesis, we model the life-cycle evolution of individual healthcare expenditures, expressed as a function of the aging process, health shocks and conditions, and distance to death. All the analyses are carried out by using a unique dataset, which allows us to focus on different types of healthcare services and different subsamples of individuals. The population of interest consists of individuals aged 50-70, the age window where the first adverse health events are expected to arise. In the first chapter, we use a two-way fixed effects model to examine the effect of age, morbidity, and time to death (TTD) on individual healthcare expenditures (HCE). The estimation is carried out by controlling for several confounding factors, including individual and General Practitioner (GP) fixed effects. We also investigate to what extent patients' and GP' characteristics contribute to the overall variability in expenditures among individuals. Our main results show that age, morbidity, and TTD are all important determinants of HCE and are among the elements that contribute most to the variability in HCE among individuals. Total HCE is increasing in age, with the latter found to be negatively correlated with the time to death, a result in contrast with the 'red herring' hypothesis. Such an increase with age of overall expenditures is mainly driven by expenses for out-of-hospital services; in contrast, no difference in hospital costs is observed over the considered lifespan once the other factors are taken into account. On the other hand, inpatient expenditures mainly drive the morbidity and end-of-life profiles of total HCE. Concerning heterogeneous analysis, we find that chronic and disabled individuals with health shocks requiring hospitalization are those who place the greatest burden on the costs borne by the Italian healthcare system. It suggests that the enhancement of preventive approaches before the onset of such shocks is a priority goal to reduce the incidence of long-lasting diseases and prevent them from deteriorating to the point of exacerbation in acute cases requiring hospital admissions. Given the results obtained in the first chapter, in the second one, we use a difference-in-difference event study approach to estimate the short- and long-run impact of the hospitalization on HCE, with hospital admissions analyzed here as a measurable subset of those first adverse health events individuals aged 50-70 experience in their life. Our main findings confirm the existence of a large effect of the first hospitalization on HCE and show that the first access is associated with substantial future medical expenses in all healthcare settings, accounted for the largest part by acute inpatient care. Indeed, the analysis of hospital expenditures indicates the occurrence of subsequent hospitalizations, mainly required for complications of cardiovascular diseases and cancer. The latter are responsible for the highest increase in inpatient expenditures and present a persistent post-admission increase also in outpatient and pharmaceutical expenses, a result driven by the high incidence of chronic and disabled individuals within the group of those affected by these two conditions. From a policy perspective, it indicates need for a strengthening of territorial care and tertiary prevention improvements, necessary to soften the impact of ongoing illnesses with lasting effects. On the one hand, it would improve patients' health by preventing complications and acute cases; on the other hand, it would also generate significant savings through reduced avoidable additional hospitalizations.

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Executive Summary

The rise in healthcare expenditures (HCE) observed over the past 50 years and the projected increase for the next 15 years are among the main concerns for the stability of public finances in most OECD countries. Many countries affected by the economic downturn reduced health spending during the financial crisis; despite this, expenditures have still grown on average by 3.4% (OECD, 2018). In particular, OECD countries are estimated to have spent, on average, 8.8% of GDP on healthcare in 2018, a figure that is nearly unchanged since 2013. HCE are then expected to exceed GDP growth and reach 10.2% of GDP by 2030 (OECD, 2019b).
Although in Italy healthcare spending is currently in line with the OECD average, the projected rise in population aging and the associated burden of chronic diseases are expected to put enormous further pressure on health expenditures (OECD, 2019b), raising sustainability concerns, as fundings are drawn mainly from public sources. Such a pressure is primarily due to critical health conditions, functional dependence, and proximity to death (Costa-Font and Vilaplana-Prieto, 2020; Di Napoli et al., 2005; Geue et al., 2015; Sona et al., 2012), which are often associated with high hospital costs, incurred for specialized and emergency care that cannot be delivered in out-of-hospital settings. Inpatient expenditures represent a large share of public health spending and account, on average, for 38% of healthcare expenditures (OECD, 2019b).

A large body of literature has tried to identify the main determinants of individual healthcare expenditures, with a significant focus on population aging. Several studies highlight the age-dependent nature of individual healthcare costs (Gabriele et al., 2006; Hogan and Hogan, 2002; Hogan and Lise, 2003; Meerding et al., 1998). They exhibit a J-shaped curve that slowly increases through adulthood and more rapidly after age 50, when the first health shocks start to arise (Cutler et al., 2011). Some of these shocks, i.e., those generated by acute pathologies, are characterized by a rapid evolution with sudden onset and followed, when possible, by a fast recovery. Others instead present a slow progression of the underlying disease, typically chronic, with permanent effects on health status and expenditures; in some cases, they are followed by a systematical decline in the individual condition. Then, HCE grow exponentially and reach their highest level during old age, where individuals over-70 incur nearly half of lifetime expenditures and those over-85 more than one-third (Alemayehu and Warner, 2004). It is due to a considerable reduction in the probability of survival (ISTAT, 2018), with a significant share of HCE taking place around the time of demise for intensive high-cost hospital treatments (Geue et al., 2015). In particular, according to the literature testing the 'red herring' hypothesis (Zweifel et al., 1999), proximity to death, rather than age, determines healthcare expenditures, with HCE depending on the remaining life and not on calendar age.

In this thesis, we model the life-cycle evolution of individual HCE for the young-old population, with expenditures expressed as a function of the aging process, health shocks and conditions, and distance to death. The underlying idea is that as the individual ages, the probability of health shocks increases; such adverse health events could have temporary or permanent effects on the individual health status and, in the worst case, could even lead to premature death. In particular, we focus on individuals aged 50-70, that is on individuals observed in the life period in which the first major adverse health events are expected to occur. As documented by the existing literature, 7% of individuals face the first heart attack, stroke, or new onset of cancer between 50 and 64 years of age (Cutler et al., 2011) while 86% of the burden of chronic diseases is found to occur in people under 70 years of age (WHO, 2005). During this period, the evolution of expenditures over time is not easily predictable as living in good health becomes, on average, less likely, but the risk of health complications and death specific to the end-of-life period is still low. It follows that an analysis focusing on this group of individuals is crucial from a policy perspective, as it allows to identify the critical point where the health condition starts to worsen systematically and, hence, when preventive interventions should be undertaken.

In the first chapter, titled 'Healthcare Expenditures and Primary Care: Aging, Morbidity and Time to Death for the Young-Old Population', we use a two-way fixed effects model to examine the effect of age, morbidity, and time to death (TTD) on individual HCE. The estimation is carried out by controlling for several confounding factors, including individual and General Practitioner (GP) fixed effects. These two components capture time-invariant unobservable heterogeneity across individuals and GPs, are allowed to be correlated with the observed individual characteristics and between each other, and are crucial in estimating individual HCE. For example, individual genetic traits, lifestyles, and preferences impact HCE in the life period. GP-specific characteristics, such as professionalism, preferences, and ability to define the right care path, may also contribute to the evolution of individual expenditures. The estimation of individual and GP fixed effects also allows us to investigate to what extent patients' and practitioners' characteristics contribute to the overall variability in individual expenditures among individuals, providing new evidence to the debate concerning the role of demand- and supply-side factors in explaining the variation in individual HCE (Chandra et al., 2011; de Meijer et al., 2013; Dormont et al., 2006; Skinner, 2011). Despite the documented relevance of individual demographic, economic, and clinical factors, a substantial portion of the variation in individual expenditures remains unexplained after such characteristics are considered (Newhouse and Garber, 2013). For this reason, a second strand of the literature considers supply-side factors as additional determinants of individual health expenditures under the hypothesis that a part of the variation in HCE is attributable to differences in the supply of healthcare (Chandra et al., 2011; de Meijer et al., 2013; Dormont et al., 2006; Skinner, 2011). While many of these analyses document patterns in HCE across regions, hospitals, and specialist physicians (Chandra et al., 2011; Newhouse and Garber, 2013; Skinner, 2011), less is known about the role of the primary care setting and the GP. Under the Italian healthcare system, the practitioner plays the role of gatekeeper for patients to further medical care, with the definition of the clinical path centered around this figure. Especially when the first health shocks are taken into account, his or her clinical decisions are crucial for the evolution over time of the individual health condition and, consequently, health expenditures. Moreover, since access to healthcare is mostly free at the point of service, the equilibrium of expenditures between demand and supply is placed at the point where the quantity defined by the GP is located, given the patient's health status and preferences.

In the second chapter, titled 'The Long-Term Effects of Hospitalization on Healthcare Expenditures: an Empirical Analysis for the Young-Old Population', we focus on the effect of hospitalizations on HCE. Hospital services provide specialized acute and emergency care for the treatment of health shocks that cannot be delivered in outpatient or primary care settings. Consequently, hospital admissions are analyzed here as a measurable subset of the adverse health events occurring over time. In particular, when the population of individuals aged 50-70 is taken into account, hospitalizations represent the response to those first health shocks individuals experience in their life, which can open up different scenarios and lead to different expenditures patterns: the complete recovery of the admitted individuals could be observed, as well as the onset of chronicity or disability, the occurrence of future admissions, or premature death. To the best of our knowledge, no previous studies analyze the effect of hospital admissions on individual healthcare expenditures. However, effective inpatient treatment is crucial for the individual health status to avoid additional accesses and, consequently, reduce healthcare costs. We study the dynamic pattern of HCE around the admission by using a difference-in-difference event study approach to estimate the short- and long-run impact of the hospitalization on HCE. As a quasi-experimental design, we compare HCE of individuals who experience a hospital admission to the expenditures of those who never have hospitalizations. The latter act as a counterfactual for the former group and allow the inclusion of individual fixed effects on top of demographic and health-related traits, and time fixed effects.

Both analyses are carried out by using a unique dataset drawn from the Health Information System of the Agency for the Health Protection (*Agenzia per la Tutela della Salute* - ATS) of the Province of Milan, consisting of about 1 million individuals observed over the period 2008-2017, for a total of roughly 8 million observations. The dataset provides information on individual expenditures covered by the Italian healthcare system, along with demographic and health-related traits. Individual expenditures include expenses for pharmaceuticals, hospital and day hospital admissions, and outpatient services. Demographics cover gender, age, citizenship, residence area, and income-related exemptions, while health-related characteristics comprise disease- and disability-related exemptions, number of co-morbidities, primary diagnoses at the hospital admission, and year of demise. Information about the GP responsible for patient care is also available.

These population data allows us to examine the determinants of HCE for the entire population and go beyond earlier studies (Felder et al., 2010; Seshamani and Gray, 2004; Shang and Goldman, 2008; Stearns and Norton, 2004; Zweifel et al., 1999) in a number of respects. First, while previous research is often limited to hospital care (Breyer et al., 2015; Felder et al., 2010; Seshamani and Gray, 2004; Shang and Goldman, 2008; Wong et al., 2011; Zweifel et al., 1999), we also focus on other services. We separately model total HCE and expenses for hospital and day hospital admissions, outpatient services, and pharmaceuticals. Second, the availability of health-related characteristics allows us to carry out several heterogeneity analyses. In particular, information on diagnostic categories and the presence of chronicity and disability makes it possible to analyze the influence of specific diseases on HCE.

Chapter 1

Healthcare Expenditures and Primary Care: Aging, Morbidity and Time to Death for the Young-Old Population

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1.1 Introduction

The rise in healthcare expenditures observed over the past 50 years and the projected increase for the next 15 years are among the main concerns for public finances' stability, especially in those countries, like Italy, where fundings are primarily drawn from public sources. On average, OECD countries are estimated to have spent 8.8% of GDP on healthcare in 2018. Moreover, health expenditures are expected to exceed GDP growth and reach 10.2% of GDP by 2030 (OECD, 2019b), a projection that is frequently considered as a result of population aging. Indeed, the share of the elderly population continuously rises and is projected to increase to 25% by 2050 (WHO, 2015).

Given these projections, a large body of literature has tried to identify the main determinants of individual healthcare expenditures (HCE). Several studies highlight the age-dependent nature of individual healthcare costs (Hogan and Hogan, 2002; Hogan and Lise, 2003). They are found to exhibit a J-shaped curve that slowly increases through adulthood and then more rapidly after age 50 (Gabriele et al., 2006; Meerding et al., 1998). Individual expenditures then reach their highest level during old age, where individuals over-70 incur nearly half of lifetime expenditures and those over-85 more than one-third (Alemayehu and Warner, 2004). Such an expenditures pattern is driven by the fact that the first health shocks start to arise around the age of 50 (Cutler et al., 2011), leading to a systematical decline in the health condition and the probability of survival (ISTAT, 2018). Then, when the individual enters the last years of life, expenditures exponentially grow, with a significant share of HCE taking place around the time of demise (Geue et al., 2015). According to the literature testing the 'red herring' hypothesis (Zweifel et al., 1999), proximity to death, rather than age, determines healthcare expenditures.

Despite the documented relevance of individual demographic, economic, and clinical factors, a substantial portion of the variation in individual expenditures remains unexplained after such characteristics are considered (Newhouse and Garber, 2013). For this reason, a second strand of the literature considers supply-side factors as additional determinants of individual health expenditures (de Meijer et al., 2013; Dormont et al., 2006) under the hypothesis that a part of the variation in HCE is attributable to differences in the supply of healthcare. While many of these analyses document patterns in HCE across regions, hospitals, and specialist physicians (Chandra et al., 2011; Newhouse and Garber, 2013; Skinner, 2011), less is known about the role of the primary care setting and the General Practitioner (GP). Under the Italian healthcare system, the GP plays the role of gatekeeper for patients to further medical care, with the definition of the clinical path centered around this figure. Moreover, since access to healthcare is mostly free at the point of service, the equilibrium of expenditures between demand and supply is placed at the point where the quantity defined by the GP is located, given the patient's health status and preferences. Practitioner's decisions hence may play an important additional role in determining the level of individual healthcare expenditures.

In this chapter, we model the effect of aging, health status, and time to death (TTD) on individual healthcare expenditures with a dual purpose. First, the estimation of their effect allows us to analyze the life-cycle evolution of total HCE and expenses for different healthcare services and provide evidence of their heterogeneous impact by gender, survival status, primary diagnosis, and presence of chronic conditions or disability. Second, we examine the extent to which heterogeneity among individuals and GPs contributes to the observed variability in individual HCE, providing new evidence to the debate concerning the role of demand- and supply-side factors in explaining the variation in individual HCE. The hypothesis we test is that, while a part of the variation is due to differences in individual characteristics, a non-negligible share may be related to the way their health conditions are treated by the GP.

We use a 10-years panel of individual records drawn from the Health Information System of the Agency for the Health Protection of the Province of Milan. Through access to population data, we examine the determinants of HCE for the entire population considered, comprising about 1 million individuals aged 50-70 observed over the period 2008-2017. The dataset provides information on individual characteristics and expenditures for several healthcare services, as well as the identification of the GP responsible for patient care. Following the extensive Labor Economics literature using employees-employers datasets (Card et al., 2013; Jinkins and Morin, 2018; Torres et al., 2018; Woodcock, 2015a), we carry out our analysis by estimating a two-way fixed effects model that allows for the inclusion of both individual and GP fixed effects, capturing time-invariant unobservable heterogeneity across individuals and GPs such as individual genetic traits, lifestyles, and preferences, and GP's professionalism, preferences, and ability to define the right care path. The advantage of using a GP-individual level panel is that it allows to net out both practitioner- and individual-specific explananations for differences in the effect of age, co-morbidities and TTD on healthcare expenditures; the remaining bias, if any, should be negligible.
The dataset allows us to go beyond earlier efforts in identifying the determinants of healthcare expenses (Felder et al., 2010; Seshamani and Gray, 2004; Shang and Goldman, 2008; Stearns and Norton, 2004; Zweifel et al., 1999) in a number of respects. First, we focus on individuals in the age window 50-70, the life period in which the first health shocks typically arise (Cutler et al., 2011), with potentially permanent consequences on the individual health status (WHO, 2005). Second, while previous research is often limited to overall or hospital expenditures (Breyer et al., 2015; Felder et al., 2010; Seshamani and Gray, 2004; Shang and

Goldman, 2008; Wong et al., 2011; Zweifel et al., 1999), we decompose total HCE into expenses for hospital and day hospital admissions, outpatient services, and pharmaceuticals to focus on different services. Indeed, the composition of the use of healthcare services changes during life towards a more intense use of high-tech inpatient services (Breyer et al., 2010; Costa-Font and Vilaplana-Prieto, 2020); consequently, demographic and health-related traits are likely to have heterogeneous effects on the expenses for different types of healthcare. Third, information on diagnostic categories and the presence of chronicity and disability allows us to analyze the influence of specific diseases on HCE. It makes it possible to investigate the role of age, morbidity, and TTD by disease group, which is likely to differ since the impact and duration of each specific condition varies considerably (Wong et al., 2011). It is even more relevant when the disease-specific effects are estimated for each service, as the various healthcare sectors may show different patterns depending on the acute or chronic nature of the disorder.

Our results show that individual observed and unobserved differences contribute most to the variance of HCE, with age, morbidity, and TTD found to be all important determinants of expenditures for individuals aged 50-70. In particular, for total expenditures, we observe a positive gradient in age that reduces when the number of co-morbidities is also controlled for. Interestingly, instead, the effect of age increases when time to death is also added. This result is in contrast to the red herring hypothesis and suggests that premature deceases imply higher expenses than those occurring at older ages. In any case, we observe an increase in total costs between age 50 and 70. It is mainly driven by expenditures for out-of-hospital services, while no difference in hospital costs is observed over the considered lifespan once the number of co-morbidities and proximity to death are taken into account. On the other hand, hospital expenditures mainly drive the morbidity and end-of-life profiles of total HCE, a result indicating a progressive shift towards more complex and expensive inpatient treatments as the severity of the health condition increases (Breyer et al., 2010; French et al., 2017). Such a substitution is confirmed by the different expenditures evolution by TTD among the services considered. While hospital costs continue their growing trend over the last period of life, those incurred for all other services fall sharply in the year of demise. Interesting results also emerge from heterogeneity analyses, and especially from those by disease. The age coefficients are never statistically significant when disease-specific hospital expenses are considered; instead, a linear increase in expenses for out-of-hospital treatments is observed for many of the diagnostic categories, with individuals affected by cancer and cardiovascular conditions showing the highest growth in HCE between age 50 and 70. Cancer-specific estimations also shows the largest effect of the number of co-morbidities, resulting from the fact that the presence of co-existing diseases largely amplifies the severity of the health condition and expenditures when cancer itself is the primary diagnosis.

The effect of TTD on HCE also varies depending on the type of the underlying disease. For acute diseases, HCE deviate from their trend only in the last two years of life to grow exponentially until death. On the contrary, for those conditions with a high incidence of long-lasting diseases, HCE start their increasing path probably before the fifth year prior to death, indicating a slow progression of the underlying condition. At the time of demise, their level is also higher, especially when cardiovascular diseases and cancer are the primary diagnoses.

From a policy perspective, the analyses carried out in this chapter contribute to identifying the critical point where those first health shocks with permanent consequences on the individual health status begin to occur and, hence, when preventive interventions should be undertaken. According to our main results and further investigations, such a critical point corresponds to age 60, where the age profile of total HCE becomes marginally increasing due to worsening health conditions of the population of chronic and disabled individuals. Hence, the enhancement of preventive approaches before such an age is a priority goal to reduce the incidence of long-lasting diseases and prevent them from deteriorating to the point of exacerbation in acute cases requiring hospital admissions, associated with greater need for medical care and higher expenditures.

The remainder of the chapter is organized as follows. Section 1.2 reviews the existing literature. Section 1.3 provides a brief overview of the Italian healthcare system, along with a description of the care path for non-emergency cases. Section 1.4 describes the data and reports the descriptive statistics. Section 1.5 illustrates the empirical strategy. Section 1.6 describes the results and Section 1.7 shows some robustness checks. Section 1.8 discusses the main findings and Section 1.9 concludes.

1.2 Related literature

Individual healthcare expenditures depend on a wide range of demographic, social, and economic factors, as well as the financing and organizational structures of the health system. Among these factors, worldwide population aging and the associated burden of chronic diseases have been considered among the most critical demographic phenomena and are frequently referred to as the main determinants of health costs.

The role of age as the primary driver has been questioned first by Zweifel et al. (1999), with the so-called 'red herring hypothesis'. Using longitudinal data, they study the relationship between healthcare expenditures and age for the deceased population and find that, at least over age 65, HCE depends on the remaining life but not on calendar age. According to the authors, this result suggests that the end-of-life period (last eight quarters of life) is costly independently of the age it starts at. Since the work of Zweifel et al. (1999), an extensive literature has emerged to test the red herring hypothesis, which has been generally confirmed. In particular, previous results indicate that the estimates of the effect of aging on healthcare expenditures are attenuated or become insignificant when alternative explanations are considered, such as time to death (TTD) and morbidity. However, several weaknesses in the relative econometric methodology have been disputed. Among the others, Breyer and Lorenz (2019) and Seshamani and Gray (2004) raise three main methodological concerns. The first one regards the exclusive use of data on people in their last years of life. In these cases, the analysis is carried out on the selected subsample of deceased individuals, which may not yield reliable insights on the overall relationship between aging and HCE. The second is about the parametric specification of age, which is usually measured by the continuous variables age and age-squared, forcing a parabolic relationship between age and HCE without considering more complicated functional relationships. The endogeneity of TTD represents, finally, the third issue. As medical services may improve the individual health status and extend life (Becker et al., 2005; Hall and Jones, 2007), estimates that do not account for the dynamic influence of current and previous HCE on life expectancy may underestimate the effect of TTD and, consequently, overestimate the effect of age (Costa-Font and Vilaplana-Prieto, 2020; Stearns and Norton, 2004). Several analyses use the instrumental variable approach to purge TTD of its endogeneity (Costa-Font and Vilaplana-Prieto, 2020; Felder et al., 2010; Karlsson and Klohn, 2011; Shang and Goldman, 2008; Stearns and Norton, 2004), but only a few of them pass the test for exogeneity (Costa-Font and Vilaplana-Prieto, 2020; Karlsson and Klohn, 2011).

The third factor of interest, morbidity, is essential in healthcare expenditures analyses because the individual overall condition has an independent effect on the outcomes of interest. Indeed, although age and TTD are often found to be significant predictors of HCE, neither of them are causes of HCE in and of themselves but merely act as proxies for morbidity. Individual health condition is frequently taken into account through indexes measuring co-morbidity. It is the presence of one or more additional conditions co-occurring with the primary disease and is associated with worse health outcomes, more complex clinical management, and increased healthcare costs. Indeed, when a patient has more than one disease, the conditions may interact such that the individual's healthcare costs are greater than the sum of the costs for the individual diseases (Cortaredona and Ventelou, 2017). Various approaches have been taken to characterize the combined burden of given conditions as a single measure, with the aim of considering not only the presence but also the severity of different diseases (Valderas et al., 2009). Among theses, the most widely used measure is the Charlson Co-morbidity Index (CCI) (Charlson et al., 1987). To calculate the CCI, each concurrent condition aside from the primary disease is assigned a weight, and the sum of the weights is the index score. Unfortunately, the data used in this chapter only report the number of co-morbidities for each individual at a given time but not the associated medical condition, making it impossible to take the burden of each disease into account. Although constructing such an index is not possible here, we assess the role of the health condition severity by estimating the effect of the number of co-existing conditions on disease-specific HCE, an exercise that we carry out in Section 1.6.4 and Section 1.6.5, where we show results from heterogeneous analyses by the presence of chronicity and disability and primary diagnosis.

According to the existing literature, other elements affect individual HCE, which act as confounding factors in analyses focusing on the effect of age, morbidity, and time to death. As far as the individual is concerned, several demographic and socio-economic characteristics, such as gender (Gabriele et al., 2006; Owens, 2008), birth cohort (Bell and Jones, 2015; Blanchard et al., 1977), citizenship (Devillanova and Frattini, 2016; Lebano et al., 2020), residence area (Di Novi et al., 2020) and the economic condition (Dalstra et al., 2006; Schäfer et al., 2012; Von dem Knesebeck et al., 2003) are found to play a substantial role. Other factors like genetic traits, lifestyles, and preferences are typically unobserved, demonstrating the importance of modeling individual HCE by including individual-specific components as additional confounding factors[1]. Regarding factors external to the individual, budgetary policies (Depalo, 2019), prices, and technological progress (Breyer et al., 2010; Dormont et al., 2006; Goldman et al., 2005; Wong et al., 2012) also impact individual HCE, as well as the role played by the main actors of the health system, such as the General Practitioner (GP). Available evidence shows that a non-negligible share of variance in HCE among patients is due to heterogeneity among GPs[2] (Harris et al., 2011; Mousquès et al., 2010; Omar et al., 2008; Sullivan et al., 2005), which are thus considered as an additional source of variability in individual expenditures.

As described in Section 1.5, we model individual HCE to analyze the effect of age, TTD, and morbidity while controlling for all the mentioned additional factors.

[1]While we estimate a linear regression model, most studies use a two-part model to take into account the statistical features of healthcare expenditures data. We analyze their characteristics in Section 1.7, where we compare our baseline results with those estimated by using a non-linear statistical model.

[2]The estimation is usually carried out by using multilevel models where individual's and practitioner's contributions are estimated as random effects, thus precluding any correlation of such effects with the observed characteristics included in the analysis and between each other. Moreover, hierarchical models assume patients to be strictly nested within GPs and, while this does not raise any concern for cross-section data where individuals are observed for only one period, it may be excessively restrictive in panel data with individuals moving among practitioners over time. In contrast to the existing literature, we estimate the GP contribution by adding to our regression GP-specific fixed effects.

1.3 Institutional setting

The Italian healthcare service (*Servizio Sanitario Nazionale* - SSN) provides universal coverage through a regionally-based organization divided into three levels. The national level is responsible for defining general objectives, fundamental principles, and the medical services covered by the SSN[3] (*Livelli Essenziali di Assistenza* - LEA). The second level, regional governments, instead organizes and delivers care through a network of population-based local health authorities, called, in the Lombardy Region, Agencies for the Health Protection[4] (*Agenzie per la Tutela della Salute* - ATS). The latter represent the third level and provide preventive medicine and public health services, primary care, community services, and secondary and specialized care. They are also responsible for paying the agents working under the SSN according to different criteria[5].

Concerning the SSN financing, care coverage is mostly free of charge at the point of access and is primarily funded through a mix of taxes at the regional and national levels. Taxes are then supplemented by co-sharing schemes related to co-payments for pharmaceuticals and outpatient services[6] in charge of the patients under the presentation of a physician's referral. However, exemptions from cost-sharing schemes are ensured to specific groups of individuals. Individuals with

[3]They include: primary and emergency care, pharmaceuticals, specialist outpatient care, integrated, prosthesis, ambulatory and home care, residential and semi-residential care and thermal therapy, hospital services and public health and occupational health services; general community and individual levels of preventive services as hygiene and public health, immunization, and early diagnosis tools. Excluded services are ineffective services, services that are covered only on a case-by-case basis, and inpatient services for which ordinary hospital admissions are likely to be potentially inappropriate.

[4]The Regional Law 23/2015 (Regional Law 11/08/2015) reformed the organization of the Lombardy health service by replacing the independent public local enterprises *Aziende Sanitarie Locali* (ASLs) with new local authorities named ATSs. This reform substantially changed the governance of the social-healthcare system. The region was subdivided into 8 areas in which each correspondent ATS undertakes the role of purchasing and coordinating health and social care for their residents. In particular, the ATS of the Province of Milan substitutes and includes the ASLs of Milano 1, Milano 2, and Lodi (residents in Lodi are excluded from the baseline sample).

[5]Ordinary and Day Hospital treatments are paid based on the Diagnostic Related Group (DRG) tariffs, set at the national level. The reimbursements for outpatient specialist care, diagnostic services, and imaging are based on tariffs per unit of service, while payments for pharmaceutical care are differentiated according to product classes (fully reimbursed products, drugs fully reimbursed only in the hospital, and not reimbursed products). GPs and pediatricians instead are mainly paid through capitation payments.

[6]Co-payments do not apply to dental care, obstetric, and gynecological services, for which the total cost is in charge of the individuals. For the other specialties, cost-sharing schemes mainly refer to co-payments for diagnostic procedures such as laboratory tests and imaging, pharmaceuticals, and specialist visits. Co-payments are also required for interventions in hospitals' emergency departments, usually free of charge, provided for unjustified and non-urgent cases.
Medical care is also offered without coverage through private providers or SSN specialists operating *intra-moenia* (professionals working in private practices inside the SSN hospitals or the local health autorities' ambulatory clinics where they operate); in such cases, individuals have direct access to the facility and pay the total cost of the service.

severe disabilities[7], low-income households[8], and prisoners are totally exempted; patients with chronic or rare diseases, HIV-positive individuals, and pregnant women are instead exempted for treatments related to their condition only.

Regarding care providers, individuals are free to choose any national public provider and private provider accredited to offer care on behalf of the SSN. Patients can also choose a GP and pediatrician within their ATS and change them once every twelve months[9]. All these actors play different roles within the medical path. Indeed, healthcare for non-emergency cases covered by the SSN is provided to the patients at different levels, including primary (GPs and pediatricians) and secondary care[10] (specialized ambulatory and hospital care). Primary care is the first point of contact within the healthcare system and is free of charge. Professionals at this level are responsible for defining a timely and accurate diagnosis and play the role of gatekeeper for individuals to further medical care by prescribing medications and referring[11] patients to specialized care. GP's and pediatrician's referrals are strictly required for additional medical services to be totally or partially covered by the SSN. After an initial contact within the primary care setting, patients who do not require hospitalization can access specialized ambulatory care, consisting of more complex services such as visits, diagnostic and laboratory services, curative therapy, and rehabilitation care. If further care is needed, health care may involve inpatient hospital admissions for acute cases. Inpatient care also includes day hospital services, a form of care to reduce the length of stay and relieve the pressure on hospital activities[12].

[7]Civil invalids and invalids for work (individuals employed in private companies), service (public employees) and war and victims of terrorism and victims for duty (Ministerial Decree 1/02/1991; Legislative Decree 29/04/1998; Law 12/03/1999; Law 3/08/2004; DPR 7/07/2006).

[8]Children under-6 and over-65 individuals belonging to a household with an annual gross income lower than or equal to 36,151.98€, individuals with social pensions, over-60 individuals with minimum-pensions and unemployed and their household with an annual gross income lower than or equal to 8,263.31€ for singles and 11,362.05€ for larger households (Law 24/12/1993). These income-related exemptions have equal application at the national level, but each region is given the option of introducing additional measures. For example, in Lombardy, subjects suffering from chronic and rare diseases belonging to a household with a total income of the previous year not exceeding 46,600€ are also exempted from the co-payment for pharmaceutical purchases (Annex 8-bis and Annex 7 of the DPCM 12/01/2017).

[9]The current registration is automatically extended if there is no explicit withdrawal. GPs and pediatricians must accept all patients up to a limit of 1,500 (a maximum that can be exceeded in specific cases) and can refuse or remove them from the list only for exceptional and proven incompatibility reasons.

[10]Primary care after hospital discharge and long-term care are also provided. If post-acute care is needed the patient path is expected to move into integrated home care (Assistenza Domiciliare Integrata – ADI) or rehabilitative care, whereas elderly, frail and disabled people can be treated in residential or semi-residential facilities (Residenze Sanitarie Assistenziali – RSA) and community nursing homes.

[11]Referrals can be provided to establish a diagnosis when it cannot be achieved within the primary care setting, for treatments and operations, to ask for advice on case management, and to obtain patients' or physicians' reassurance.

[12]For a more detailed description of the Italian healthcare institutional setting, see Ferré et al. (2014).

1.4 Data and Descriptive Statistics

For our analysis, we use a unique dataset drawn from the Health Information System of the ATS of the Province of Milan, consisting of about 3,000 GPs and 1 million individuals observed over the 2008-2017 period, for a total of roughly 8 million observations[13]. The dataset provides information on healthcare expenditures covered by the Italian healthcare system[14] for the whole population aged 50-70, along with individuals' demographic and health-related traits and GP's characteristics[15].

To carry out our within-individual estimation, we select only individuals observed for at least two consecutive years, remaining with 1,144,179 individuals (7,810,863 observations) and 2,354 GPs.

Table 1.1 reports some sample statistics, calculated first for each year; then, averages across years are drawn and reported as final statistics. The sample is composed of less than half of males (47.50%), while the most significant part is represented by Italian and European citizens (95.66%) and individuals living in areas belonging to the province of Milan (60.14%). Individuals are quite equally distributed across cohorts and present average age of 59 years. Concerning health-related characteristics, in our sample, 27% of individuals present one coexistent condition, 12% two, 4.7% three, and 1.60% four or more. More than half, then, meets at least one criterion for cost-sharing exemptions. Statistics show that 18.96%, 42.32% and 6.82% are exempted for, respectively, the income, chronicity and disability. Note that the chronic and disability-related exemptions are used here as proxies for the onset of chronic conditions or disabilities[16]. Finally, the share of deceased individuals is lower than 3%. For those who present at least one hospital access during the observed period, more detailed information about the individual health condition is provided by the Major Diagnostic Categories (MCDs), aggregations of DRGs (Diagnostic Related Groups) related to the specialty for which hospital or Day Hospital admission is required. We use this information to identify the primary diagnosis for each hospitalized

[13] Adjustments and modifications made on the sample are described in Appendix 1.A, along with the name, type and description of all the variables used in the analysis (Table 1.A.1).

[14] Note that, since expenditures reflect the cost per individual in charge of the healthcare system, out-of-pocket spendings are not observed.

[15] The average GP is 56 years old, has 29 years of working experience, and treats 1,349 patients every year, of whom 422 are aged 50-70 (Table 1.B.1 in Appendix 1.B).

[16] Instead, the income-related exemption cannot be used as a proxy for economic status, since it does not identify solely the economic condition of the individual. In fact, as described in footnote 8, in the Lombardy region some classes of exemptions are issued for the simultaneous presence of specific economic and health conditions.

Table 1.1: Descriptive statistics.

Demographic characteristics		
	Percentage	Mean expenditures[a]
Male	47.50	1,559
Female	52.50	1,206
Age	59	
Cohorts		
1938 - 1947	24.53	1,915
1948 - 1952	22.54	1,506
1953 - 1957	23.11	1,185
1958 - 1967	29.82	918
Citizenship		
European	95.66	1,376
Non-European	4.34	1,096
Residence Area		
Urban area	39.86	1,311
Province	60.14	1,403
Income exemption	18.96	1,854

Health-related characteristics		
	Percentage	Mean expenditures[a]
Disease exemption	42.32	2,239
Disability exemption	6.82	4,717
Number of co-morbidities		
No co-morbidities	54.76	425
1	26.92	1,243
2	12.08	2,511
3	4.66	4,258
4+	1.60	7,926
Deceased	2.66	8,454
Major Diagnostic Categories[c] (*MDCs*)		
Infectious disease	1.03	3,259
Mental disorder	1.88	2,709
Nervous System disease	5.13	2,557
Cancer	15.59	3,349
Cardiovascular Disease	18.24	3,603
Chronic Obstructive Pulmonary Disease (COPD)	4.68	2,737
Digestive System disease	13.66	1,458
Musculoskeletal disease	6.31	2,294
Other	33.48	2,184

Healthcare volumes and expenditures				
	Percentage	Volume[a]	Cost[ab] (€)	SD[a] (€)
Hospital	7.15	1.59	7,427	11,377
Day Hospital	2.17	1.39	1,969	2,516
Outpatient services	79.23	26.20	479	1,644
Pharmaceuticals	72.45	28.31	329	727

Note:
[a] Statistics calculated on the population of individuals with positive values.
[b] Expenditures data are deflated by dividing current expenditures by the Italian consumer price index for the health sector provided by the OECD. The reference year is 2015.
[c] Percentage of individuals for each MDC calculated on the population of individuals affected by at least one disease.

individual[17]. In second place after the residual category 'Other'[18], cardiovascular disease is the most frequent primary disease, with 32.57% of the sample belonging to this category. It is then followed by cancer (15.59%) and disorders related to the digestive system (13.66%).
Concerning the use of different healthcare services, hospital and day hospital admissions are together the least required, with 9.32% of the individuals reporting each year at least one access. Among those hospitalized, the average annual number of admissions per person is less than 2 in both cases, and the average cost per person is about 7,400€ for hospital and 1,970€ for day hospital. On the other hand, more than half of the population uses outpatient services and pharmaceuticals (respectively, 79.23% and 72.45%), with average volumes of 26 visits and 28 medicinal boxes per person and an average cost of respectively 480€ and 330€[19]. Total HCE, calculated as the sum of expenses for the different services, broadly vary within the population. While no significant differences are observed between those living in the urban area and the province, non-European individuals spend slightly less than European citizens. Young cohorts spend less than old cohorts, while we observe higher expenditures for males than females. Then, as expected, individuals affected by several co-morbidities and those who dye during the observed period spend more than healthier and surviving individuals, with the latter intended as those who do not die during the observed period.

Figure 1.1a and Figure 1.1b describe the age profile of total HCE for males and females by cohort[20]. The interesting feature of these graphs is that they contemporaneously illustrate the longitudinal and cross-sectional pattern of average total expenditures by age. On the one hand, they exhibit the life-cycle HCE trend of the average individual within each cohort (grey lines). On the other hand, they show mean expenditures of individuals of different ages in a given year, 2017 in this case (red dashed line). The figures indicate a longitudinal and cross-sectional positive relationship between age and HCE, with the rise in total expenditures

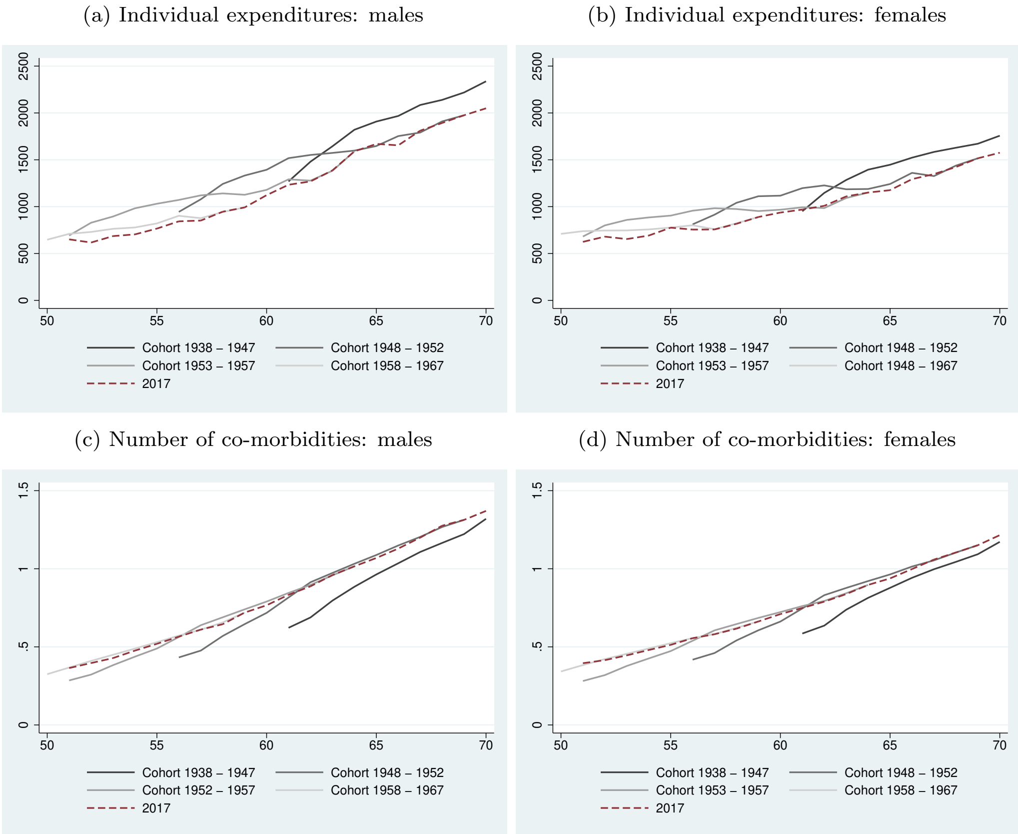
[17]Since patients may be hospitalized for more than one condition over time, each individual is assigned to a given category if such category is associated with the highest expenditures, considering the whole period the individual is observed. That is, if for a patient the sum of yearly expenditures for hospital or Day Hospital admissions is higher for cardiovascular diseases than for other categories, then such patient is considered as primarily affected by cardiovascular diseases. Note that the primary diagnosis is identified only for those who present at least one hospital or day hospital admission over the period they are observed.

[18]It contains all the MDCs that are not identified in the dataset. They are diagnosis related to ear, nose, mouth, and throat; liver and pancreas; skin, subcutaneous tissue, and udder; endocrine, nutritional and metabolic diseases; diagnosis related to kidney and urinary tract; diseases of male and female reproductive systems; birthing diagnosis and services for regular neonate; diseases of hematopoietic organs; disorders for alcohol, medicines abuse and other types of dependency; traumatisms, intoxications, and toxic effect; other factors influencing the individual health status.

[19]All the expenditures data shown in this section are deflated by dividing current expenditures by the Italian consumer price index for the health sector provided by the OECD. The reference year is 2015.

[20]Cohorts are chosen to obtain similar groups size.

Figure 1.1: Age profile of individual total HCE and number of co-morbidities by gender and cohort.



steeper for males than for females, probably due to the different use of healthcare services described in Section 1.6.3. For the average individual in each cohort, it means that HCE increase with age, and that, in the same year, the older spend more than the youngest. We also note that age profiles are steeper and higher for both males and females when moving towards older cohorts. Indeed, when individuals of the same age are compared, those belonging to the oldest cohorts (light grey lines) spend more than the youngest (dark grey lines), and HCE rises more as they age. Since individuals in the oldest cohort reach a certain age earlier than those in the youngest cohort, it means that average expenditures decrease over the years at each age.

To understand whether these findings are driven by the evolution of the population's average health status, in Figure 1.1c and Figure 1.1d, we replicate the same exercise on the number of co-morbidities. We first note that the increase in the number of co-morbidities is steeper for men than for women, a feature discussed in more detail in Section 1.6.3. Moreover, the longitudinal and cross-sectional increase of the number of co-morbidities with age suggests that the respective HCE evolutions are associated with a deteriorating health status of the average individual in each cohort over time and that, in the same year, the oldest individu-

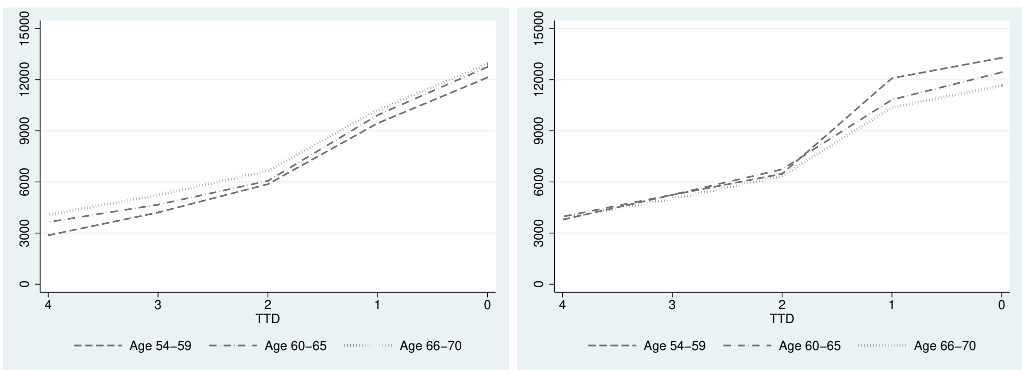
als are less healthy than the youngest. However, when individuals of the same age are compared, the number of co-morbidities reduces when we move towards older cohorts, suggesting that, at each age, the health status of the population worsens over the years. It follows that the reduction of HCE over the years observed in Figure1.1a and Figure 1.1b is due to other causes that are independent of the population health status or to a combination of the latter and other factors. One of them may be the implementation of cost-containment policies carried out by the Lombardy healthcare system during the considered period. The provision of services has been significantly rationalized within the inpatient settings to reduce unjustified and inappropriate hospital admissions and consequent costs[21].
The evolution of individual expenditures over time is also illustrated by Figure 1.2a and Figure 1.2b, which show the pattern of total HCE by time to death and age-at-death class for both males and females. Time to death is indicated by the variable TTD. It ranges from 0 to 5 and equals 0 in the year of death, 1 in the year before, 2 in the second year before, and so on. As shown in the figures, HCE are increasing in proximity to death. They reach about 12,000€ in TTD=0, with differences between men and women and among age-at-death-classes. For both men and women, the increase in expenditures grows from the second year before death, with the change of inclination sharper for women than men. While in $TTD = 0$ HCE set at a similar level, in $TTD = 1$, women who die younger spend considerably more than men dying at the same age. Moreover, while men's expenditures are decreasing with age at death at each period, in the last two years of life women belonging to younger age groups spend more than those belonging to older classes, with a gap between classes at the two extremities of about 1,500€ in $TTD = 0$.

The findings reported in this section provide some interesting evidence. First,

Figure 1.2: Individual total HCE by time to death and age-at-death class.

(a) TTD: males

(b) TTD: females



[21]From 1999 to 2014, hospital beds were reduced by 20% (from 45,400 to 37,500), while hospitalizations by 26% (from 1,294,000 to 958,000) (Lombardia, 2014).

from a longitudinal and cross-sectional perspective, individual total HCE increase in age, and this evidence seems to be associated with a deterioration of the health status over time, which, when it leads to premature death, is related to a substantial rise in expenditures. The worsening of the health condition and the consequent increase in expenditures is faster for men than for women, even if no considerable differences are observed between the two groups in the end-of-life period, except for the last two years of life. Second, while, at each age, average expenditures decrease over the years, the health status of the population seems to worsen, showing the relevance of both period and cohort effects.

1.5 Empirical strategy

The analysis is carried out by estimating a two-way fixed effects model where observed and unobserved individual's and GP's characteristics are included as regressors along with other controls. From a theoretical perspective, observed healthcare expenditures at any time can be thought of as the equilibrium between the demand and supply of medical care, represented, respectively, by the patient and the GP. Their characteristics are the drivers that, leading to shifts of demand and supply curves, cause variations in HCE equilibrium across individuals[22]. Hence, the equilibrium results from the combination of both GP's and individual's traits, with the latter being explicitly modeled to reflect the life-cycle evolution of HCE, expressed as a function of the aging process, health status, and distance to death. The underlying idea is that as the individual ages, the probability of health shocks increases; such adverse health events could have temporary or permanent effects on the individual health status and, in the worst case, could even lead to premature death.

Consider an unbalanced panel of $i = 1, ..., N$ individuals and $p = 1, ..., P$ GPs, observed in each period[23] $t = 1, ..., T_i$. The model is specified as follows:

$$y_{it} = \sum_{a=51}^{70} \alpha_a A_{a,it} + \beta CI_{it} + \sum_{d=0}^{4} \gamma_d TTD_{d,it} + \delta x_{it} + t_t + \nu_i + \zeta_{p(i,t)} + \epsilon_{it} \quad (1.1)$$

y_{it} is the outcome of individual i at time t, representing, alternatively, total HCE and expenses for hospital and day hospital admissions, outpatient visits, and pharmaceuticals. A_a is the set of age dummies, with $a = 50$ the omitted category. In this specification, α_a captures the effect of age on y non-parametrically, allowing

[22]Models theorizing variations in HCE as a result of interactions between patients and physicians characteristics are developed by Chandra and Skinner (2012) and Cutler et al. (2019). In the Thesis Appendix, we present a theoretical model drawn from the cited authors, with some modifications introduced to adapt it to the Italian institutional setting.

[23]As individuals and GPs enter and exit the panel each year, the total number of observations is given by $N^* = \sum_{i=1}^{N} T_i$, with T_i the number of observations for the individual i.

any functional relationship between age and HCE. CI includes the number of co-morbidities, indicating the severity of the individual health condition at a given time. TTD_d is the set of dummies referred to the number of years remaining until death. Following the existing literature (Atella and Conti, 2014; De Meijer et al., 2011), the categorical variable for time to death is constructed so that it ranges from 0 to 5, with $TTD = 0$ at the time of the demise and $TTD = 5$, the omitted category, for those that are at five or more years from death and for survivors[24]. The vector x includes the area of residence (Urban area or Province of Milan), citizenship (European or non-European), and the release of the income-related exemption. Other confounders are captured by time, individual, and GP fixed effects, represented, respectively, by t_t, ν_i, and $\zeta_{p(i,t)}$. t_t includes dummy variables for each year to control for yearly changes that simultaneously affect all the individuals in the sample, such as price changes, technology progress, budgetary policies, and diseases epidemiology. Individual and GP fixed effects instead allow us to take into account the heterogeneity across individuals and practitioners by capturing the effect of unobserved characteristics such as gender, cohort, education, genetic factors, and lifestyles, for individuals, and ability, previous training, preferences, and behavior-related traits while for GPs.
Finally, ϵ_{it} is the model residual[25].

Given this set-up, we face the problem of the perfectly linear dependence among age, time, and cohort. The first two factors are included in our model as regressors, while time-invariant cohort effects are captured by individual fixed effects. The contemporaneous presence of all three factors precludes their effects from being separately identified, as, at a given point in time, $A = t - c$, with c indicating the year of birth. One solution often applied is ignoring one of the three independent variables, letting the other two capture all or part of the effect of the third. However, age, period, and cohort effects represent three distinct ways in which health can change over time and constitute different sets of causal factors[26].

[24]We also estimate a model where TTD is allowed to take the highest possible value, i.e. $TTD = 8$, assigned to survivors and those who are 8 years or more from death. Results are reported in Figure 1.B.1a in Appendix 1.B and show that HCE start their increasing trend even before 8 years prior to death. However, in this way, the effect of TTD is estimated on the population of individuals who remain in the sample for all 10 years of observation, with the deceased dying in the last year available. It could generate collinearity issues between TTD and age, especially when subsamples are analyzed, with the number of those who are observed for longer time being even smaller. For this reason, we prefer to follow the literature and model TTD in order to consider only the last 5 years of life.

[25]To test for the presence of multicollinearity, we report a correlation matrix (Table 1.B.3) and the centered variance inflation factors (VIF) for the independent variables specified in a linear regression model without fixed effects, along with their reciprocals (Table 1.B.2). The correlation matrix shows that no couplets of independent variables are highly collinear. Moreover, by using the rule of thumb on which most analysis rely (Chatterjee et al., 1986), we do not observe strong evidence of multicollinearity, as the mean of all the VIFs is not considerably larger than 1. Hence, results show that our model is fairly parsimonious

[26]Understanding what mix of age, period, and cohort effects causes changes in health is of

First, individuals age, meaning that they change as they progress through their life course, independently of cohort membership and time period. Second, changes can occur over time due to differences between cohort groups, whereby as new cohorts replace old cohorts, the social composition and thus the health of society as a whole can change, regardless of the process of aging and time. Third, changes can occur as a result of period effects, whereby passage through time results in a change in health, independently of the age and cohort of the individual (Bell and Jones, 2015). Hence, an analysis that attempts to describe the evolution of expenditures in terms of only two of these dimensions is likely to be subject to omitted variable bias (OVB). To avoid biased results, we estimate all three factors and impose the constraint that there exists a short time interval, 2016-2017, over which the period effects do not vary[27]. With this restriction, the relationship between age, cohort, and time is no longer perfectly linear, with each of them now being allowed to be estimated. Note that the constraint on the years 2016-2017 is justified by the fact that the unconditional total HCE and expenditures for each healthcare service remain relatively constant between these two years[28], as illustrated by Figure 1.B.2 in Appendix 1.B.

Another issue is the potential endogeneity of TTD, arising from the correlation between the regressor and the error term. In this setting, such a correlation emerges from two sources. First, it is due to omitted variables that are correlated to those included in the specification. For example, if health status were unobservable, this would be part of the error term, which, in turn, would be correlated with TTD, as the latter is mostly linked to the individual's health condition. Second, endogeneity arises because of simultaneity or reverse causality between TTD and healthcare expenditures. It happens because the use of medical services may improve the individual health status and extend life, influencing the remaining life expectancy. In this case, the variable TTD is determined partly as a function of y_{it} and the regressor and the error term are generally correlated. A number of studies address the problem of reverse causality implementing an instrumental variable strategy (Costa-Font and Vilaplana-Prieto, 2020; Felder et al., 2010; Karlsson and Klohn, 2011; Stearns and Norton, 2004). Unfortunately, our data

great importance since different combinations can have different public health policy implications. It is especially relevant in analyses of longitudinal datasets describing the characteristics of elderly populations, whose trends have been demonstrated to result from a composite of aging, period, and cohort effects (Blanchard et al., 1977).

[27] According to the work of Mason et al. (1973), age, cohort, and period effects are estimable under the assumption that two coefficients are equal within one of the three dimensions. It means assuming that any two ages, periods, or cohorts have identical effect parameters.

[28] When all other adjacent pairs of years are taken as omitted categories, the increase (reduction) observed in the average unconditional expenditures between the two years is reflected in an increase (reduction) of the age coefficients, making the latter dependent on the choice of the reference years. However, according to the evidence reported, there is no reason to believe that the grouping imposed is not valid, allowing the model to produce correct and non-arbitrary inference.

lack appropriate instruments, making it difficult to deal with the simultaneity between TTD and HCE. On the other hand, we mitigate omitted variable bias in several ways. First, the inclusion of the number of co-morbidities as a regressor allows us to control for the fact that it is not TTD itself, but the health condition experienced before death which drives the demand for healthcare services, with time to death acting as a proxy for individual health status[29] (De Meijer et al., 2011; Howdon and Rice, 2018). Second, the inclusion of individual fixed effects limits OVB by reducing unobserved heterogeneity related, for example, to genetic traits and lifestyles. The same reasoning applies to GP fixed effects. According to Breyer et al. (2015), when medical treatment is decided upon, the physician and the patient will weigh the risks involved against the potential gains, which depend upon the patient's general health status, and his life expectancy. It implies that more will be spent on those patients who will profit from the treatment for a more extended time period[30]. Hence, by including GP-fixed effects, we control for the practitioner's preferences about patient care in the end-of-life period and his or her ability to predict the patient's life expectancy and define the right care path, conditional on the treatments that could be provided.

The empirical strategy described here has been chosen following the extensive Labour Economics literature using employees-employers fixed effects models (Card et al., 2013; Jinkins and Morin, 2018; Torres et al., 2018; Woodcock, 2015a). The advantage of using this model, adapted to an individual-GP panel, is that it allows to net out both practitioner- and individual-specific explanantions for differences in the effect of age, co-morbidities and TTD on healthcare expenditures. Once all these characteristics are controlled for, and with standard errors clustered at the individual level to account for the within-individual correlation in HCE over time, the remaining bias, if any, should be negligible. Note, however, that such models do not deal with the challenges of healthcare expenditures distribution, typically characterized by zero-mass and over-dispersion, addressed by a large part of the related existing literature (Atella and Conti, 2014; Felder et al., 2010; Seshamani and Gray, 2004) through the use of non-linear two-part models. To detect differences in the results between the two specifications, as a robustness check, in Section 1.7, we compare our baseline findings with those obtained by using a two-part model.

[29]Evidence is provided in Figure 1.B.1b in Appendix 1.B where we report the estimated coefficients on TTD from a specification where all factors are included excepts the number of co-morbidities and those from the preferred specification. Results show that when morbidity is not added, the effect of TTD is overestimated.

[30]Note that the relationship between TTD and HCE is non-monotonic. On the one hand, a lower value of TTD indicates greater proximity to death and, therefore, worse health and higher HCE for emergency treatments to avoid or at least postpone death. On the other hand, a higher value indicates a better chance to benefit from medical treatments for a longer time, leading to higher HCE.

1.6 Results

1.6.1 Variance decomposition

To examine the extent to which individual's and GP's characteristics contribute to the observed variation in HCE across individuals, we estimate the model described in Equation 1.1 and decompose the variance in total HCE and expenses for hospital and day hospital admissions, outpatient services, and pharmaceutical. The hypothesis we test is that, while a part of variation across individuals is due to differences in health conditions, a non-negligible share may be related to the way such health conditions are treated by the GP. The variability in healthcare expenditures is decomposed as follow:

$$\begin{aligned} Var(y_{it}) = {} & Var(\beta x_{it}) + Var(\nu_i) + Var(\zeta_{p(i,t)}) \\ & 2Cov(\nu_i, \beta x_{it}) + 2Cov(\zeta_{p(i,t)}, \beta x_{it}) + 2Cov(\nu_i, \zeta_{p(i,t)}) + Var(\epsilon_{it}) \end{aligned} \tag{1.2}$$

Decomposed variances are summarized in Table 1.2, which reports the variability of the dependent variable (y_{it}), model residuals (ϵ_{it}), estimated individual (ν_i) and GP ($\zeta_{p(i,t)}$) fixed effects, the variance of time-varying regressors (βx_{it}) and the covariances between the last three components. Since Var(y_{it}) is the sum of the variances of the terms on the right-hand side of Equation 1.1, the contribution of each component is normalized so that the sum is equal to 100.

The variability of total HCE is composed of nearly 40% by individual observed and time-invariant unobserved differences ($\beta x_{it} + \nu_i$) and about 60% by heterogeneity due to unobserved time-variant shocks (ϵ_{it}). The first finding is mainly driven by the way the variability of expenditures for out-of-hospital services is formed, while the second one by the composition of inpatient expenses variance. Indeed, in line with the results found by Felder et al. (2010), the explained variation is higher

Table 1.2: Variance decomposition.

	Total	**Hospital**	**Day Hospital**	**Outpatient**	**Pharma.**
Var(y_{it})	100	100	100	100	100
Var(βx_{it})	11.82	6.95	0.73	6.09	11.85
Var(ν_i)	28.50	22.10	27.56	53.88	49.26
Var($\zeta_{p(i,t)}$)	0.81	0.87	0.64	0.58	0.56
Var(ϵ_{it})	60.27	72.88	72.14	40.68	32.63
2Cov(ν_i, $\zeta_{p(i,t)}$)	-1.44	-1.61	-1.18	-0.95	-0.92
2Cov(ν_i, βx_{it})	0.08	-1.16	0.14	-0.28	6.57
2Cov($\zeta_{p(i,t)}$, βx_{it})	-0.04	-0.04	-0.02	-0.01	0.06

for outpatient and pharmaceutical expenditures than for inpatient expenses. For out-of-hospital services, covariates and individual fixed effects account together for about 60% of the total variance. On the contrary, observed and unobserved individual traits contribute less to the variability in inpatient (hospital and day hospital) expenses, which instead present the highest variability of model residuals. In that case, more than 70% of variability remains unexplained, reflecting the typical features of healthcare analyses and, in particular, those involving hospital care. Inpatient expenses are particularly characterized by the intrinsic randomness of the demand driven by the occurrence of unanticipated health shocks, which make many health expenditures impossible to be foreseen.

While individual heterogeneity significantly contributes to the overall variability in total HCE, a minor role is found for practitioners. The latter exhibit less dispersion, contributing to the overall variability for less than 1%[31]. This result indicates limited heterogeneity across GPs, which is generally interpreted as evidence of appropriate use of resources and efficiency (Scott, 2000). The decision-making process aimed at defining the care path carried out by the practitioner involves complex and refined judgments. Hence, those unobserved time-invariant GP factors that may drive to suboptimal decisions (such as cognitive biases, inadequate knowledge, risk aversion and other habits), may generate variations across practitioners, often interpreted as evidence of misuse of health treatments, wasteful spending, and, hence, inefficiency[32] (OECD/EU, 2016).
The covariance between individual and GP fixed effects is also little[33], suggesting

[31] The related literature shows an average explained variance of roughly 75%, of which 60% is across patients and 9% across practitioners (Harris et al., 2011; Mousquès et al., 2010; Omar et al., 2008; Sullivan et al., 2005). However, in these cases the estimation is carried out by using multilevel models where individual's and practitioner's contributions are estimated as random effects, thus precluding any correlation of such effects with the observed characteristics included in the analysis and between each other. Moreover, hierarchical models assume patients to be strictly nested within GPs. While this does not raise any concern for cross-section data where individuals are observed for only one period, it may be excessively restrictive in panel data with individuals moving among practitioners over time.

[32] Note that other results would probably be obtained if the estimations were performed by using datasets covering more than one Italian Region. Under the Italian healthcare system, each Region has direct responsibility for both government and expenditures for the achievement of the country's health objectives and has exclusive competence in the regulation and organization of services and health protection activities, and in the criteria for financing local health agencies and hospitals. Hence, clinical decisions are likely to be relatively homogeneous across healthcare providers within each Region, concealing possible differences in terms of cognitive biases, inadequate knowledge, risk aversion, and other habits, which may lead to suboptimal decisions and inefficiency (OECD/EU, 2016).

[33] Note that the estimated GP fixed effects and the covariance between GP and individual effects are probably biased because of a small number of movers for each practitioner (data are not reported). As a result of this limited mobility bias, the variance of GP effects tends be overstated, while the covariance between GP and individual effects tends to be negatively biased, since those two terms enter Equation 1.2 additively. Bonhomme et al. (2020) find that the fewer the number of movers per GP, the larger the variance of GP effects and that the covariance between individual and GP effects increases monotonically as the number of movers per GP increases.

limited or absent sorting of patients to practitioners. However, if it is not the case and patients move among practitioners in a non-random way, our analysis would suffer from omitted variable bias affecting estimated individual and GP fixed effects and estimated returns to those observable characteristics correlated with the individual-GP match. We test for endogenous mobility in Section 1.7, where we augment our model by including match fixed effects.

The results shown in this section provide new evidence to the debate concerning the role of demand- and supply-side factors in explaining the variation in individual HCE. Our findings indicate that, while supply- and, in particular, GP-specific factors are relatively unimportant, demand attributes exclusively determine variations in HCE across individuals, with the substantial portion of unexplained variation to be attributed to the occurrence of unanticipated health shocks. Given this result, the remainder of the chapter is devoted to a more in-depth analysis of individual characteristics and, in particular, those reflecting the dynamic of healthcare expenditures over the life cycle.

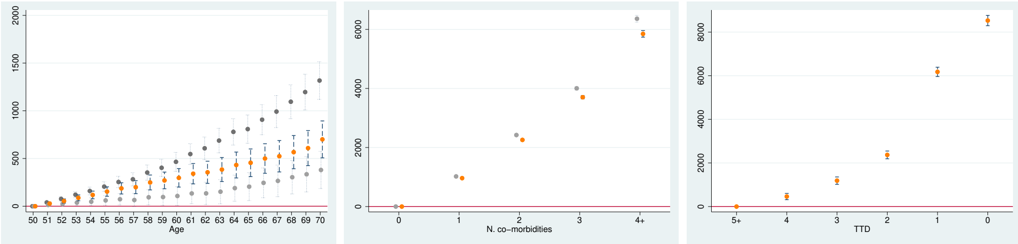
1.6.2 Total HCE and expenditures by service

Figure 1.3 illustrates the contribution of age, number of co-morbidities, and TTD to the evolution of total HCE and expenses for hospital and day hospital admissions, outpatient services, and pharmaceuticals, according to different specifications.

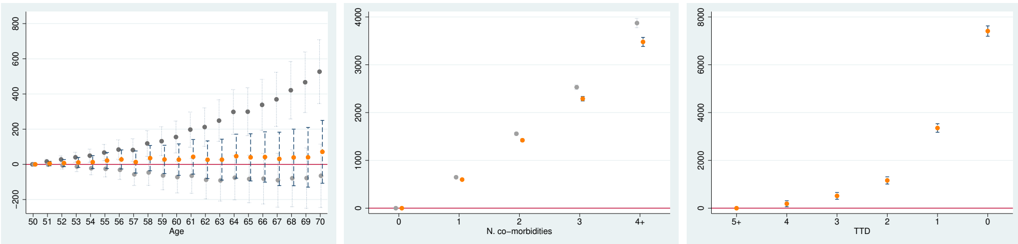
We first analyze total expenditures to provide a general picture of the HCE pattern. The first panel of Figure 1.3a shows a positive and strong gradient in age when only demographic and socio-economic characteristics are taken into account (dark grey dots). Age coefficients then reduce when the number of co-morbidities is included in the regression (light grey dots). In particular, at age 70, they reduce by 71%, resulting from both a downward rotation of the age profile and a decrease in the curve convexity. It suggests that the health condition deteriorates as individuals age; moreover, such a worsening is more and more severe over time, leading to a marginal increase in expenditures, a pattern discussed in more detail in Section 1.8. While such a reduction in the age gradient is not surprising when health characteristics are included, the increase in the effect of age when TTD is added (orange dots) is less expected. In that case, the estimated age coefficients increase by 84% at age 70 with respect to the previous specification, a result in contrast with the red herring hypothesis. Figure 1.B.3 in Appendix 1.B illustrates that total HCE is decreasing in age in the last two years of life and, with the severity of the health condition kept constant, it indicates that premature death implies higher expenses than those incurred by older individuals. For the latter, the demise is probably due to complications of already existing diseases whose worsening has probably been predicted and adequately treated; instead, most of the health shocks leading to death at an early age are more often unanticipated,

Figure 1.3: Impact of individual characteristics on total HCE and expenses for different spending categories.

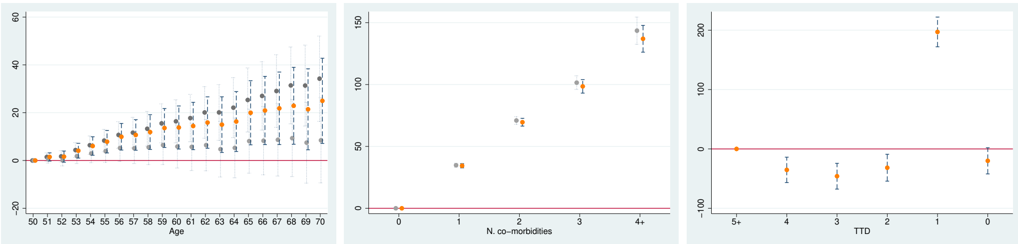
(a) Total HCE



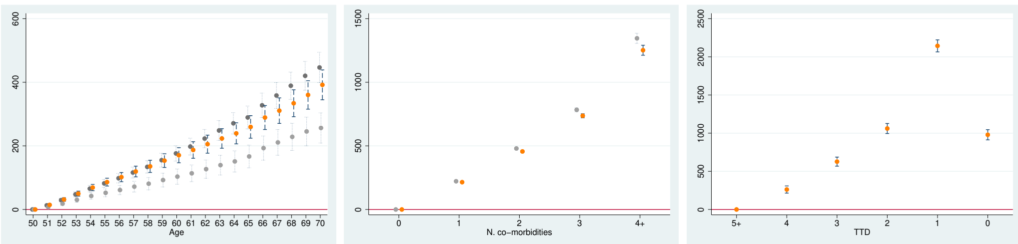
(b) Hospital expenditures



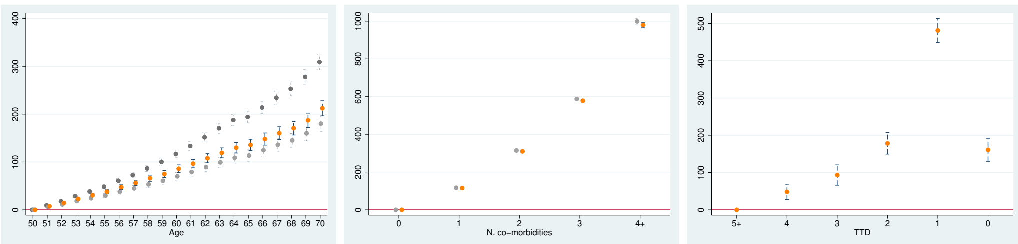
(c) Day hospital expenditures



(d) Outpatient expenditures



(e) Pharmaceutical expenditures



Note: Regressors included in each specification:
Dark grey dots: age dummies, citizenship, residence area and income-related exemption, time, individual and GP fixed effects.
Light grey dots: age dummies, citizenship, residence area, income-related exemption and number of co-morbidities, time, individual and GP fixed effects.
Orange dots (preferred specification): age dummies, citizenship, residence area and income-related exemption, number of co-morbidities and TTD, time, individual and GP fixed effects.

requiring more intensive treatments not only for the cure but also for the diagnosis of the underlying condition. A second non-alternative explanation involves what Breyer et al. (2015) call the 'Eubie Blake effect'[34]. According to the authors, patients are treated more aggressively if the results of the treatments pay off over a longer time span, i.e., if individuals are expected to live long enough to enjoy the benefits of the treatments. In our analysis, the increase in the effect of age when TTD is taken into account, which is quite substantial, hence may mirror the medical profession's willingness to perform expensive treatments on younger patients. In any case, the results estimated from the preferred specification where also TTD is added show a statistically significant positive and linear relationship between total HCE and age, with 70-years-old individuals spending about 700€ per year more than those who are 50. Given the average unconditional total HCE of 670€ for 50-years-old individuals, it indicates, in absolute terms, overall expenditures of nearly 1,370€ (700 + 670€) for those aged 70, a value that is slightly above the average total HCE for the whole population.
Regarding the effect of the number of co-morbidities and TTD, it is estimated to be substantial. The second panel of Figure 1.3a shows that having only one co-morbidity compared to having zero leads to higher expenditures of about 1,000€ while having four or more of nearly 6,000€. Interestingly, when TTD is also taken into account, the impact of the number of co-morbidities does not significantly reduce (-8% at 4+ co-morbidities), showing that this factor exerts an independent effect on total HCE. The third panel instead illustrates the evolution of total HCE over the last five years of life. At the time of death ($TTD = 0$), individuals spend nearly 9,000€ (about two times the standard deviation of total HCE) more than those at five or more years from death and survivors, corresponding to nearly 10,000€ per year in absolute terms (given average unconditional total HCE for those at TTD=5 of about 1,000€).

By looking at the other panels of the figure, the heterogeneity of the effect of age, number of co-morbidities, and TTD among the different healthcare services is immediately visible. The first interesting evidence is that the increase in total HCE between age 50 and 70 is mainly driven by expenditures for out-of-hospital services. Indeed, the effect of age on hospital expenses is not statistically significant when the individual condition is taken into account (Figure 1.3b, first panel), meaning that there is no difference in hospital expenditures among individuals of equal health status. Instead, the effect is statistically significant and positive on outpatient and pharmaceutical expenses (Figure 1.3d and Figure 1.3e, first panel). Differently from the age profile, the morbidity and end-of-life profiles of total HCE

[34] James Hubert Blake, known as Eubie, was an American pianist and composer. On his 100th birthday, he said: ≪If I'd known I was going to live this long, I would have taken better care on my self≫. Breyer et al. (2015) cite this quote to explain their findings.

are mainly driven by hospital expenses. It indicates a progressive shift towards more complex treatments, usually provided through expensive high-tech inpatient services, as the severity of the health condition increases (Breyer et al., 2010; French et al., 2017). The heterogeneous evolution of expenses for the different services by TTD provides clear evidence of such a substitution. While hospital expenditures continue their growing trend, those incurred for all other services fall sharply in the year of death. Expenditures for day hospital admissions are even lower than those incurred by survivors or individuals at five or more years from death, with the sole exception of the year before the demise (Figure 1.3c, third panel).

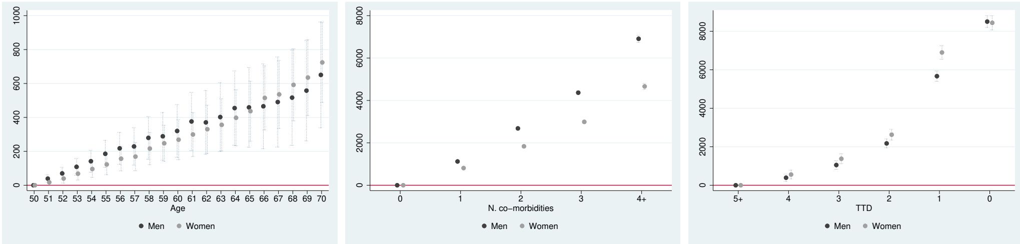
1.6.3 Heterogeneous analyses

Gender

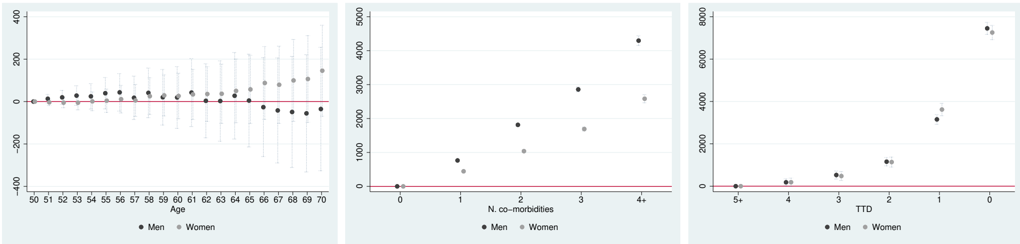
With individual fixed effects, the time-invariant impact of gender on HCE is absorbed by the individual-specific component. Hence, to investigate differences between men and women, we replicate our estimations separately on both. Figure 1.4 shows that the relationship between age and all spending components is very similar between men and women. The most noticeable difference concerns the expenditures profile by number of co-morbidities, with men generally spending more than women. For example, total HCE for men with 4 or more conditions is about 7,000 € more than those with zero co-morbidities and about 1.5 times more than expenditures incurred by women with the same health status. According to the existing literature (Almagro et al., 2010; Marrie et al., 2016), it is related to the type and combination of co-morbidities. Hence, we estimate the relationship between the number of co-morbidities and total HCE by gender and primary diagnosis, whose definition is described in Section 1.6.4. Differences are present for almost all the pathologies considered, with large gender gaps especially in the case of digestive system, musculoskeletal and infectious disease, and cancer (Figure 1.B.4 in Appendix 1.B). It means that, for these specific diseases, the combination of co-morbidities is such that men health condition is likely to be more severe than that of women, a feature that the raw number of additional diseases is not able to capture, resulting in higher HCE for the same number of co-morbidities. Expenditures by gender also depend on the different use of the healthcare services. The literature claims that women generally tend to rely significantly more on outpatient services and pharmaceuticals than males (Gabriele et al., 2006; Owens, 2008; Williams et al., 2017), with the latter spending more for inpatient services. This is particularly reflected in the expenditures evolution by TTD, where women are found to spend slightly more on out-of-hospital treatments. In any case, by comparing the estimations by gender with those carried out on the whole sample, we note that the latter are slightly closer to those of men.

Figure 1.4: Impact of individual characteristics on total HCE and expenses for different spending categories by gender.

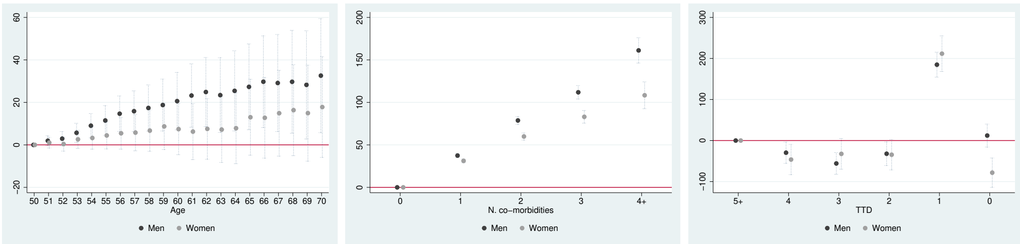
(a) Total HCE



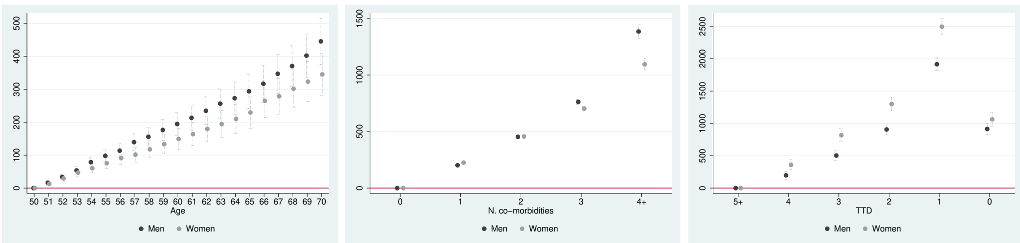
(b) Hospital expenditures



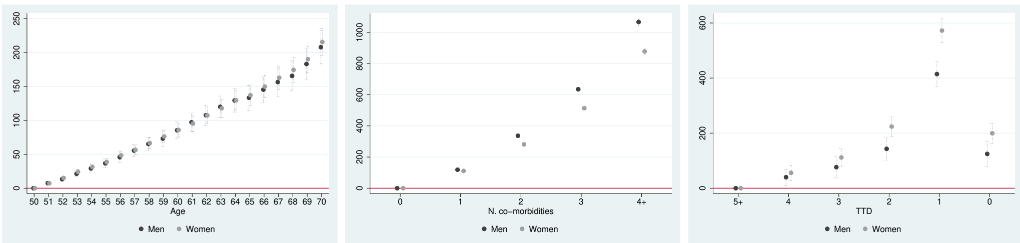
(c) Day hospital expenditures



(d) Outpatient expenditures



(e) Pharmaceutical expenditures



Survival status

In most existing works testing the red herring hypothesis, the estimation is generally done separately for survivors and deceased. Hence, in this section, we carry out heterogeneous analyses by survival status to deal with the differences in HCE patterns between the two groups. Results are reported in Figure 1.5.

For the survivors, the effect of age reflects that estimated for the whole population[35]. It is instead never statistically significant for the deceased, with the impact of TTD completely absorbing that of age due to the collinearity between the two terms (see Figure 1.B.5 in Appendix 1.B reporting the results from different specifications). Indeed, since an individual who gets one year closer to death also gets one year older, the impact of TTD is picked up by age if the former is not controlled for. For the deceased group, the evolution of expenditures by TTD is similar to that observed in Figure 1.3, with the difference that here the reference category is represented only by deceased individuals who are at five or more years from death and not also by survivors. It implies a reduction in the estimated coefficients compared to the baseline estimation, which results to be significant especially for total and hospital expenses. However, the effect of TTD for the deceased remains statistically significant and large in magnitude for each type of service.
To investigate whether the evolution of expenditures in the last years of life changes with age, we replicate our estimation by dividing the deceased group into four age-at-death classes. The latter have been constructed so as to have roughly the same number of individuals in each group[36] and are age 51-60, 61-65, and 66-70 (Figure 1.B.6 in Appendix 1.B). Interestingly, for individuals in the oldest age group, hospital expenses increase only in the last two years of life up to about 6,000€ more than those who are at 5 or more years from death. It means that, once age and morbidity are controlled for, there is no difference in expenditures in previous periods and that the path leading to death is significant only when the demise is extremely close. Also, individuals who die later have slightly lower total expenditures than the other two groups at any given time to death. This result recalls the difference between unanticipated shocks and those that have already occurred, as well as the already mentioned 'Eubie Blake effect' (Breyer et al., 2015), i.e., the doctors' preference to treat older patients less intensively, keeping the severity of the health condition constant.

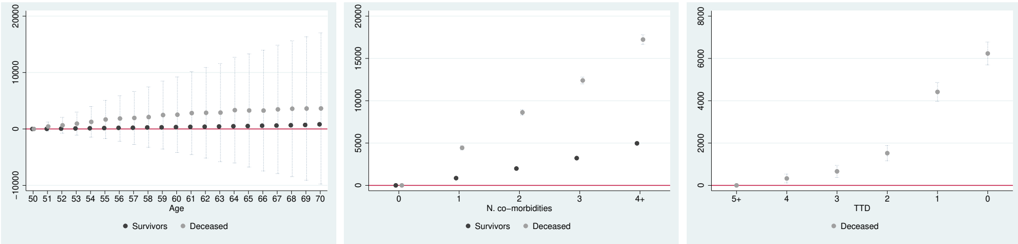
The difference in health status between deceased and survivors is immediately visible from the co-morbidity HCE profiles. Whatever the type of health service

[35]Note that, for the population of survivors, the estimation is carried out without controlling for TTD, as the variable would have the same value for the whole sample in consideration.

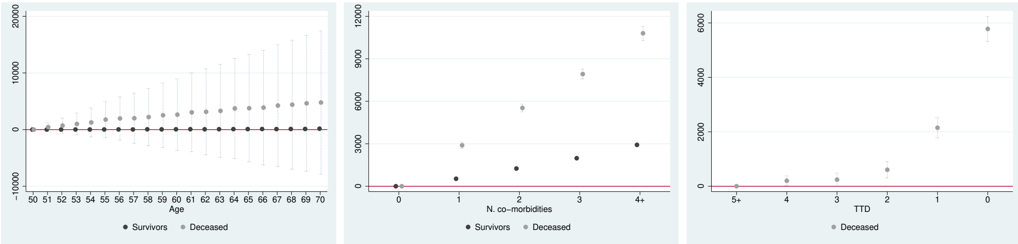
[36]Individuals who die at 50 years of age are not included because, since everyone enters the sample at 50 years of age, they would be observed for only one year, making within-individual estimations unfeasible.

Figure 1.5: Impact of individual characteristics on total HCE and expenses for different spending categories by survival status.

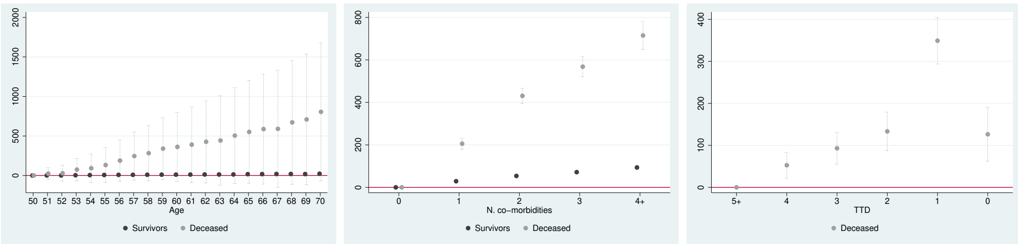
(a) Total HCE



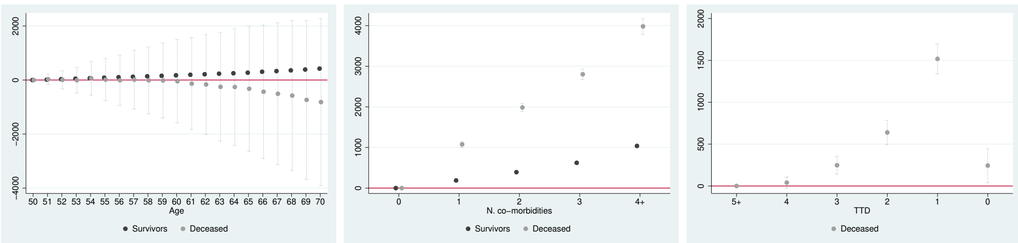
(b) Hospital expenditures



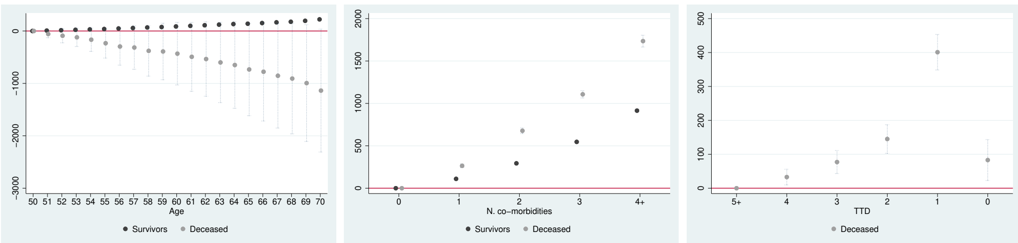
(c) Day hospital expenditures



(d) Outpatient expenditures



(e) Pharmaceutical expenditures



considered, the latter show a gap that widens as the number of co-existing diseases increases. Overall, those dying during the observed period who present four or more co-morbidities spend nearly 3.5 times more than survivors with the same number of additional diseases and about 17,000€ more than those with no additional conditions. To give an idea of the magnitude of this value, note that it corresponds to almost four times the standard deviation of total HCE. However, while the smallest difference is observed for pharmaceutical expenses, the largest one is found for hospital expenses. As already observed in the heterogeneous analysis by gender, this result is probably driven by different combinations of co-morbidities between the two groups and, consequently, different treatments and costs. In any case, the expenditure patterns estimated on the whole sample mainly reflect those found for the survivors, except for TTD, whose effect is estimated exclusively on the population of the deceased.

1.6.4 Major Diagnostic Categories

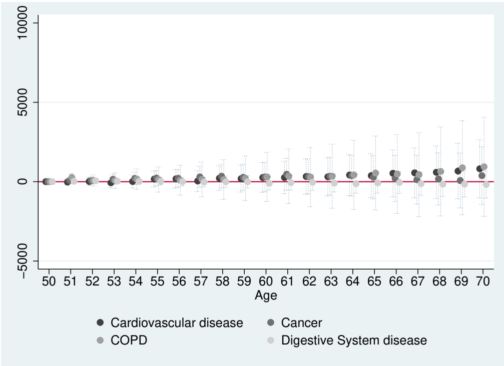
Individual healthcare expenditures significantly vary according to the presence of specific diseases and their type (OECD, 2013, 2016). To investigate how the relationship among age, morbidity, and TTD and HCE changes according to medical specialty, we carry out heterogeneous analyses by Major Diagnostic Categories (MDCs), aggregations of Diagnostic Related Groups (DRGs) representing epidemiologically relevant groups of patients with similar problems and treatment patterns. The MDCs are related to the specialty for which hospital or day hospital admission is required; hence, the sample considered comprises only individuals who experience at least one ordinary or diurnal hospitalization during the period of observation. Since hospital admissions may occur more than once over time and may be required for different diseases, we identify a primary diagnosis for each individual in the sample. It is represented by the MDC related to the highest cumulative hospital expenses[37] and characterizes the individual for the whole period. In this way, expenditures are allocated to different disease groups in a mutually exclusive manner.

Results are illustrated in Figure 1.6 for total HCE and in Figures 1.B.7-1.B.9 in Appendix 1.B for the spending categories. In all figures, results are reported by dividing the MDCs into two groups. The first group, 'Primary Care diseases', combines disorders (cardiovascular diseases, tumors, Chronic Obstructive Pulmonary Disease (COPD), and diseases of the digestive system) that can be more effectively prevented and controlled within the outpatient and primary care setting (OECD, 2019a). Moreover, these conditions together affect more than half of the population (as reported in Table 1.1) and are related to roughly 50% of

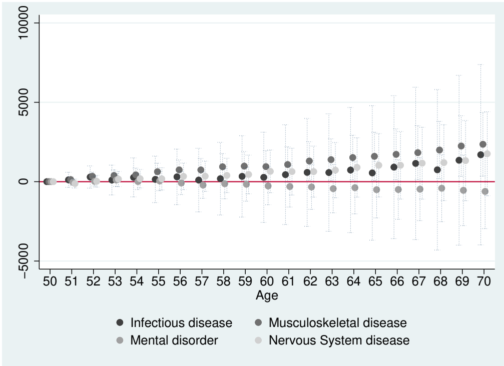
[37]First, we calculate overall expenses for each MDC by summing expenditures incurred each year. Then we select the MDC with the highest value. See footnote [17].

Figure 1.6: Impact of individual characteristics on total HCE by MDC.

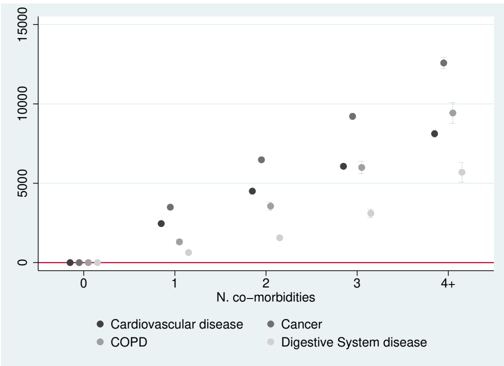
(a) Primary Care diseases



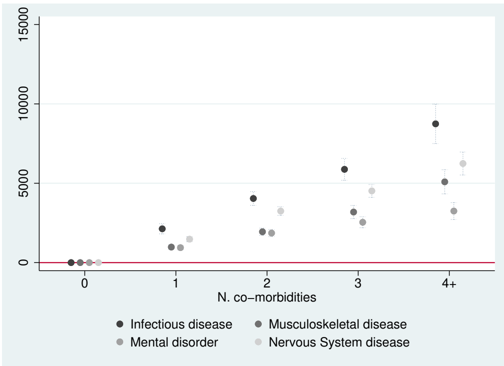
(b) Other diseases



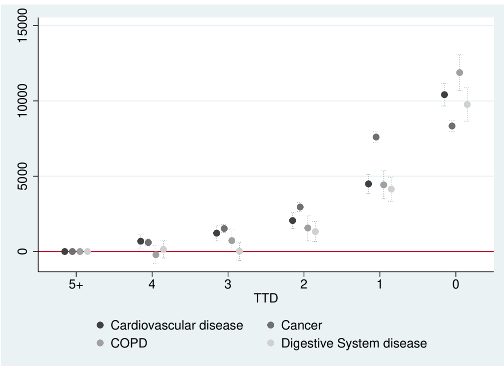
(c) Primary Care diseases



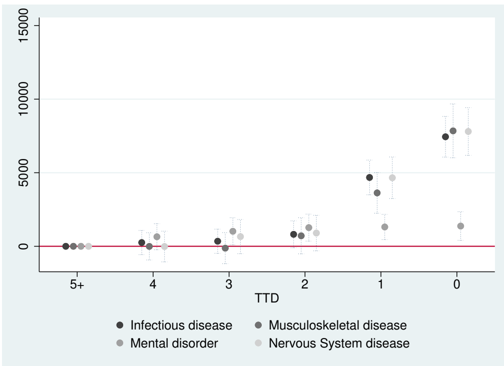
(d) Other diseases



(e) Primary Care diseases



(f) Other diseases



hospital admissions and expenditures recorded in our dataset. The second group, 'Other diseases', includes all the other MDCs (infectious diseases, musculoskeletal diseases, mental disorders, and nervous system diseases), except the residual category 'Other'[38].

The relationship between age and total HCE is generally not statistically significant. This result is driven by the hospital expenditure patterns, which show no differences in expenses between individuals of different ages, whatever is the disease analyzed. It indicates that when individuals with similar conditions are taken into account, hospital costs are exclusively determined by the evolution of the different pathologies, which leads, in some cases, to premature death. On the contrary, most of the primary diseases present a linear increase in HCE for out-of-hospital services by age. In these cases, the deterioration of the health status caused by aging still plays a crucial role in shaping expenditures patterns among individuals aged 50-70. For outpatient expenses, the highest growth in expenditures is observed in individuals affected by cancer. At the age of 70, cancer patients spend on outpatient services almost 1,500€ more than a 50-year-old and 1.75 times more than those affected by cardiovascular diseases and COPD. Regarding pharmaceutical costs, expenditures increase faster for individuals with cardiovascular diseases, who, at age 70, spend 1,000€ more than the youngest and 2 times more than those with cancer and COPD.

Regarding individuals' health conditions, this analysis well approximates the severity and the stage of the primary disease, allowing the identification of the pathologies that, when combined with others, are linked to the highest costs, reflecting greater severity of the health condition and greater need for medical care. The disease showing the largest impact of the number of co-morbidities on total HCE is cancer. When it is the primary diseases, the presence of co-morbidities largely amplifies the severity of the health condition (Buddeke et al., 2019; Geraci et al., 2005; Kendir et al., 2018), as well described by the evolution of expenditures for outpatient and day hospital services by number of co-morbidities. Cancer individuals with 4 or more conditions spend for outpatient treatments about 3,000€ (about two times the standard deviation of outpatient expenditures) more than those with no additional diseases and 3 times more than those affected by cardiovascular and digestive system diseases and COPD. In the case of out-of-hospital treatments, the effect of the number of co-morbidities on HCE is relatively homogeneous for the other conditions. Given the large number of practices offered in inpatient settings and the different costs associated with each of them (de Meijer et al., 2013), greater heterogeneity is observed instead for hospital expenditures, with cancer, cardiovascular diseases and COPD showing

[38] The latter is not included because it combines diseases that are not related each other. See footnote [18].

the largest impact of number of co-morbidities on hospital expenditures.

Finally, TTD estimates allow us to analyze how the evolution of total HCE differs in the end-of-life period for different diseases. For many of the pathologies in the category 'Other diseases' (Figure 1.6f), expenditures deviate from their trend only in the last two years of life to grow exponentially until the time of death. These are typically acute diseases, characterized by a rapid evolution with sudden onset, short duration, and high severity. Moreover, the magnitude of the impact is relatively homogeneous among the pathologies within this group, except for mental disorders. For the latter, the expenditures pattern grows from the fourth year before death and then remains stable, with a level of total expenditures in $TTD = 0$ of about one-fifth that observed for the other diseases. Possible explanations are premature demise from self-violence, poor access to medical care, and under-treatment (Shalev et al., 2017).
More extended expenditures patterns by TTD are generally observed for those MDCs with a high incidence of long-lasting conditions. For example, total HCE of individuals affected by cardiovascular disease and cancer probably start their increasing path before the fifth year prior to death, indicating a slow progression of the underlying condition. Among primary care diseases, a general homogeneity in total HCE is also observed. However, it is less marked in the last two years of life, especially for outpatient and pharmaceutical expenditures. In the latter case, cancer patients spend much more than individuals with any other disease and almost twice as much as those affected by cardiovascular diseases do.

According to our findings, variations in HCE exist across individuals affected by different pathologies, with cardiovascular disease and cancer being the conditions generally associated with the highest severity and, consequently, healthcare expenditures. In general, the disease-specific pattern of expenditures is related to their nature of acute or long-lasting disorders, with the underlying health process well approximated by the evolution of HCE in the last years of life. End-of-life expenditures begin to increase long before death for long-lasting diseases, whose symptoms have probably manifested earlier, while the growth is sharper for acute conditions.

1.6.5 Chronic diseases and disability

Given the results reported in the previous section, as a last heterogeneity exercise, we analyze how the relationship between our factors of interest and HCE changes between non-chronic/non-disabled and chronic/disabled individuals, i.e., between acute individuals and those affected by long-lasting conditions. The latter are identified as those presenting disease- or disability-related exemptions, used here as proxies for the presence of chronicity or disability[39]. Results are reported in Figure 1.7.

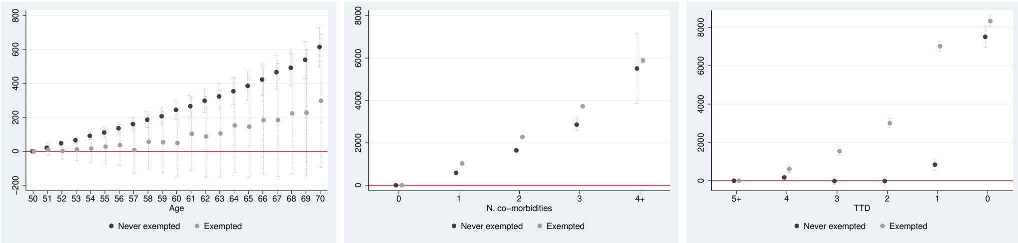
Age coefficients on total HCE of chronic and disabled individuals are non-statistically significant. It results from the combination of the positive impact of age on expenses for out-of-hospital treatments and the negative one on inpatient expenditures. This last finding is driven by the individual age, the setting, and the costs associated with the first diagnosis of chronicity and disability. First, the probability of being first diagnosed (first part of Table 1.B.4 in Appendix 1.B) is decreasing in age. It follows that the younger the individuals, the greater the likelihood that they are diagnosed the first time with a chronic condition or disability; in other words, the older the individuals, the greater the likelihood that they have already been diagnosed. Second, the diagnosis is often defined during an inpatient stay (second part of Table 1.B.4 in Appendix 1.B). In particular, being diagnosed the first time increases the probability of being hospitalized by 12% with respect to being not yet or already diagnosed. Third, unconditional hospital costs largely increase at the time of the first diagnosis and then decrease in the following periods (Figure 1.B.10 in Appendix 1.B). It follows that younger individuals, who are more likely to experience the first onset of chronicity or disability, are often diagnosed during hospitalization, which involves higher hospital costs than treating already diagnosed and under-control conditions, specific to individuals with advanced ages. It results in higher average hospital expenditures for younger individuals than for older ones.
Concerning non-exempted individuals, expenditures are increasing in age for all services, with expenses for out-of-hospital treatments growing more slowly than that observed for exempted individuals. At age 70, the latter spend for both pharmaceuticals and outpatient services about 200€ more than non-exempted. Holding constant health condition and proximity to death, this result shows a faster exacerbation of health status for chronic/disabled individuals than for non-chronic/non-disabled individuals, with the former requiring greater assistance outside the hospital or more expensive treatments.

Regarding the number of co-morbidities, we observe a negligible gap in the expenditures patterns of the two groups for hospital and pharmaceutical services. Instead, chronic and disabled individuals spend more on outpatient and day hospital services, with the difference growing in the number of co-existing diseases, indicating heterogeneity in the use of health services. For the individuals with long-lasting conditions, the type and combination of co-morbidities result in greater intensity in the use of services intended for the diagnosis of the underlying

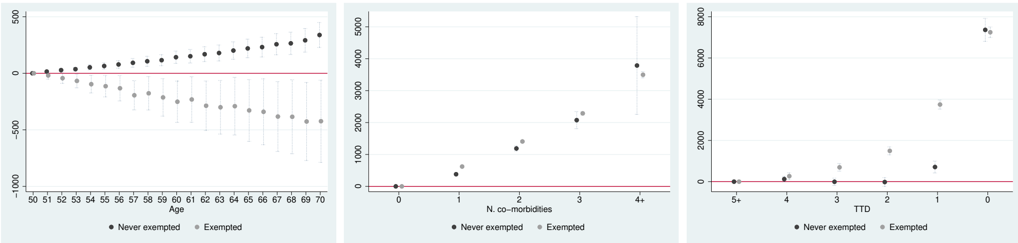
[39] Individuals are classified as chronic or disabled if exempted for an appropriate number of years during the period they are observed. In particular, the ratio between years with exemption and years of observation cannot be less than 0.3, with those with a lower ratio not included in the analysis.

Figure 1.7: Impact of individual characteristics on total HCE and expenses for different spending categories by presence of chronicity or disability.

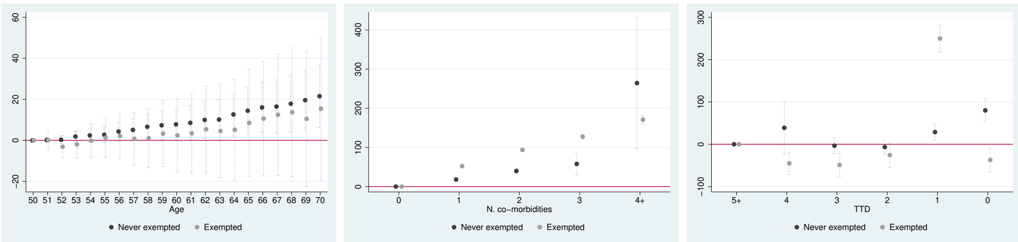
(a) Total HCE



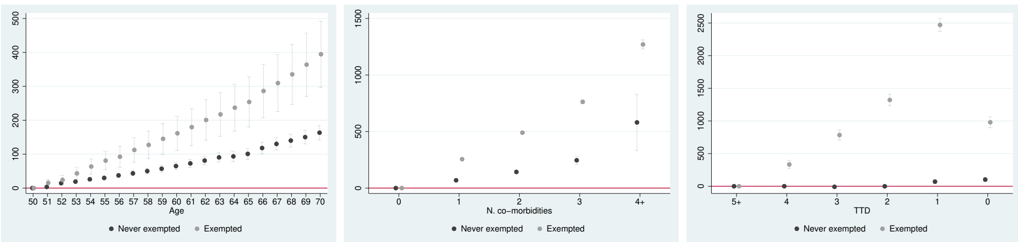
(b) Hospital expenditures



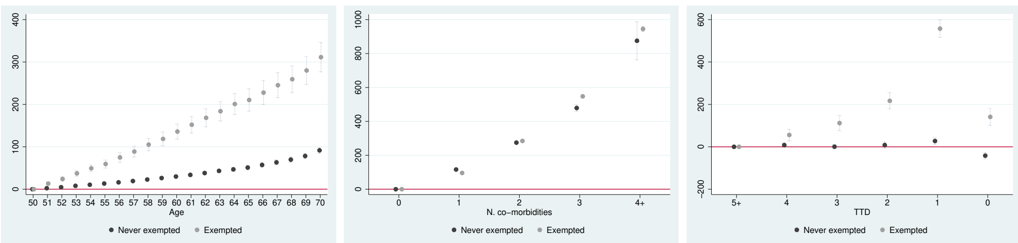
(c) Day hospital expenditures



(d) Outpatient expenditures



(e) Pharmaceutical expenditures



pathology or non-pharmaceutical treatments not requiring an overnight stay, i.e., outpatient and day hospital services. In particular, individuals affected by cancer as a primary diagnosis seem to drive this result the most, as shown by the analyses by MDC discussed in the previous section and illustrated in Figure 1.B.8.

Finally, the expenditures patterns by TTD reflect the differences observed in the previous section between individuals with acute and long-lasting illnesses. While the total HCE pattern of the exempted begins to grow exponentially probably before the fifth year prior to death, end-of-life costs of non-exempted rise significantly only in the last two years of life, with the last year presenting a level similar to that of chronic/disabled individuals[40] (about 8,000€ more than those at 5 or more years from death and survivors, which corresponds to two times the standard deviation of total HCE).

Interestingly, the results found for the entire population are driven, alternatively, by the subsample of the exempted and the never-exempted, depending on the services considered. In particular, while the contribution of age to inpatient expenditures is mainly driven by healthier individuals, that to outpatient expenses reflects the one observed for the individuals affected by chronicity or disability, as well as the impact of the number of co-morbidities (on outpatient services) and TTD (on any services).

1.7 Robustness checks

In this section, we analyze whether our main results are robust to different specifications. We model HCE differently to take into account the healthcare expenditures statistical features and test whether estimated returns to observable characteristics and individual and GP fixed effects are biased due to endogenous patients mobility among practitioners.

1.7.1 Two-part models

Healthcare expenditures data usually display a distribution with substantial skewness, manifesting in empirical densities with long and thin right tails and a considerable point mass at zero. The most common way to model a dependent variable with a large mass at zero and many positive values is to estimate a two-part model. It is based on a statistical decomposition of the density of the outcome into a process that generates zeros and a process that generates positive

[40] Note that, in the comparison between chronic/disabled and non-chronic/non-disabled patients, the exemption from co-payment may play a key role in shaping the evolution of expenses for outpatient services and pharmaceuticals, resulting in a greater share of costs in charge to the healthcare system that is unrelated to the patient's health status. Unfortunately, data do not allow us to measure the extent to which our results are due to the presence of the exemption or other health-related factors.

values. A logit or probit model typically estimates the parameters that determine the threshold between zero and non-zero values of the outcome, while several non-linear models are used to estimate the parameters that determine positive values, depending on the dataset and the dependent variable. These non-linear models accommodate skewness in natural ways, give considerable modeling flexibility, and fit healthcare expenditures extremely well[41] (Deb and Norton, 2018). Hence, two-part models explicitly allow for estimation of the extensive and intensive margins separately and take into account the source of heterogeneity also in the extensive margins, i.e., the source of heterogeneity giving rise to zero versus non-zero expenditures. However, these models have some disadvantages. With individual fixed effects, estimators of non-linear panel data models are severely biased because of the incidental parameter problem and the perfect prediction problem[42]. Moreover, although the last few decades have seen a proliferation of sophisticated statistical methods that solve these problems, their estimation is still computationally intensive, if only because each analysis requires two estimates, making it challenging to perform investigations involving several estimations. This issue is even more severe when models with fixed effects are estimated when two high-dimensional fixed effects, such as individual and GP fixed effects, are controlled for[43] (Guimarães and Portugal, 2009). For this reason, and for the undisputed advantages of netting out unobserved time-invariant factors, we carry out our analysis by using a linear regression model with fixed effects. In this section, however, we replicate the estimation by using a two-part model to investigate changes in our main results. We first model the probability that an individual has any healthcare expenditures with a probit model using the whole sample. Then we estimate the linear regression model specified in Equation 1.1 on the subset of individuals who have positive expenditures[44].
Results are reported in Figure 1.B.11-1.B.13 in Appendix 1.B. The marginal effects

[41] For example, generalized linear models (GLMs) generalizes the ordinary linear regression model by allowing the expectation of the outcome variable to be a function of the linear index of covariates, not simply a linear function of the index. In addition, GLMs also explicitly model heteroskedasticity, allowing the variance of the outcome to be a function of its predicted value by the choice of an appropriate distribution family.

[42] First, estimated fixed effects are technically inconsistent. It is caused by only having T observations to estimate each fixed parameter, so that as N grows it remain random. While in linear models this randomness gets 'averaged out', in non-linear models it does not. Second, estimated fixed effects do not exist if $y_{it} = 0$ or $y_{it} = 1$ for each t the individual is observed (Fernández-Val, 2009; Fernández-Val and Weidner, 2016).

[43] To the best of our knowledge, only in the work of Costa-Font and Vilaplana-Prieto (2020) the analysis is carried out by estimating a two-part model with fixed effects. However, the authors control for only one high-dimensional fixed effects, with the other included in the specification through the addition of dummy variables.

[44] The general practice is that any variable that is in either the first-part of the second-part model will be in both, meaning that no variables are included in one part but excluded from the other. However, given the complexity of including fixed effects discussed above, the latter are added only in the second part modeling positive expenditures.

of age, number of co-morbidities, and TTD on the probability of positive expenditures show different patterns depending on the healthcare service considered. In particular, similarities are observed within inpatient services (hospital and day hospital admissions) and within out-of-hospital treatments (outpatient services and pharmaceuticals), with the latter driving the results on the probability of total HCE. Regarding the extensive margins, the results are pretty similar to our baseline findings. The age profiles of hospital and day hospital expenditures are never statistically significant, while those of pharmaceutical and outpatient expenses are increasing in age, with the estimated coefficients on positive values slightly above those from the baseline specification. With respect to the impact of the number of co-morbidities and TTD, significant differences between the baseline and the two-part model are observed only for hospital and day hospital expenses, where the zero-mass problem and over-dispersion is more relevant than in the case of expenditures for pharmaceuticals and outpatient services.

1.7.2 Endogenous mobility

Another issue we face is that estimated GP fixed effects are biased if patients sort into practitioners in a non-random way. Endogenous mobility may arise if individuals with specific characteristics are more successful at generating matches driving expenditure variations than others. For example, suppose high-income individuals, who prefer spending more for medical treatments, tend to sort into practitioners who also have higher spending propensity. In that case, the convergence of their preferences may lead to an increase in expenditures reflected in an overestimation of the fixed effects associated with the chosen GPs. Hence, an analysis of HCE that excludes a match-specific component is likely to suffer from omitted variable bias, resulting in biased individual and GP estimated fixed effects and estimated returns to observable characteristics that are correlated with match quality (Woodcock, 2015b). To verify the presence of endogenous mobility, we replicate our estimation by including in our regression individual-GP match fixed effects. In this way, each individual-GP combination receives a separate dummy variable that is allowed to be correlated with observed individual characteristics and measures the time-invariant interaction effect between the patient and the GP and the value of the match quality[45].

Total HCE variance decomposition of a model with individual-GP match fixed effects is illustrated in Table 1.B.5 in Appendix 1.B. The contribution of estimated match fixed effects ($\gamma_{ip_{(i,t)}}$) to the overall variance is negligible and amounts to

[45]Note that the fixed effect estimator assumes that match effects are orthogonal to person and GP effects. An orthogonal match effect is identified whenever the corresponding person and GP effects are identified in a model without match effects. However, if an individual enters only one match, the associated match effect is zero.

2.20%. Even if small, it indicates the presence of a systematic sorting of patients into practitioners. The sorting direction is illustrated by the sign of the covariance between individual and GP fixed effects ($2Cov(\ni_i, \zeta_{p_{(i,t)}})$). It is positive, showing a non-random allocation of high-spending individuals towards high-spending GPs. Looking at the other variance components, we observe a slight reduction in the contribution of the estimated individual and GP fixed effects and to a comparable reduction in the error term (about 2.36%), reflecting decreased omitted variable bias.

1.8 Discussion

Analyses on the age window 50-70 are crucial from a policy perspective, as they allow to identify the critical point where health shocks start to occur with permanent effects on the individual health status and expenditures and, hence, when and which type of preventive interventions should be undertaken.

By looking at the first panel of Figure 1.3a, we note that the age profile estimated without controlling for health status and TTD (dark grey dots) shows a convex relationship between age and total expenditures, with the HCE pattern becoming to increase marginally from age 60 onwards. The relationship then remains linear up to 64 years when the individual's morbidity is also taken into account and up to 67-68 when TTD is added. It indicates that the observed convexity largely depends on a worsening health condition, which leads to a marginal increase in expenditures from age 60 for all spending categories except day hospital expenses (see the other panels of Figure 1.3). To identify which group of individuals is most characterized by this pattern, we replicate this simple analysis for various population groups. We find that the exponential growth of total HCE from age 60 is typical of individuals with chronic diseases or disabilities (Figure 1.B.14a in Appendix 1.B) and that this expenditures evolution is due to the onset timing of additional diseases and acute cases, to which these subjects are particularly exposed (Grumbach, 2003), requiring intensive and expensive treatment. Using hospital admission as a proxy for the occurrence of such acute health shocks, we estimate the predicted probability of being hospitalized for those who are already diagnosed and find that it starts to marginally increase from age 60, as illustrated in Figure 1.B.14b. This result suggests the need to enhance secondary prevention approaches (Kisling and Das, 2020), which are crucial for reducing the incidence of recurrent clinical events and premature death. Their relevance is further documented by comparing individuals characterized by different disease progressions. To this end, we estimate the age profile of expenditures for three groups of chronic and disabled individuals who present a similar initial health level; in particular, we select only individuals who enter the sample as healthy and only later experience the onset of a chronic condition or disability. The first group consists of individuals who do not present any co-morbidities, the second of individuals who have co-morbidities, and the third of individuals who have co-morbidities and one or more hospitalizations, used again as proxies for the occurrences of more critical acute events requiring inpatient treatments. All groups are then compared to the subset of healthy individuals who do not present chronicity and disability and are never hospitalized. Results are reported in Figure 1.B.14c in Appendix 1.B. At age 70, chronic or disabled individuals spend almost four times more than healthier individuals, while those who also experience the onset of multiple conditions almost five times more. However, the largest difference is observed between those who are also hospitalized and the other groups. Indeed, 70-years-old admitted individuals spend about 8,000€ more than the hospitalized of age 50 and more than seven times more than those with co-morbidities.

The results shown in this section suggest that the enhancement of preventive approaches before age 60 is a priority goal to deal with the increasing prevalence of chronic diseases and multiple long-lasting illnesses or functional impairments among the elderly (OECD, 2014). Effective monitoring and follow-up have the potential to reduce the incidence of chronic diseases and their rate of progression to prevent them from deteriorating to the point of exacerbation in acute cases that, when hospital treatments are required, are associated with a significant increase in expenditures.

1.9 Conclusions

Using a two-way fixed effects model, in this chapter we model the effect of age, morbidity, and time to death on total HCE and expenses for different healthcare services for the population of individuals aged 50-70 and several subsamples. Moreover, we decompose the variance in HCE to investigate the extent to which heterogeneity across individuals and GPs contributes to the variability in expenditures across individuals. According to our results, age, morbidity, and TTD are all important determinants of HCE and, along with unobserved individual-specific factors and idiosyncratic shocks, are the elements that contribute most to generating variability in expenditures among individuals. For total HCE, we observe a positive gradient in age that reduces when the number of co-morbidities is controlled for; instead, in contrast to the red herring hypothesis, age coefficients increase when time to death is also added, with higher expenses for premature demises than those incurred for deaths at older ages. In any case, the results from the preferred specification with all regressors included show that 70-years-old individuals spend, overall, about 700€ more than individuals aged 50 and nearly 1,400€ in absolute terms, a value that is slightly above the average unconditional total HCE for the whole population. Such an increase by age is mainly driven by expenses for out-of-hospital services; in contrast, hospital expenditures mainly drive the morbidity and end-of-life profiles of total HCE, indicating a substitution among health services in favor of complex and expensive inpatient treatment as the severity of the health condition increases. Such a substitution is confirmed by the different evolution of expenses by TTD among the services: while hospital costs continue their growing trend over the last period of life and reach, in absolute value, 10,000€ at the time of death (more than twice the standard deviation of total HCE), those incurred for all other services fall sharply in the year of demise. Heterogeneity in the effects of the factors analyzed is also found among different groups of individuals, and interesting results emerge especially when disease-specific expenditures evolutions are compared. The effect of age on HCE is never statistically significant when disease-specific hospital expenses are considered. Instead, the impact of the number of co-morbidities is always statistically significant, with the largest effect found for individuals affected by cancer, especially on outpatient expenses. For those with four or more conditions, the latter are about three times the costs incurred by individuals with cardiovascular and digestive system diseases and COPD with the same number of co-morbidities. Finally, the effect of TTD is quite heterogeneous with respect to the type of the underlying disease. For acute conditions, end-of-life costs rise significantly only in the last two years of life, indicating their rapid evolution with sudden onset, short duration, and high severity. On the contrary, for long-lasting conditions, the HCE pattern begins to grow exponentially before the fifth year prior to death, suggesting a slow disease progression.

This analysis allows us to identify the critical point where the health shocks start to have permanent effects on the individual health status and expenditures and, hence, when preventive interventions should be undertaken. Such a critical point corresponds to the interval where the HCE pattern starts to marginally increase due to worsening health conditions of the population and, in particular, of chronic and disabled individuals. The enhancement of preventive approaches before such a critical point is a priority goal to reduce the incidence of long-lasting diseases and prevent them from deteriorating to the point of exacerbation in acute cases requiring hospital admissions, associated with a greater need for medical care and higher expenditures.

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Appendices

1.A Data handling and variables description

The original sample of the dataset drawn from the Health Information System of the ATS of the Province of Milan consists of about 820,000 individuals per year, recorded over the period 2006-2017 for a total of 10,031,350 observations. However, some manipulations of the sample are needed to obtain a clean and reliable dataset. The underlying criterion is to eliminate individuals only when dropping observations would generate time gaps in individual records.

First of all, 1,596,701 observations recorded for the first two years in the dataset are excluded because information on the number of co-morbidities and survival status per individual is absent in, respectively, 2006 and 2007. Moreover, data on health expenditures and volumes in these periods are much lower than in the following years.

Second, data on individuals are analyzed. Some observations (69) are recorded also for years following the individual demise. Therefore, they are dropped from the sample for the period in which they should not have been observed. Moreover, observations presenting null costs but positive volumes for hospital and day hospital admissions, outpatient visits, and pharmaceuticals are excluded (110,616). Then, we drop individuals when they are arbitrarily considered as outliers (527 observations).

Third, some manipulations are carried out at the GP level. Observations associated to a GP whose year of birth is 1901 or 1 or whose year of the license is 0 are dropped from the sample (17,658).
Moreover, some individuals are related to a GP whose year of activity cessation (i.e. the year in which they stop working as GP) precedes the observed year. For example, it is possible to observe an individual who is related in 2010 to a GP the last working year of which is 2008. Since data present several of these cases, this inconsistency requires to be handled in different ways. The general criterion is to eliminate observations only when it is not possible to link the irregularity to an error in reporting individual information (e.g., a delay in recording the GP change); otherwise, the previous or the new GP is arbitrarily associated to the individuals also for years in which he or she is theoretically no longer or not yet responsible for those patients. In order to manage these inconsistencies, we divide the sample into two groups: individuals who never changed their GP and individuals who did. Regarding the first group, 17,860 observations are excluded from the sample. Indeed, they are associated with a practitioner whose year of activity cessation is not consistent over the entire period or to a GP who stops working without being replaced (in this last case, observations are dropped from the sample only for years following the practitioner's activity cessation). Among those belonging to the second group, some individuals are associated with a practitioner who no

longer works before the GP change. In these cases, the new GP is assigned to them also for the years of discrepancy preceding the real take-up (in which he or she is not yet theoretically responsible for those patients). In other cases, the year of activity cessation of the new practitioner is not valid from the very first year of his or her take-up; when it occurs, the previous GP is also assigned for the following years (in which he or she is theoretically no longer responsible for those patients). Finally, all the observations related to individuals who changed their GP and who are also observed for years following the time their last practitioner stopped working are excluded from the sample for the same periods (619).
Individuals treated by GPs with a number of patients lower than the first percentile are also dropped (48,609).

Finally, individuals with gaps in years of observation (83,726), as well as individuals observed for only one year (123,155), are eliminated.

After these manipulations, the final sample includes 7,810,863 observations recorded over the period 2008-2017.

Table 1.A.1: Variables used for the analysis.

Dependent variables			
Name	Type	Min-Max	Description
Total expenditures	Continuous		Sum of expenses for hospital and day hospital admissions, outpatient services and pharmaceuticals.
Hospital expenditures	Continuous		Expenses for elective and emergency admissions.
Day Hospital expenditures	Continuous		Expenses for day hospital admissions.
Outpatient expenditures	Continuous		Expenses for outpatient services.
Pharmaceutical expenditures	Continuous		Expenses for pharmaceuticals.
Independent variables			
Name	Type	Min-Max	Description
Age	Categorical	50 - 70	Individual's age. Omitted category: 50.
Citizenship	Binary	0 - 1	Individual citizenship (European, Non-European). Omitted category: European.
Residence area	Binary	0 - 1	Area of residence (Province, Urban area). Omitted category: province.
Income exemption	Binary	0 - 1	Income-related exemption. Time absorbing variable.
Co-morbidities	Categorical	0 - 4+	Number of co-moribidities.
TTD	Categorical	0 - 5	Time to death, with TTD-0 indicating the year of death. Omitted category: TTD-5.
Years	Categorical	2008 - 2017	Years of observations. Omitted categories: 2016, 2017.
Other variables			
Name	Type	Min-Max	Description
Male	Binary	0 - 1	Individual's gender.
Deceased	Binary	0 - 1	Death.
MDCs	Categorical		Major Diagnostic Categories for which the individual is hospitalized.
Disease exemption	Binary	0 - 1	Disease-related exemption. Time absorbing variable.
Disability exemption	Binary	0 - 1	Disability-related exemption. Time absorbing variable.

1.B Additional tables and figures

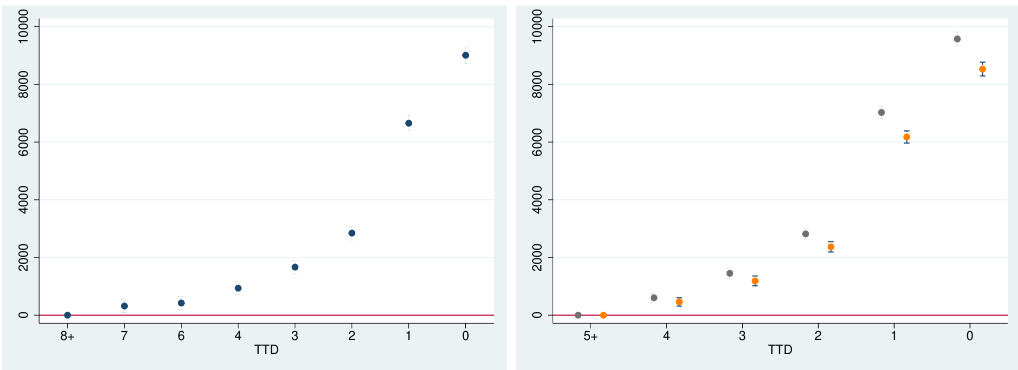
Table 1.B.1: Descriptive statistics - General Practitioners.

GP's characteristics					
	Mean	SD		Mean	SD
Age	56	6	List size	1,349	466
Working experience	29	6	Patients aged 50-70	422	29

Figure 1.B.1: Total HCE by TTD.

(a) Last 8 years of life

(b) Effect of TTD from different specification

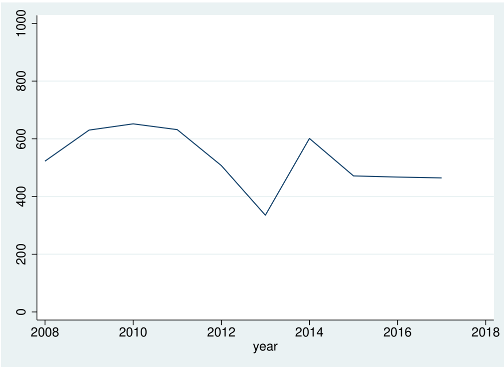


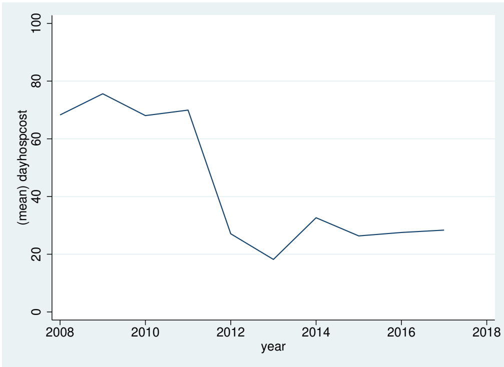
Note: Blue dots: estimated coefficients of TTD specified to include the last 8 years of life; Grey dots: coefficients of TTD estimated from the specification where the number of co-morbidities is not included; Orange dots: coefficients of TTD estimated from the preferred specification.

Figure 1.B.2: Average unconditional expenditures by year.

(a) Hospital expenditures

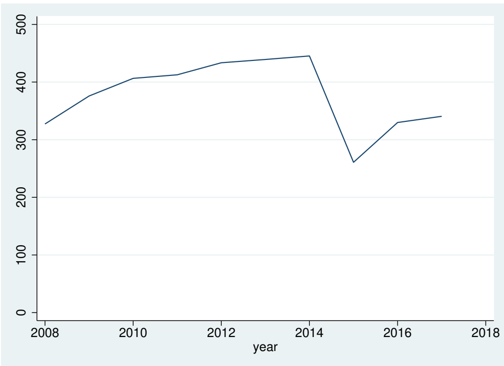
(b) Day hospital expenditures

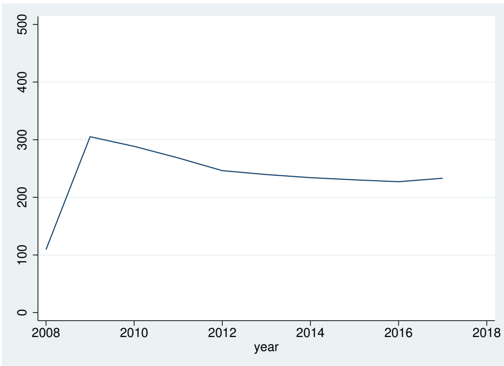




(c) Outpatient expenditures

(d) Pharmaceutical expenditures





(e) Total HCE

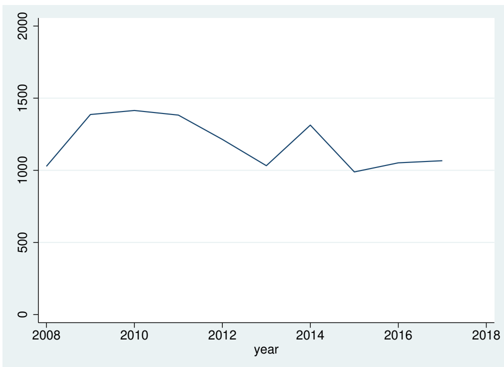


Table 1.B.2: Variance Inflation Factor.

	VIF	**1/VIF**		**VIF**	**1/VIF**
Age			Residence area	1.03	0.9743
51	1.99	0.5030	Income exemption	1.42	0.7062
52	1.96	0.5113	*N. co.morbidities*		
53	1.92	0.5205	1	1.15	0.8704
54	1.89	0.5300	2	1.15	0.8666
55	1.86	0.5383	3	1.09	0.9180
56	1.84	0.5450	4+	1.05	0.9561
57	1.82	0.5509	*TTD*		
58	1.80	0.5550	4	1.00	0.9964
59	1.79	0.5572	3	1.00	0.9962
60	1.80	0.5568	2	1.00	0.9956
61	1.80	0.5562	1	1.01	0.9931
62	1.81	0.5537	0	1.01	0.9914
63	1.79	0.5571	*Year*		
64	1.79	0.5584	2008	1.42	0.7043
65	1.81	0.5524	2009	1.45	0.6919
66	1.82	0.5498	2010	1.45	0.6911
67	1.83	0.5474	2011	1.37	0.7310
68	1.84	0.5441	2012	1.36	0.7347
69	1.84	0.5425	2013	1.36	0.7342
70	1.76	0.5671	2014	1.36	0.7330
Citizenship	1.04	0.9617	2015	1.35	0.7392
Mean VIF			1.52		

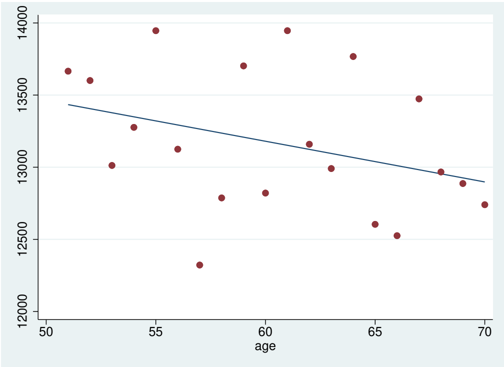
Table 1.B.3: Correlation matrix for the variables included in the preferred specification.

Correlation matrix							
	Age	Citizenship	Residence area	Income exemption	Co-morbidities	TTD	Years
Age	1.0000	-	-	-	-	-	-
Citizenship	−0.1204	1.0000	-	-	-	-	-
Residence area	0.0033	0.1373	1.0000	-	-	-	-
Income exemption	0.3102	−0.0091	−0.0590	1.0000	-	-	-
Co-morbidities	0.2802	−0.0503	−0.0382	0.2529	1.0000	-	-
TTD	−0.0508	0.0141	−0.0062	−0.0175	−0.1256	1.0000	-
Years	−0.0224	0.0634	−0.0072	0.3434	0.0442	0.0179	1.0000

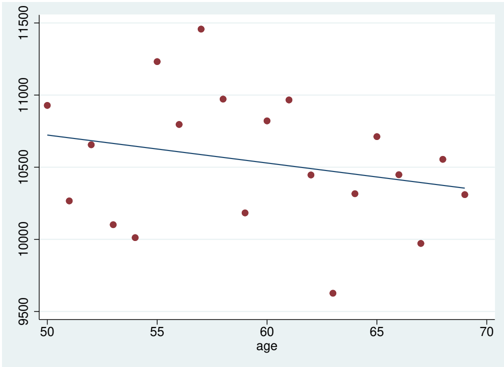
Note: All the coefficients are significant at 1% level.

Figure 1.B.3: Average unconditional total HCE at demise by age.

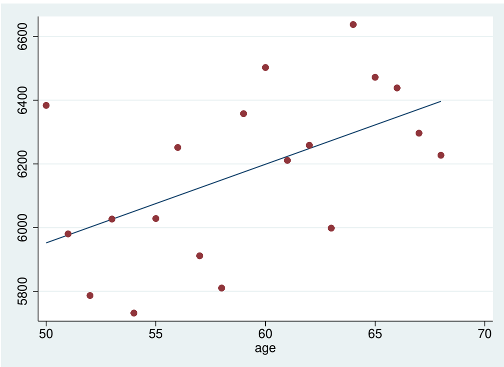
(a) TTD = 0



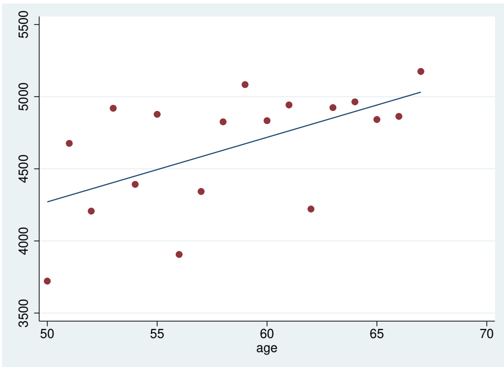
(b) TTD = 1



(c) TTD = 2



(d) TTD = 3



(e) TTD = 4

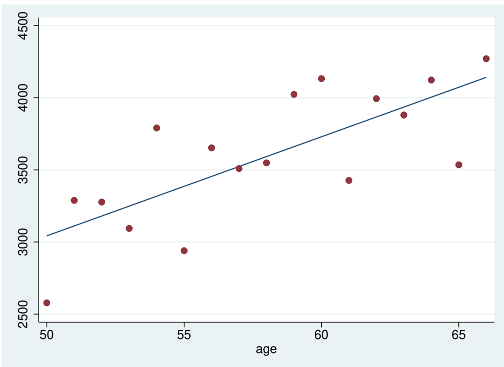
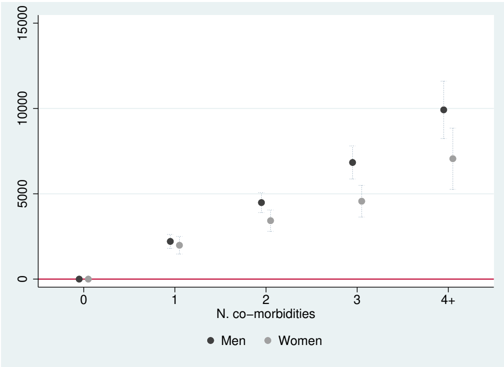
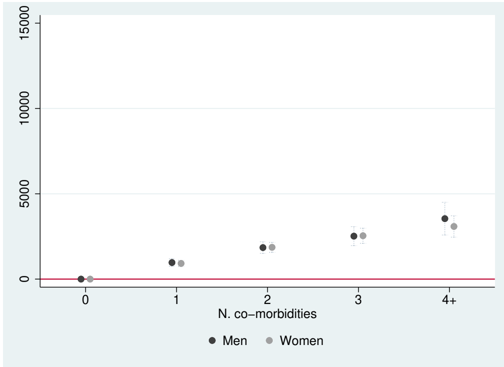


Figure 1.B.4: Impact of number of co-morbidities on total HCE by gender and MDC.

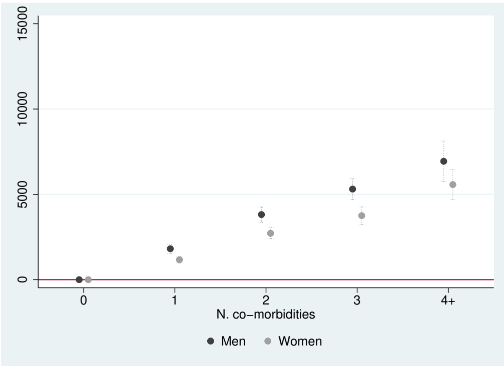
(a) Infectious disease



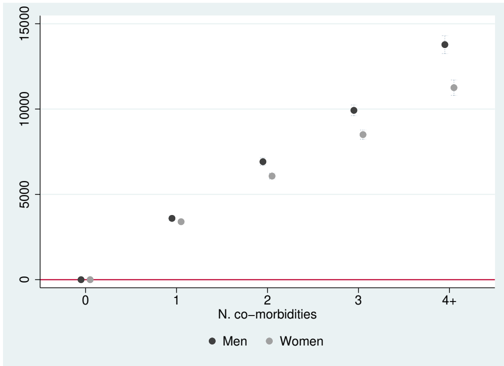
(b) Mental disorder



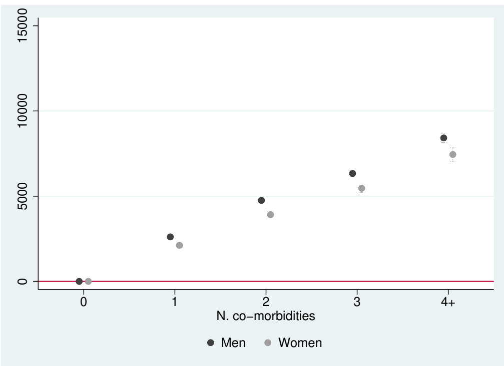
(c) Nervous System disease



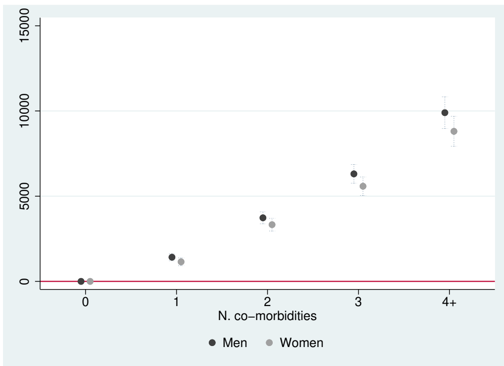
(d) Cancer



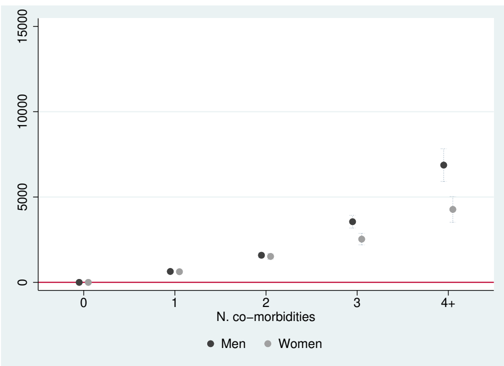
(e) Cardiovascular disease



(f) COPD



(g) Digestive System disease



(h) Musculoskeletal disease

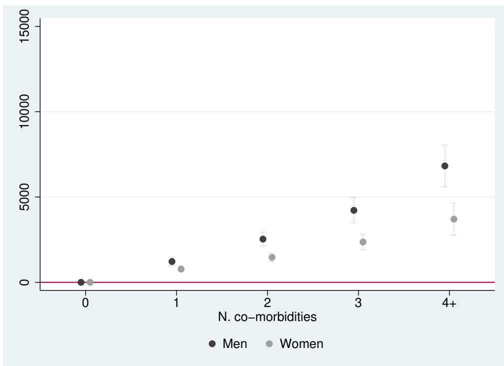
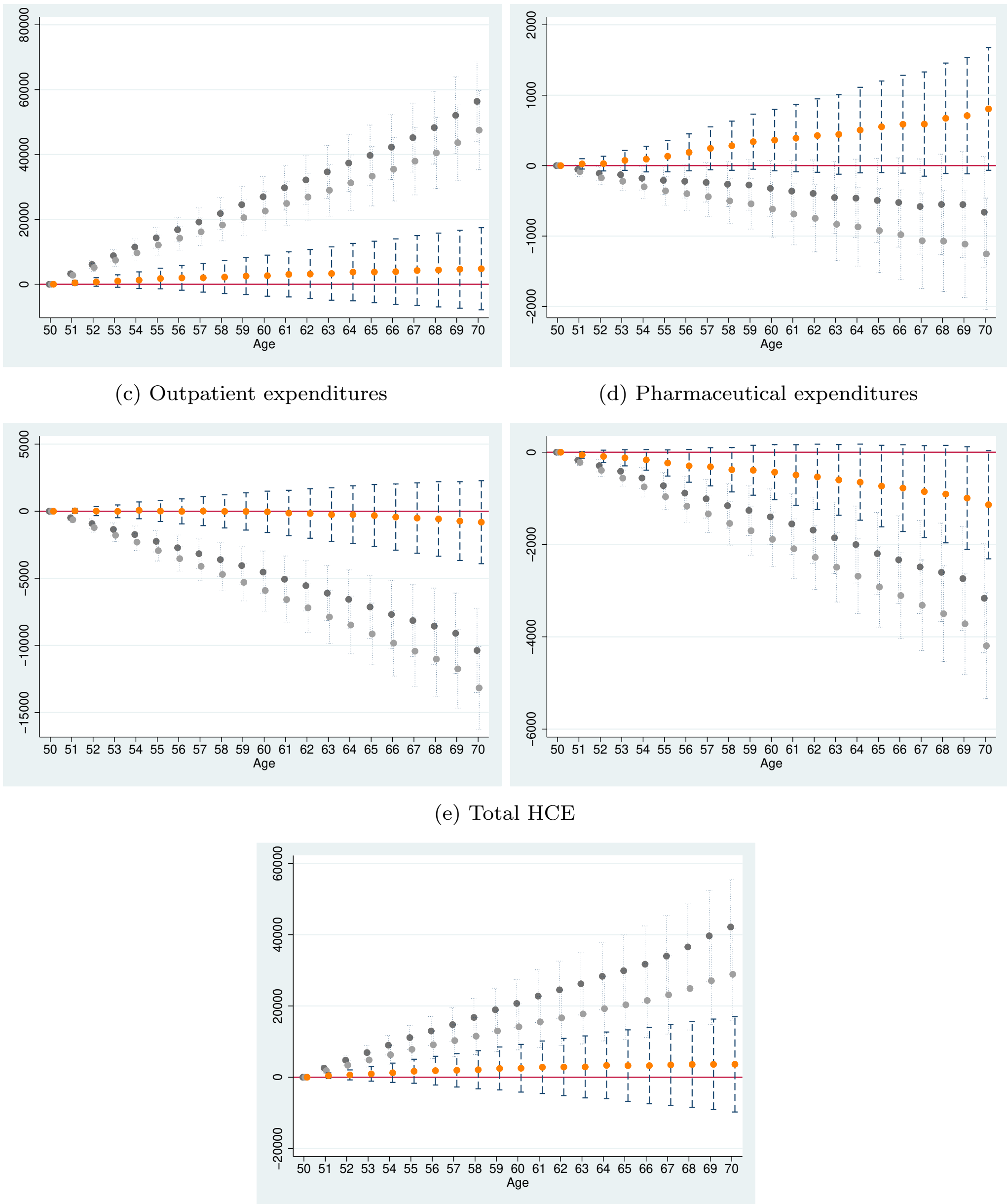


Figure 1.B.5: Impact of age on total HCE and expenses for different spending categories of the deceased according to different specification.



(a) Hospital expenditures

(b) Day hospital expenditures

(c) Outpatient expenditures

(d) Pharmaceutical expenditures

(e) Total HCE

Note: Regressors included in each specification:

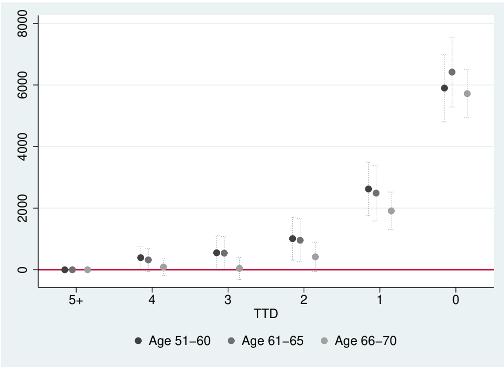
Dark grey dots: age dummies, citizenship, residence area and income-related exemption, time, individual and GP fixed effects.

Light grey dots: age dummies, citizenship, residence area, income-related exemption and number of co-morbidities, time, individual and GP fixed effects.

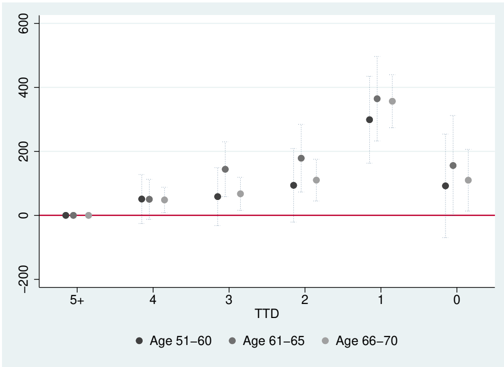
Orange dots (preferred specification): age dummies, citizenship, residence area and income-related exemption, number of co-morbidities and TTD, time, individual and GP fixed effects.

Figure 1.B.6: Impact of TTD on total HCE and expenses for different spending categories by age at demise.

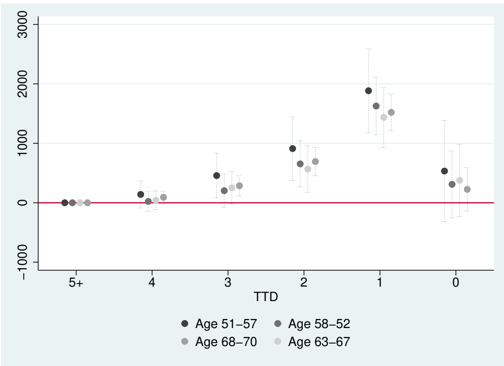
(a) Hospital expenditures



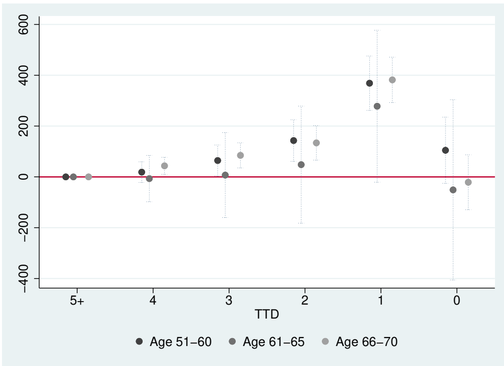
(b) Day hospital expenditures



(c) Outpatient expenditures



(d) Pharmaceutical expenditures



(e) Total HCE

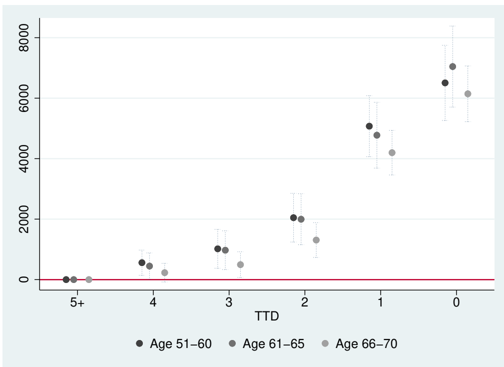
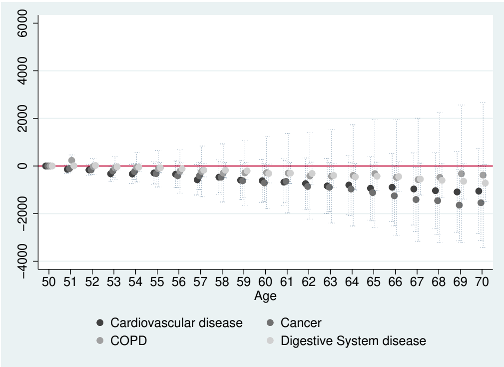
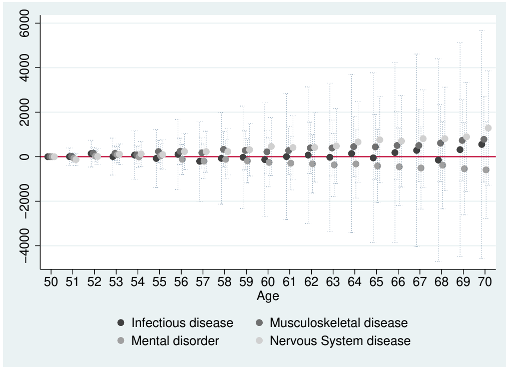


Figure 1.B.7: Impact of age on expenses for different spending categories by MDC.

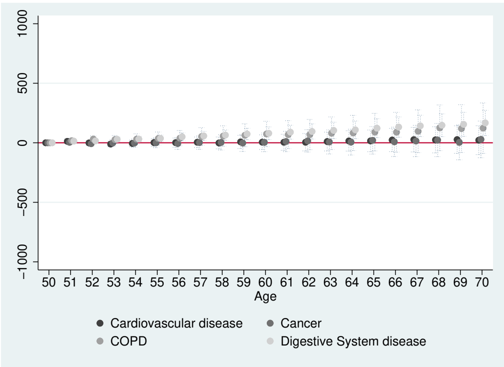
(a) Hospital: Primary Care diseases



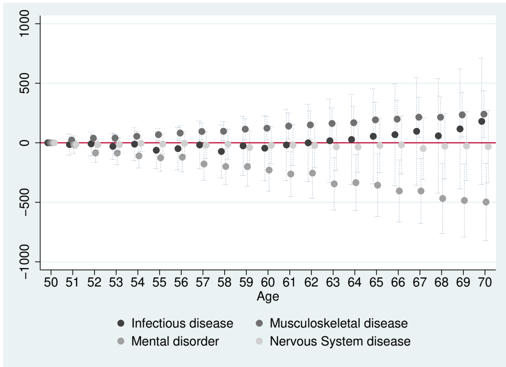
(b) Hospital: Other diseases



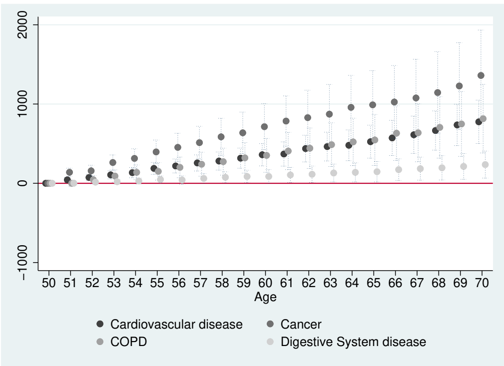
(c) Day Hospital: Primary Care diseases



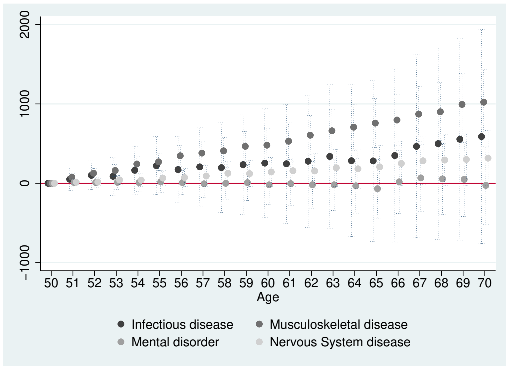
(d) Day Hospital: Other diseases



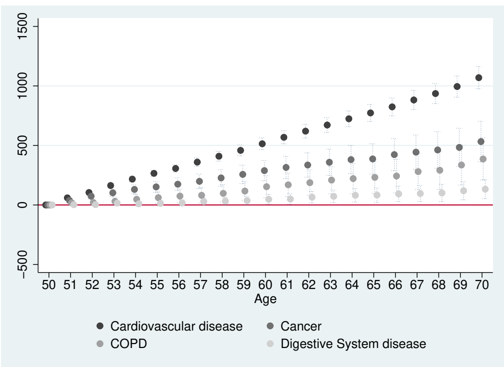
(e) Outpatient: Primary Care diseases



(f) Outpatient: Other diseases



(g) Pharma.: Primary Care diseases



(h) Pharma.: Other diseases

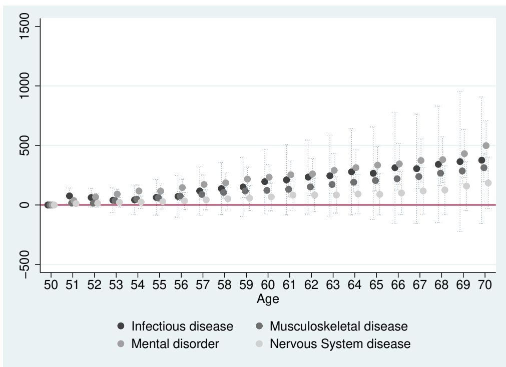


Figure 1.B.8: Impact of number of co-morbidities on expenses for different spending categories by MDC.

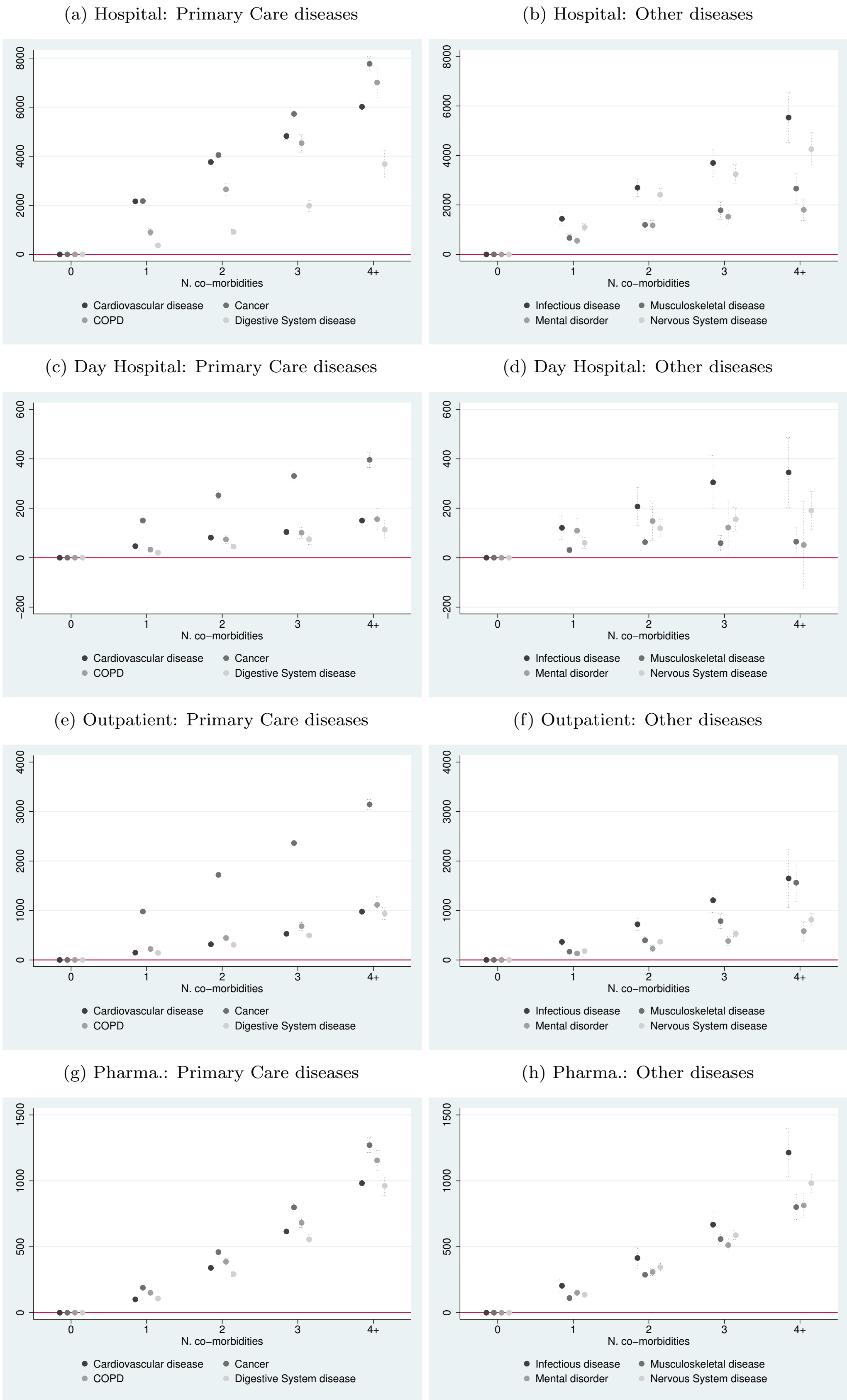
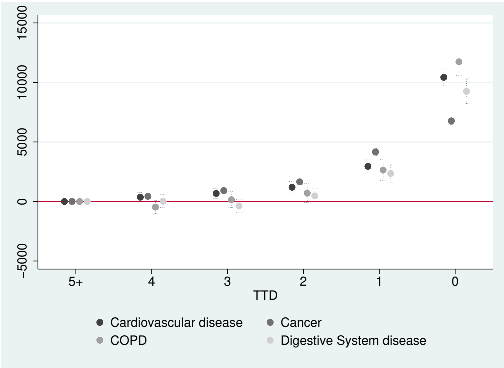
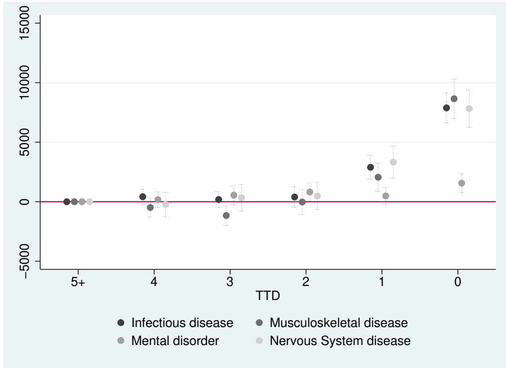


Figure 1.B.9: Impact of TTD on expenses for different spending categories by MDC.

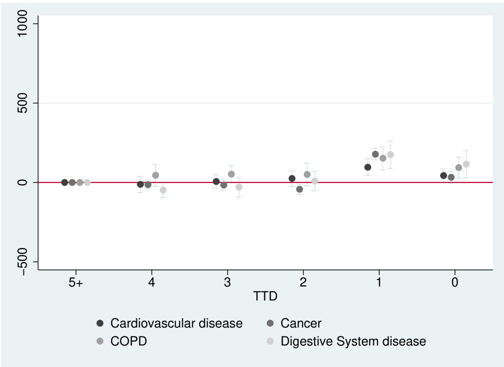
(a) Hospital: Primary Care diseases



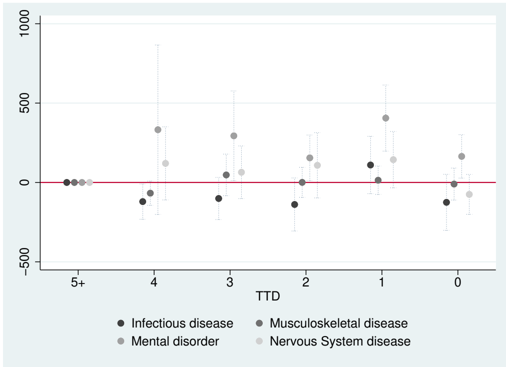
(b) Hospital: Other diseases



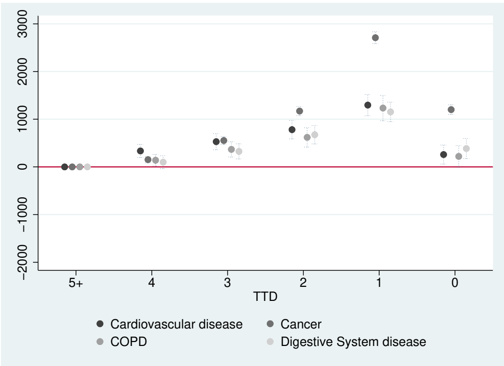
(c) Day Hospital: Primary Care diseases



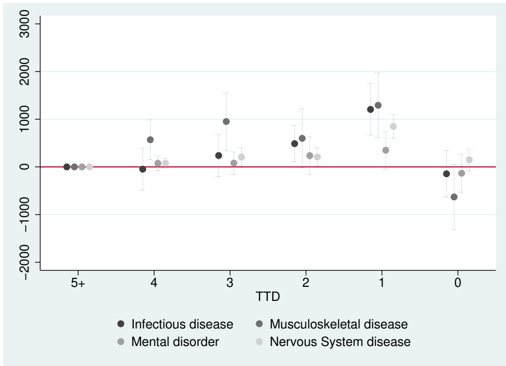
(d) Day Hospital: Other diseases



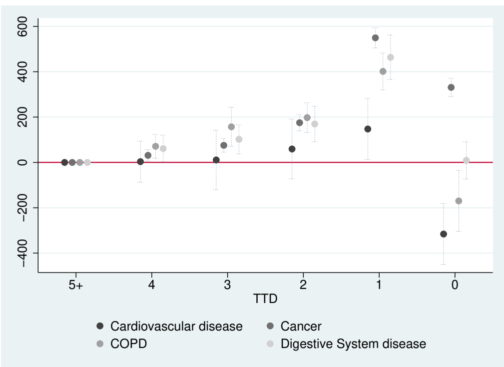
(e) Outpatient: Primary Care diseases



(f) Outpatient: Other diseases



(g) Pharma.: Primary Care diseases



(h) Pharma.: Other diseases

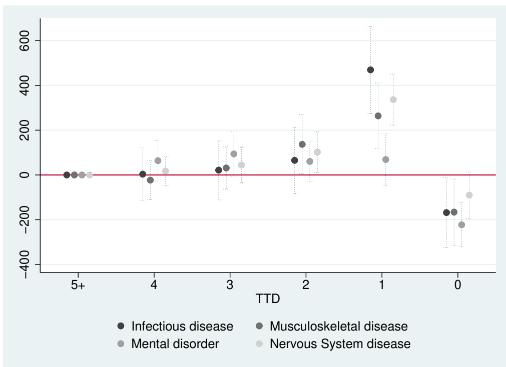


Table 1.B.4: Marginal effects.

Marginal effect of age on the probability of being diagnosed[a].	
Age	
52	-0.0724***
	(-23.97)
53	-0.1084***
	(-38.90)
54	-0.1329***
	(-50.43)
55	-0.1484***
	(-58.63)
56	-0.1587***
	(-64.46)
57	-0.1643***
	(-67.99)
58	-0.1658***
	(-69.37)
59	-0.1696***
	(-71.50)
60	-0.1711***
	(-72.40)
61	-0.1716***
	(-72.82)
62	-0.1719***
	(-73.07)
63	-0.1745***
	(-74.46)
64	-0.1726***
	(-73.34)
65	-0.1779***
	(-75.51)
66	-0.1811***
	(-76.64)
67	-0.1768***
	(-74.07)
68	-0.1709***
	(-70.59)
69	-0.1554***
	(-62.32)
70	-0.1336***
	(-51.03)
Marginal effect of being diagnosed on the probability of hospitalization[b].	
First diagnosis	0.1201***
	(191.22)
N. observations	1,332,985

Note: t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at individual level.

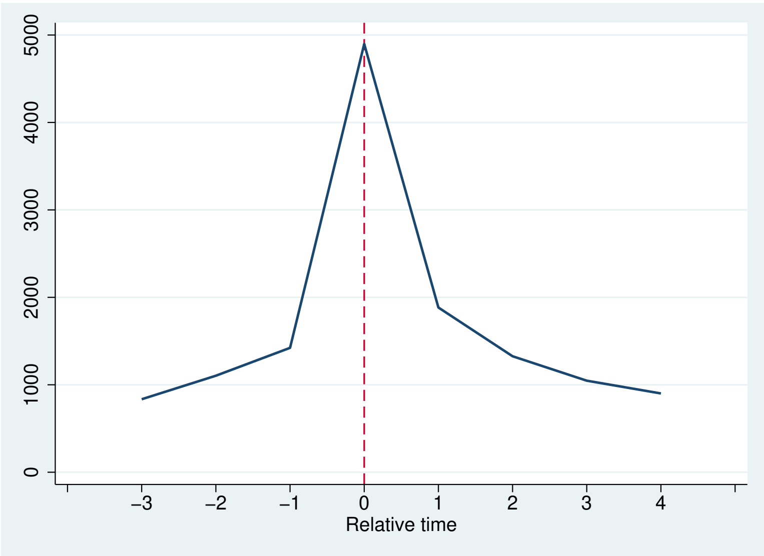
Marginal effects from two probit models carried out on individuals exempted during the observed people, except those who enter the sample already affected by chronicity or disability. Since 50-years old individuals and year 2008 predict failure perfectly, respective observation are excluded.

Other controls: age (second model), citizenship, residence area, number of co-morbidities, time to death, years fixed effects.

[a] Omitted categories: Age 51.

[b] Omitted categories: Not exempted or already exempted.

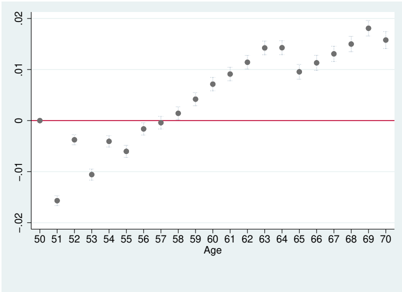
Figure 1.B.10: Average unconditional hospital expenditures by relative time to the release of disease- or disability-related exemption.



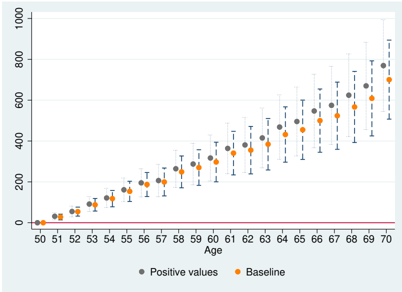
Note:
Evolution of hospital expenditures around the release of the disease- and disability-related exemption, occurring at relative time 0.
Only individuals observed at least three years before and four years after the exemption are taken into account.
Expenditures data are deflated by dividing current expenditures by the Italian consumer price index for the health sector provided by the OECD. The reference year is 2015.

Figure 1.B.11: Two-part model: effect of age.

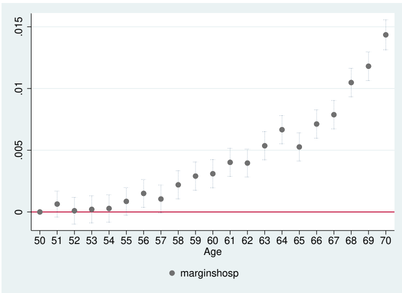
(a) Total HCE: intensive margins



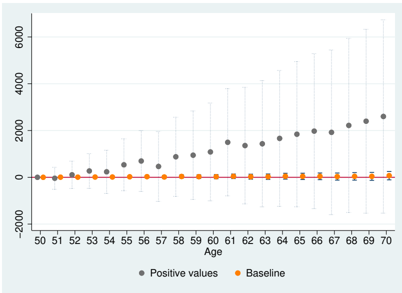
(b) Total HCE: extensive margins



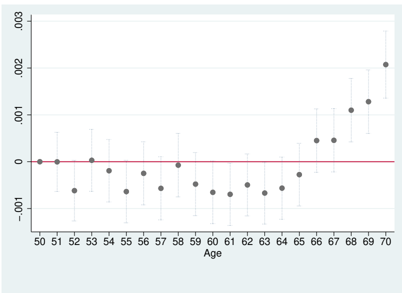
(c) Hospital: intensive margins



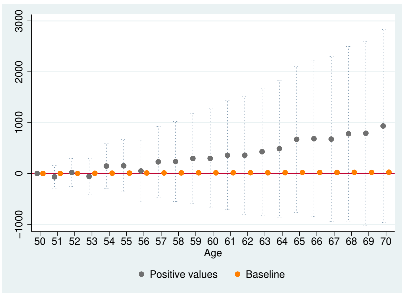
(d) Hospital: extensive margins



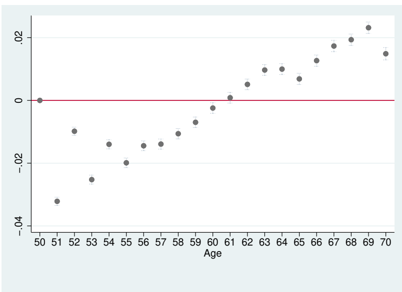
(e) Day Hospital: intensive margins



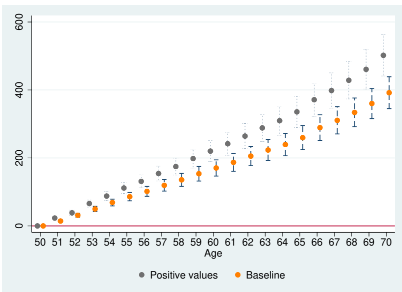
(f) Day Hospital: extensive margins



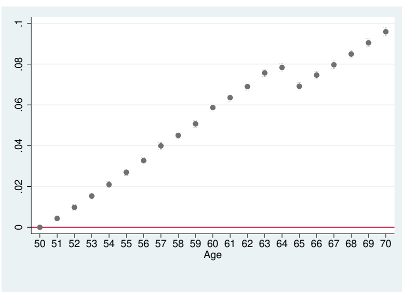
(g) Outpatient: intensive margins



(h) Outpatient: extensive margins



(i) Pharmaceutical: intensive margins



(j) Pharmaceutical: extensive margins

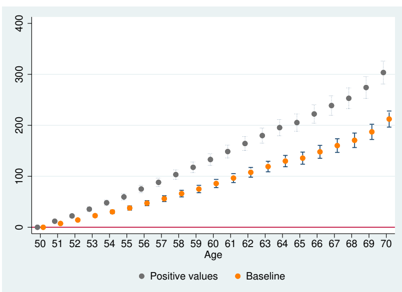
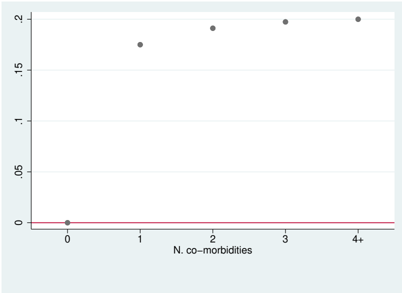
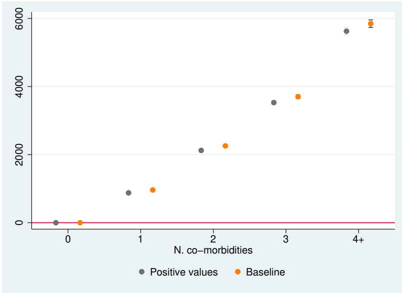


Figure 1.B.12: Two-part model: effect of number of co-morbidities.

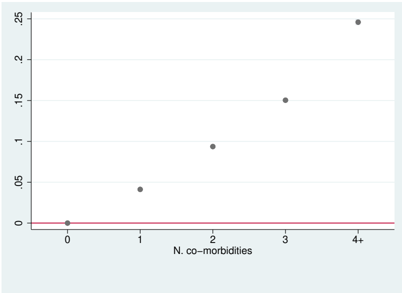
(a) Total HCE: intensive margins



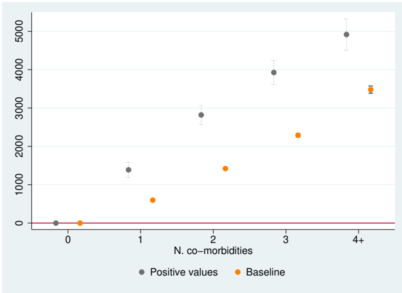
(b) Total HCE: extensive margins



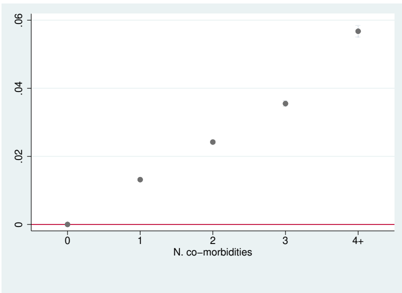
(c) Hospital: intensive margins



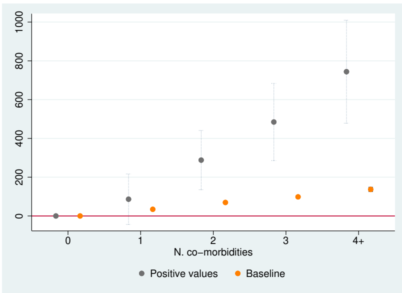
(d) Hospital: extensive margins



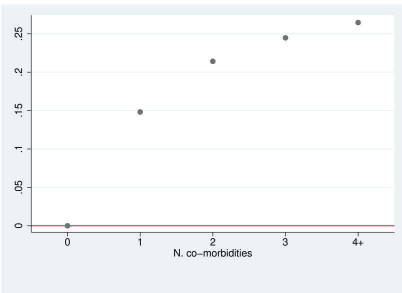
(e) Day Hospital: intensive margins



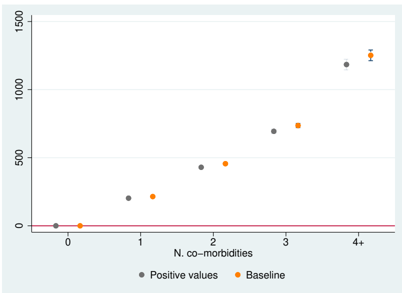
(f) Day Hospital: extensive margins



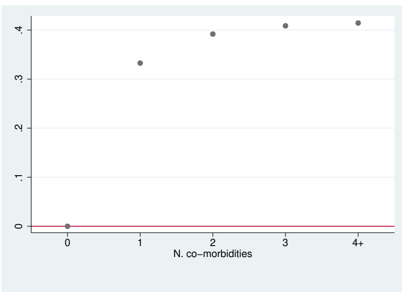
(g) Outpatient: intensive margins



(h) Outpatient: extensive margins



(i) Pharmaceutical: intensive margins



(j) Pharmaceutical: extensive margins

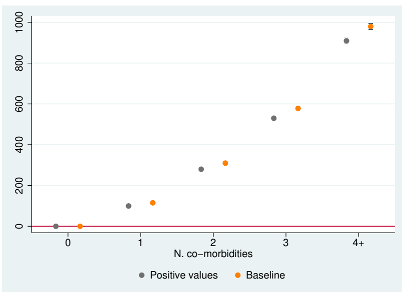
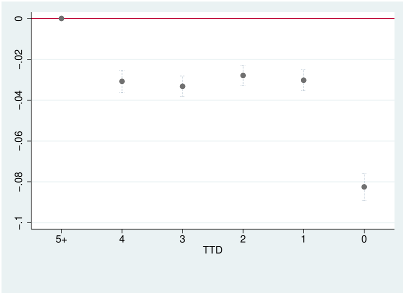
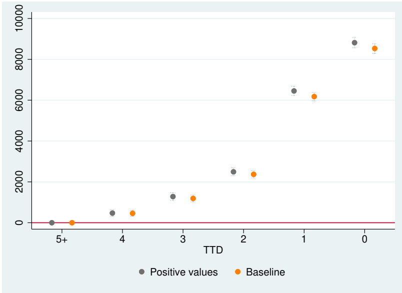


Figure 1.B.13: Two-part model: effect of TTD.

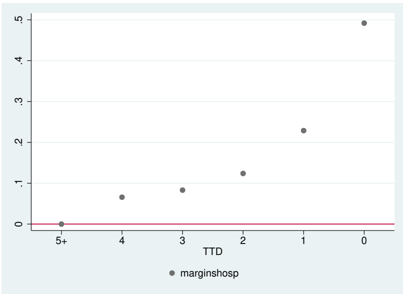
(a) Total HCE: intensive margins



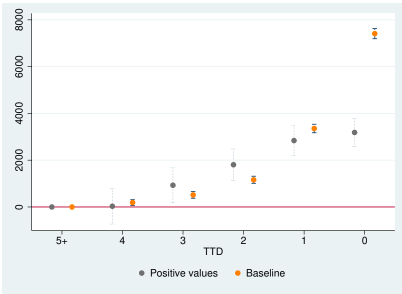
(b) Total HCE: extensive margins



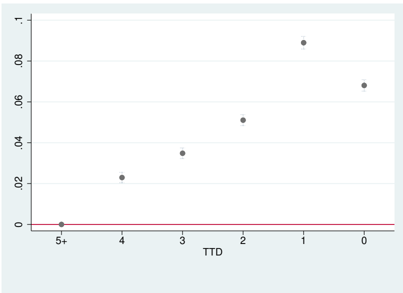
(c) Hospital: intensive margins



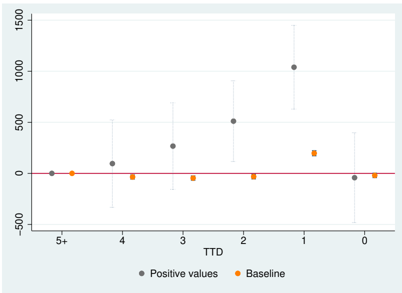
(d) Hospital: extensive margins



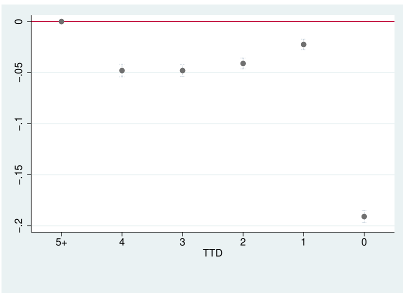
(e) Day Hospital: intensive margins



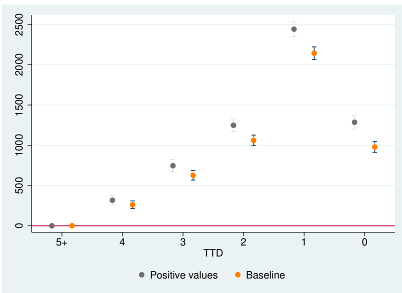
(f) Day Hospital: extensive margins



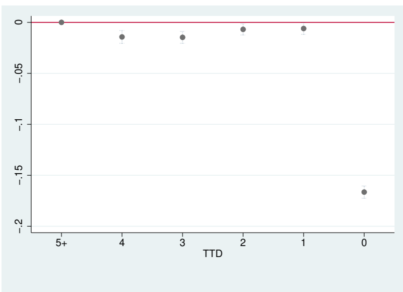
(g) Outpatient: intensive margins



(h) Outpatient: extensive margins



(i) Pharmaceutical: intensive margins



(j) Pharmaceutical: extensive margins

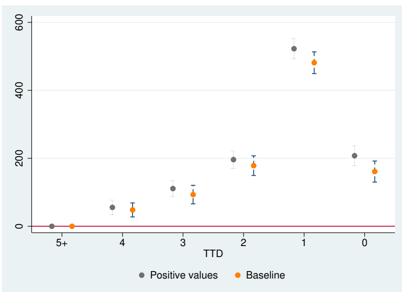
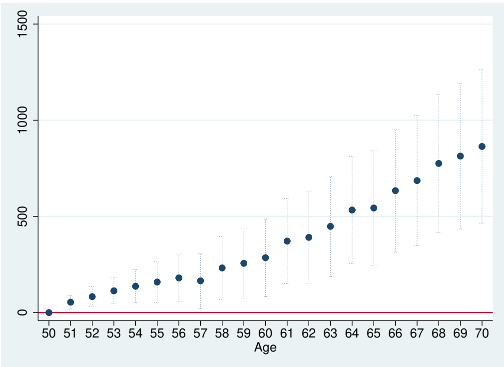


Table 1.B.5: Variance decomposition when match fixed effects are also included.

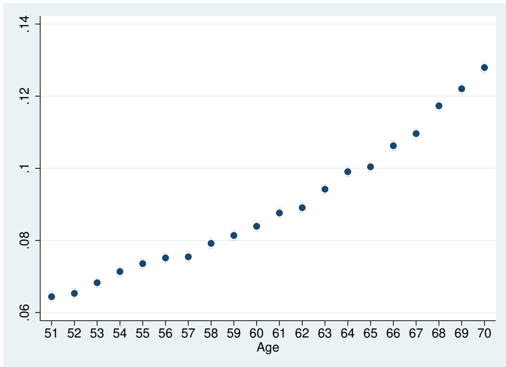
	Baseline	**Match fixed effects**
Var(y_{it})	100	100
Var(βx_{it})	11.82	11.42
Var(ν_i)	28.50	27.99
Var($\zeta_{p_{(i,t)}}$)	0.81	0.01
Var($\gamma_{ip_{(i,t)}}$)	-	2.20
Var(ϵ_{it})	60.27	57.91
2Cov(ν_i, βx_{it})	0.08	0.46
2Cov($\zeta_{p_{(i,t)}}$, βx_{it})	-0.04	0
2Cov($\gamma_{ip_{(i,t)}}$, βx_{it})	-	0.02
2Cov(ν_i, $\zeta_{p_{(i,t)}}$)	-1.44	0.01
2Cov(ν_i, $\gamma_{ip_{(i,t)}}$)	-	-0,01
2Cov($\zeta_{p_{(i,t)}}$, $\gamma_{ip_{(i,t)}}$)	-	0

Figure 1.B.14: Age profile for chronic and disabled individuals.

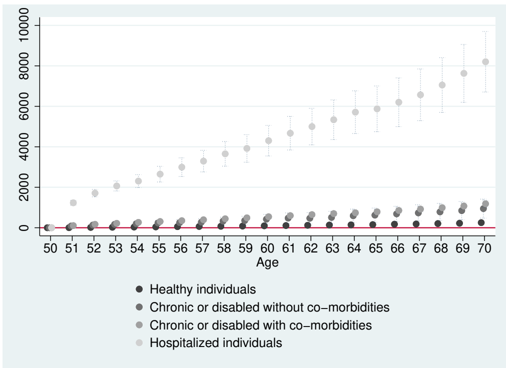
(a) Total HCE for chronic and disabled individuals



(b) Predicted probability of being hospitalized



(c) Total HCE for different groups of chronic and disabled individuals



Chapter 2

The Long-Term Effects of Hospitalization on Healthcare Expenditures: An Empirical Analysis for the Young-Old Population

Irene Torrini, Claudio Lucifora, Antonio Russo (2021)

2.1 Introduction

Hospital services are a key component for each health care system, as they provide specialized acute and emergency care for the treatment of health shocks that cannot be delivered in outpatient or primary care settings. Given the cost-intensive nature of inpatient treatments, hospital services represent a large share of public health spending[46] and are often targeted by cost-containment policies to address the challenges imposed by aging populations and stringent public finances.

The existing literature provides extensive evidence on the determinants of hospital expenditures. The elderly population accounts for a high proportion of hospitalization costs, as indicated by the J-shaped age-profile of inpatient expenses (Gabriele et al., 2006). After the first year, hospital costs are the lowest for children, rise slowly throughout adult life, and increase exponentially from middle age. Hence, advancing age is associated with a deterioration of the individual health status, with large effects on hospital expenditures. In particular, critical health conditions, functional dependence (Di Napoli et al., 2005; Sona et al., 2012), and proximity to death (Costa-Font and Vilaplana-Prieto, 2020; Geue et al., 2015; Kelley et al., 2011; Kliebsch et al., 2000; Wong et al., 2011) represent the main determinants of inpatient expenses.

While the main driving factors of hospital expenditures are extensively identified, less is known about the hospitalization consequences in terms of expenses for healthcare services. Several works analyze the impact of admissions on out-of-pocket payments (Dobkin et al., 2018; Smith, 2005; Wagstaff, 2007), but mainly within a broader framework concerning household wealth. Hence, to the best of our knowledge, no previous studies analyze the effect of hospital admissions on individual healthcare expenditures (HCE). In addition to providing insight into the evolution of expenses around hospitalization, it helps to understand whether inpatient and out-of-hospital treatments are effective in caring for patients. It is crucial for the individual health status to avoid additional accesses and, consequently, reduce healthcare costs.

This chapter contributes to the existing literature by investigating the dynamic effect of hospitalization on healthcare expenditures for the young-old population, defined as the group of individuals aged 50-70. Given the high cost of hospital services, a temporary increase in HCE resulting from the hospital admission is hardly unexpected. However, for such a population, the post-admission evolution of expenditures is less predictable. According to the existing literature, 7% of individuals face the first heart attack, stroke, or new onset of cancer between the ages of 50 and 64 Cutler et al. (2011), while 86% of the burden of chronic diseases

[46] They account, on average, for 38% of healthcare expenditures. Of all hospital spending, 6% is allocated to day hospital services (OECD, 2019).

are found to occur in people under 70 years of age (WHO, 2005). Hence, the span 50-70 represents the age window in which the first adverse health events arise and the life period in which living in good health becomes, on average, less likely, but the risk of health complications and death specific to the end-of-life period is still low. Consequently, inpatient care can be required for acute conditions with temporary effects on the health status or the treatment of ongoing or new chronic diseases and can open up different scenarios: the complete recovery of the admitted individuals, the onset of a chronic condition or disability, future hospitalizations, and premature death. These scenarios lead to different expenditures patterns for inpatient and out-of-hospital services that we will examine for several groups of individuals. Our primary focus is on how expenditures for such services evolve for individuals affected by different diseases, as well as for the broader group of the admitted experiencing a contemporaneous or subsequent onset of chronicity or disability.

Using a 10-year panel of individual records drawn from the Health Information System of the Agency for the Health Protection (*Agenzia per la Tutela della Salute* - ATS) of the Province of Milan, we carry out a difference-in-difference (DID) event study to estimate the short- and long-run impact of the hospitalization on different outcomes. As hospitalization represents one of the responses to such earliest shocks, throughout the chapter we call it 'first' hospitalization and consider it our event of interest. First, we analyze the effect of the first admission on total HCE to provide a general picture of the expenditures pattern around the event of interest. Second, we decompose total HCE to examine the evolution of expenses for hospital and day hospital admissions, outpatient services, and pharmaceuticals[47]. As a quasi-experimental design, we compare HCE of individuals who experience the first hospital admission (treatment group) to the expenditures of those who never have hospitalizations (control group). The latter act as a counterfactual for the treatment group and allows the inclusion of individual fixed effects on top of demographic and health-related traits and time fixed effects. The period considered is between 2008 and 2017.

Our main findings confirm the existence of a large effect of the first hospitalization on HCE that, in many cases, persists over time. This result suggests that the first admission is associated with substantial future medical expenses in all healthcare settings, accounted for the largest part by acute inpatient care. Indeed, the analysis of hospital expenditures indicates the occurrence of subsequent hospitalizations, mainly required for complications of cardiovascular diseases and cancer. These two diagnostic categories are responsible for the highest increase

[47] Note that, because the data collect the expenses incurred by the ATS per resident, the individual expenditures analyzed here does not represent the expenditures incurred by individuals for health care, but rather those incurred by the healthcare system of the area under consideration.

in inpatient expenditures and also present a persistent post-admission increase in outpatient and pharmaceutical expenses. In particular, the use of outpatient services appears to be intensive in the first few years after the admission, while pharmaceutical treatments seem to support the patients continuously during post-hospitalization. This result is driven by a high incidence of chronic and disabled individuals within the group of those affected by these two conditions[48]. Indeed, while non-chronic/non-disabled individuals are admitted for temporary health shocks that the hospitalization can promptly and successfully treat, individuals affected by long-lasting disorders require greater post-admission assistance within both the inpatient and out-of-hospital settings. We also note differences in the HCE evolution between those diagnosed at the first admission and those diagnosed later. For the latter, post-admission expenditures for hospital services are always above those of earlier-diagnosed individuals, suggesting that, in these cases, the hospital discharge is not followed by a care continuity path, resulting in subsequent hospitalizations for the treatment of a worsened health state.

From a policy perspective, hospitalization rates represent relevant outcomes in terms of both population health and economic performances. On the one hand, the quality of hospital admissions affect the health status of the population in the short and long run. On the other hand, cost-containment policies focused on the inpatient setting are the fastest way to cut costs. Consequently, our results, which show a significant rate of re-admission over the post-event period, raise questions about the quality of the healthcare system. They suggest the lack of effective rehabilitation to a health condition that can be treated successfully within the outpatient or primary care setting. In this scenario, a strengthening of territorial care, to be implemented alongside hospital-oriented cost-containment policies, seems necessary to reduce costs while improving population health. In particular, our results reveal the need for prevention enhancements aimed at softening the impact of ongoing illnesses with lasting effects, i.e., improvements of tertiary prevention approaches (Kisling and Das, 2020). On the one hand, it would improve patients' health by preventing complications and acute cases; on the other hand, it would also generate significant savings due to the prevention of avoidable additional hospitalizations.

The chapter is organized as follows. Section 2.2 explains the institutional context. Section 2.3 describes data and descriptive statistics. Section 2.4 presents our empirical strategy. Section 2.5 shows the main results, while Section 2.6 illustrates different robustness checks. Finally, Section 2.7 discusses the findings and Section 2.8 concludes.

[48]Indeed, those who survive an acute form of cardiovascular disease, such as acute myocardial infarction and angina pectoris, become chronically ill (della Salute, 2014); moreover, when the tumor cannot be completely eliminated, through immunotherapy it can be transformed into a chronic disease (Crombet and Lage, 2016; Phillips and Currow, 2010).

2.2 The evolution of the Lombardy healthcare system

The Lombardy healthcare system is designed as a network of public and private[49] actors and is based on the subsidiarity principle. The public system finances and regulates, while public and accredited-private third parties provide the services. In such a setting, objectives of effectiveness and efficiency are pursued through the competition among providers, while those of public interest through the regulation and control of Region and local health authorities, i.e., the Agencies for the Health Protection[50]. Moreover, following the citizens' free choice principle, the quality of the service provided, rather than the structure's ownership, is promoted as a priority value.
Another key feature of the Lombardy social-healthcare system is the complete separation of territorial care from the hospital one. The latter is aimed at individuals requiring overnight care, that can be planned or resulting from emergencies evaluated in the emergency room. In the former case, the hospitalization is usually preceded by a series of medical treatments and diagnostic tests to prepare the patient for the hospital stay that can be carried out several months before the access within the territorial setting. Indeed, the latter provides day-to-day healthcare for non-acute conditions that can be managed and controlled through pharmaceutical treatments, diagnostic tests, and minor surgical procedures. In both cases, however, access is facilitated by the financial contribution of the Italian healthcare service (*Servizio Sanitario Nazionale* - SSN). In particular, hospital care is free of charge for emergencies and under the presentation of physicians' referrals. Territorial assistance, instead, is also generally financed by patient's contributions according to cost-sharing schemes. The provision of total or partial exemptions from co-payment is ensured to specific groups of patients for pharmaceuticals and outpatient services. Chronic individuals, as well as individuals with rare diseases, HIV-positive individuals, and pregnant women, are partially exempted for the treatments related to their condition; total exemption, instead, is ensured to individuals with severe disabilities[51], low-income households[52], and

[49] Under the healthcare system, private providers are accredited to offer care on behalf of the Nation Healthcare System.

[50] The Regional Law 23/2015 (Regional Law 11/08/2015) reformed the organization of the Lombardy healthcare system by introducing new local authorities named *Agenzia per la Tutela della Salute*, i.e. Agencies for the Health Protection. In particular, the ATS of the Province of Milan substitutes and includes the ASL of Milano 1, Milano 2, and Lodi (residents in Lodi are excluded from the baseline sample).

[51] Civil invalids and invalids for work (individuals employed in private companies), service (public employees) and war and victims of terrorism and victims for duty (Ministerial Decree 1/02/1991; Legislative Decree 29/04/1998; Law 12/03/1999; Law 3/08/2004; DPR 7/07/2006).

[52] Children under-6 and over-65 individuals belonging to a household with an annual gross income lower than or equal to 36,151.98€, individuals with social pensions, over-60 individuals with minimum-pensions and unemployed and their household with an annual gross income lower than or equal to 8,263.31€ for singles and 11,362.05€ for larger households (Law 24/12/1993). These income-related exemptions have equal application at the national level, but each region

prisoners.

This organization has contributed, over time, to the construction of an articulated and differentiated supply system, which particularly excels in the treatment of acute cases. The high quality of hospital services is demonstrated by the fact that, in 2014, only 60,000 hospitalizations each year were provided for Lombardy citizens outside the region, and about 160,000 were provided to patients from other regions, with a particular concentration in high-complex care areas such as cancer and cardiovascular diseases (Lombardia, 2014). However, like any advanced system, the Lombardy healthcare system has to face the challenge of the exponential growth of the elderly population, parallel to the expansion of the chronic population, often affected by co-morbidities and consequent fragility. In 2017, individuals over-65 were 23% of the 10,036,258 total residents in Lombardy, and those defined as chronic was 34%. In particular, 40% presented at least one chronic disease, while 19% at least two (Istat, 2017). Altogether, in 2012 they accounted for almost 80% of the total healthcare expenditures if only hospitalizations, outpatient services, and pharmaceuticals are considered.

In an attempt to address these demographic changes and the changing need and demand of the population, several interventions have been implemented. In particular, the provision of services has been rationalized mostly within the inpatient settings to reduce unjustified and inappropriate hospital admissions and consequent costs. It has resulted in a 'de-hospitalization' phenomenon, which, although the provision of services has been mainly maintained within the inpatient setting, has brought a progressive shift from the hospital assistance to the territorial setting, where continuity of care, essential especially for chronic and disabled individuals, can be provided more effectively and at lower costs. From 1999 to 2014, hospital beds were reduced by 20% (from 45,400 to 37,500), while hospitalizations by 26% (from 1,294,000 to 958,000). During the same period, reductions in hospitalizations were complemented by an increase in the number of outpatient services provided, which passed from 108 to 170 million (Lombardia, 2014).

Although tempered by the new needs for territorial assistance, hospital care is still considered a crucial component within the Lombardy healthcare system, but with tasks increasingly aimed at treating acute pathologies of high-clinical content.

is given the option of introducing additional measures. For example, in Lombardy, subjects suffering from chronic and rare diseases belonging to a household with a total income of the previous year not exceeding 46,600€ are also exempted from the co-payment for pharmaceutical purchases (Annex 8-bis and Annex 7 of the DPCM 12/01/2017).

2.3 Data and descriptive statistics

2.3.1 Data and sample selection

We use a unique dataset drawn from the Health Information System of the ATS of the Province of Milan to investigate the effect of the first hospital access on healthcare expenditures. The dataset consists of about 1,000,000 individuals observed over the period 2008-2017, for a total of roughly 8,000,000 observations[53]. It provides information on individual expenditures covered by the Italian healthcare system, along with demographic and health-related traits. Individual expenditures include expenses for pharmaceuticals, scheduled and emergency hospitalizations as a whole, day hospital and outpatient services. Demographics cover gender, age, residence area, and income-related exemptions, while health-related characteristics comprise disease- and disability-related exemptions, the number of co-morbidities, as well as the year of demise[54].

The sample includes the whole population of the Province of Milan aged 50-70[55]. As already discussed, the choice of this lifespan aims to identify more reliably the first adverse health shocks that a person experiences during his or her life. Such shocks represent critical events that may have temporary or permanent impacts on the individual health status, defining the evolution of future healthcare expenditures. Hence, in this context first hospitalizations are analyzed as a measurable subset of such events which can lead to different scenarios, such as the complete recovery of the admitted individuals, the onset of chronicity or disability, future admissions, or death. Note that the number of hospital admissions and expenditures are recorded in the dataset on a yearly basis. It implies that, when multiple admissions occur in a year, we only know the total number of accesses, but not how spaced in time they are. In those cases, the first hospitalization is identified as the first year an admission is recorded, although there may be more than one.

To carry out our event study, we divide the sample between individuals who never experience a hospitalization during the whole period (control group) and those who experience the first admissions between 2011 and 2013 (treatment group), a time window ensuring a sufficiently long time span before and after the event. In particular, we focus on individuals who have not had a prior hospitalization for several years preceding the first access, restricting the two groups to individuals observed at least three years before the event (treatment

[53] Adjustments and modifications made on the sample are described in Appendix 2.A.

[54] Name, type and description of all the variables used throughout the analysis are reported in Table 2.A.1 in Appendix 2.B.

[55] The dataset is constructed so that the registered individuals are those who are 50-70 years old between 2008 and 2017. It means that those who enter in 2008 at the age of 70 remain only one year in the sample, as well as those who turn 50 in 2017.

group) or the year 2011, 2012, or 2013 (control group). In addition, to observe the expenditures trend in the post-event period, we select only those who remain in the sample for at least one year after hospitalization[56], or after the year 2011, 2012, or 2013 for the control group. The final sample includes 65,882 individuals in the treatment group and 393,878 in the control group, for a total of more than 4 million observations.

2.3.2 Descriptive Statistics

The number of first admissions declines over time, going from 27,891 in 2011 to 15,503 in 2013 (Table 2.B.1 in Appendix 2.B). This decrease is likely due to the reduction of hospital beds and admissions carried out by the Lombardy healthcare system (Figure 2.B.1 in Appendix 2.B) to cut back unjustified and inappropriate hospital admissions and consequent costs, and progressively shift care from the hospital to the territorial setting. First accesses are associated with average total individual expenses of about 8,300€ (SD = ± 10,560€). At the time of the event, treated individuals are, on average, 62 years old, and most of them are admitted only once (70%). Regarding health status, 14% and 2% obtain the disease- and disability-related exemption[57], while 34%, 24% and 14% present, respectively, 1, 2, 3 or more co-morbidities. Moreover, in addition to the pathologies included in the residual category 'Other'[58], the most common causes of admissions are cardiovascular diseases, cancer, digestive system disorders, and Chronic Obstructive Pulmonary Disease (COPD). The first access is then associated with subsequent health events during the post-event period: 27% and 14% of individuals are re-admitted, respectively, once and two or more times; 2.24% and 1.62% obtain, respectively, a disease- and a disability-related exemption; 1.42% die.

Table 2.1 shows some pre- and post-event sample means of several individual traits by treatment status. In the absence of treatment, we would expect similarities between the two groups in terms of health-related traits. However, the population of those who experience a hospitalization appears to be less healthy than individuals in the control group. Indeed, among the treated, about 45% is

[56]In Section 2.6.1, we perform a robustness check where we remove such sample restrictions to analyze the presence of selection bias that these restrictions could potentially generate. We also address the problem of attrition bias, arising from individuals leaving the sample after the first hospitalization because of non-random mortality or other causes related to the admission.

[57]48.33% and 8.27% of admitted individuals, instead, have already obtained the exemption for chronic disease or disability.

[58]It contains all the MDCs that are not identified in the dataset. They are: diagnosis related to ear, nose, mouth and throat; liver and pancreas; skin, subcutaneous tissue and udder; endocrine, nutritional and metabolic diseases; diagnosis related to kidney and urinary tract; diseases of male and female reproductive systems; birthing diagnosis and services for regular neonate; diseases of hematopoietic organs; disorders for alcohol, medicines abuse and other types of dependency; traumatisms, intoxications and toxic effect; other factors influencing the individual health status.

Table 2.1: Descriptive statistics.

Individual characteristics				
	Pre-event		**Post-event**	
	Control	Treatment	Control	Treatment
Age	57	59	61	63
Male (%)	44.03	52.01	44.69	51.58
Disease exemption (%)	29.61	44.59	38.44	67.83
Disability exemption (%)	3.05	7.63	3.55	14.80
N. of co-morbidities (%)				
0	70.41	54.98	57.58	27.63
1	21.26	27.62	28.57	32.64
2	6.45	12.21	10.25	22.92
3+	1.89	5.20	3.61	16.81
Deceased (%)	-	-	0.08	1.20
Healthcare expenditures [a]				
Total HCE	365	665	384	2,221
Hospital	-	-	-	1,069
Day Hospital	26	54	17	53
Outpatient services	207	363	207	640
Pharmaceuticals	131	247	160	459

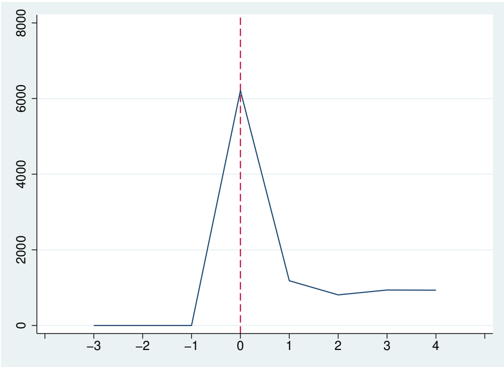
Note:
Yearly statistics.
All the differences between the treatment and the control group are significant at 1% level.
In constructing pre-event characteristics, we focus on the years prior to the event window 2011-2013, while in constructing post-event characteristics we focus on the years after 2013.
[a] Expenditures data is deflated by dividing current expenditures by the Italian consumer price index for the health sector provided by the OECD. The reference year is 2015.

exempted for disease and 8% for disability, against, respectively, 30% and 3% among those never treated. The percentage of individuals with 1, 2, and 3+ co-morbidities is also higher in the treatment group. The share of unhealthy individuals then increases in the post-event period for both groups, with large pre-post differences observed especially for the hospitalized. For the control group, such increases are probably due to aging. For the treatment group, instead, the extensive variation presumably results from the combined effects of aging and the first health shocks, represented here by the first hospitalizations, which often permanently impact individual health status.

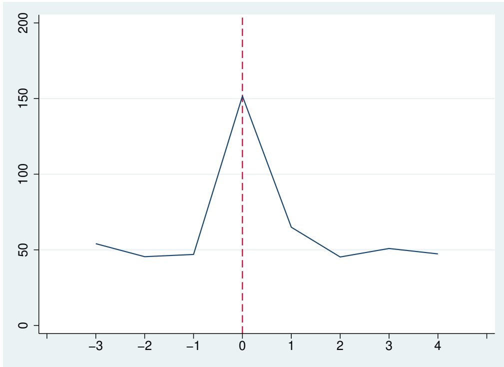
As expected, the compositional disparities between treated and never-treated individuals are reflected in differences in average HCE reported at the bottom of the table. Average total expenditures, which corresponds to the sum of individual average costs for hospital and day admissions, outpatient services, and pharmaceuticals, in the pre-event period are higher for the treatment group, as a result of about 28€ more for day hospital treatments, 156€ more for outpatient

Figure 2.1: Average unconditional HCE by event time.

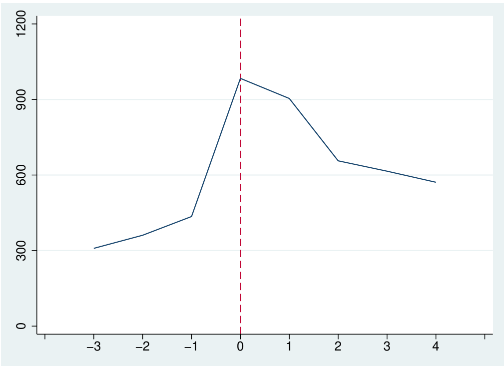
(a) Hospital



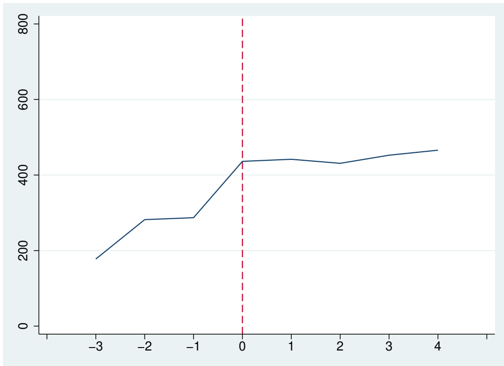
(b) Day Hospital



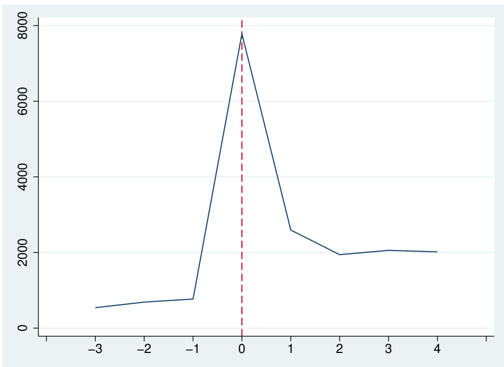
(c) Outpatient services



(d) Pharmaceuticals



(e) Total HCE



Note:
Yearly average expenditures.
Graphs are made by using a balanced sample of individuals.
Expenditures data is deflated by dividing current expenditures by the Italian consumer price index for the health sector provided by the OECD. The reference year is 2015.

services and 116€ more for pharmaceuticals. Then, interestingly, in the post-event period, only treated individuals go through a sharp increase in expenditures, with total HCE about four times higher than the pre-event level. Hence, the compositional change observed within the control group is not followed by a simultaneous rise in expenditures, revealing and highlighting, even more, the economic burden of the first hospital admission for those who experience them.

A more in-depth insight into health expenditures evolution is provided in Figure 2.1, which illustrates the dynamic trend of average unconditional HCE incurred by treated individuals around the event of interest, i.e., the first hospital admission. Here, the vertical red dashed lines represent the time treated individuals experienced the first hospitalization ($s = 0$), while the x-axis reports the relative time to the event. Total HCE (panel e) show a remarkable peak at the time of the first access, reaching an average of 8,000€ per person per year. After the event, expenditures gradually settle on and remain stable around a considerably higher level than the pre-admission one (roughly 2,000€). While the pattern of total HCE in $s = 0$ and post-event periods is mainly driven by the evolution of inpatient expenses (panel a), the increasing trend before the admission reflects the pattern observed for outpatient (panel c) and pharmaceutical expenditures (panel d). Interestingly, the latter keeps its growing trend even after the hospitalization.

The findings reported in this section show that, except for day hospital expenses (Figure 2.1b), expenditures increase at the access and remain higher than the pre-event level for all the spending categories, suggesting large post-event healthcare expenditures for both inpatient and out-of-hospital settings. However, in order to interpret this evidence in causal terms, several issues need to be addressed. The pre-event compositional difference between treated and never treated and, although small, the resulting gap in spending, represents a threat for the identifying assumption of the DID event study, which requires the two groups to maintain a similar expenditures pattern in the absence of treatment. In addition, the dynamic pre-event trend of HCE, with the first hospitalization preceded by an increase in outpatient and pharmaceutical spending, suggests that the first hospitalization is not entirely unexpected for the treated, probably due to the occurrence of elective hospitalizations. Hence, these characteristics should be considered in the estimation strategy, which we describe in the next section.

2.4 Empirical strategy

2.4.1 Main specification and identifying assumption

We analyze the dynamic effects of the first hospitalization on HCE by specifying a non-parametric difference-in-difference (DID) event study. This design aims to estimate the impact of an event that occurs for certain units in specific time periods. By considering the variation in outcomes around the event compared

with a baseline reference period, both event lags and leads are estimated, allowing for a clear visual representation of the causal impact of the event, provided that key identifying assumptions are met (Acemoglu et al., 2011).
Consider an unbalanced panel of $i = 1, ..., N$ individuals observed in $t = 1, ..., T_i$ years (calendar times), where each person is randomly hospitalized for the first time in a given period E_i. Let $S_{it} = t - E_i$ denote the relative time, that is, the relative distance to the event. We estimate the following model:

$$\begin{aligned} Y_{it} = \beta c_{it} + \gamma_{A-} \cdot 1\{S_{it} \leq A\} + \sum_{s=A}^{B} \gamma_s \cdot 1\{S_{it} = s\} + \gamma_{B+} \cdot 1\{S_{it} \geq B\} \\ + \alpha x_{it} + \eta_i + \nu_t + \epsilon_{it} \end{aligned} \tag{2.1}$$

Y_{it} is the outcome of interest, which describes, alternatively, total HCE and expenditures for hospital, day hospital and outpatient services, and pharmaceuticals[59]. x_{it} is the set of time-varying controls described in the next section; c_{it} is a continuous variable capturing any linear trend prior to the hospitalization; η_i and ν_t are individual and time fixed effects, and ϵ_{it} is the unobserved error term.

The factors of interest are the coefficients γ_s of the leads $s_{<0} = -1, ..., A$ and lags $s_{\geq 0} = 0, ..., B$ of treatment, which are binary variables indicating the number of periods a given individual is distant from the first admission, occurring at $s = 0$. In particular, $A = 3$ leads and $B = 4$ lags of treatment are included for the estimation of short-run effects, while the two single variables $1\{S_{it} \leq A\}$ and $1\{S_{it} \geq B\}$ are added for all longer-run effects exceeding $A = 3$ leads and $B = 4$ lags, respectively[60] (Borusyak and Jaravel, 2017; Freyaldenhoven et al., 2019). The associated coefficients γ_s estimate the outcome change at a given relative time S_{it} with respect to the omitted category $\gamma_{s=-1}$, i.e., the year before the event. Hence, for $s < 0$, they show pre-event trends; for $s \geq 0$, they capture the effective treatment effects, that is, the dynamic impact of the event on the outcome of interest.

The specification suffers from a fundamental under-identification problem. The presence of individual and time fixed effects makes it impossible to disentangle the passing of absolute time from the passing of relative time to the event. Indeed, since there is a perfect linear relationship between the calendar year t, the year in which the event occurs E_i, and the relative time S_{it} ($S_{it} = t - E_i$), it is impossible to observe independent variations in these variables. A common approach to address this under-identification issue is to add a control group to estimate the year

[59]We specify Equation 2.1 in levels rather than in logs to be able to keep the zeros in the data.

[60]More precisely, $1\{S_{it} \leq A\}$ indicates that the event took place more than A periods in the past and $1\{S_{it} \geq B\}$ indicates that the event is more than B periods in the future.

effects independently of the causal effect of treatment[61] (Borusyak and Jaravel, 2017). Therefore, the control group of the never hospitalized is included in the estimation sample[62]. These individuals have zeros in all lag and lead terms and act as the counterfactual for the estimation of impacts. Indeed, with a control group, lags and leads capture the difference between the groups compared to the baseline difference, normalized to zero in the omitted base period $s = -1$.

In the presence of a control group, unbiased estimation of post-event treatment effects relies fundamentally on the classical DID parallel-trends assumption[63]. In the empirical analysis, we assess its validity by testing for the presence of pre-trends, i.e., differences in trends between treated and never-treated individuals before the admission[64] Note that the identifying assumption also requires that there are no factors correlated with the outcome that, conditional on the included controls, occur contemporaneously with the hospital admission.

Finally, it is worth pointing out that the estimates obtained according to the specification described here are based on the full population of admitted individuals, irrespective of the total number of accesses they undergo during the observed period. Therefore, the dynamic post-event patterns include the effects of hospitalizations that occurred after the first one, that, especially when unplanned, are found to be rather frequent (Downer et al., 2019; Merkow et al., 2015; Upadhyay et al., 2019; Whitney et al., 2017). While this issue may be solved by controlling for future admissions, we choose not to for two reasons that are linked to the fact that some of the future hospitalizations may be re-admissions[65], that is hospitalizations required for health complications related to the first admission. First, if subsequent admissions are linked to each other, it would generate endogeneity issues. Second, to the extent that future hospitalizations are re-admissions, there is no reason to remove their effect from the estimates of the coefficients on the event time. In that case, the impact of subsequent events is a direct implication of the first access and controlling for future hospitalizations would not

[61] Previous studies (Dobkin et al., 2018; Kleven et al., 2019) use an event study specification to analyze the effect of interest by considering only the population of the treated. However, in this way, it would not be possible to include individual fixed effects, which are crucial in health studies. Indeed, within-individual estimates allow for time-invariant heterogeneity across individuals, as they capture the impact of unobservable individual-specific characteristics, such as genetic traits or lifestyle choices.

[62] As a robustness check, in Section 2.6.1 we drop the individual fixed effects and balance the sample of the treated around the event.

[63] In the absence of treatment, it is assumed that the treatment and control group would have maintained similar differences as in the baseline period. Therefore, to interpret the estimated coefficients as the causal effect of the admission, for the individuals in the treatment group, the timing of the first hospitalization, conditional on the included time trends and individual time-variant and -invariant controls, has to be uncorrelated with the outcome.

[64] In practice, we examine the patterns of the outcome in the years leading up to the first hospitalization and verify whether individuals are on an upward or downward trend.

[65] Note that in this analysis we consider re-admission each subsequent hospitalization following and linked to the first one.

allow us to draw any conclusions on the effectiveness of inpatient treatments in terms of health rehabilitation. Therefore, the estimated long-run impacts shown in the next sections are interpreted as capturing the total impact of admissions, according to the assumption that future events are strictly related to the one of interest. The implications of multiple admissions are further explored in Section 2.6, where we also analyze violations of the identifying assumption due to attrition and selection bias and verify whether the empirical strategy is robust to different specifications and alternative samples.

2.4.2 Controls included in the main specification

To control for observable confounding factors, we augment the specification with several controls, which, according to the existing literature (Howdon and Rice, 2018), represent the main determinants of healthcare expenditures. Their inclusion also allows us to meet the common-trend assumption by controlling for differences in characteristics between the treatment and the control group analyzed in the previous section (Table 2.1).

First, we control non-parametrically for age and end-of-life period[66], where the latter is captured by dummies indicating time to death[67] (TTD). In this way, we estimate the effect of the first admission net of life-cycle patterns to obtain unbiased estimates of the impact of the passage of time on HCE.

Second, the number of co-morbidities and the linear term c_{it} are added for the event to be completely unanticipated, conditional on the included controls, i.e., to control for factors that could be contemporaneously correlated with the outcome and the event, generating concerns about the strict exogeneity of the first admission[68]. The first one captures the severity of the individual health condition by recording the presence of health disorders occurring along with a primary disease[69]. The second one, c_{it}, is a continuous variable capturing any linear trend prior to the hospitalization, with the coefficient β representing the slope of the

[66] A large share of HCE among the elderly is often found to be caused by proximity to death more than aging (Breyer and Lorenz, 2019; Costa-Font and Vilaplana-Prieto, 2020; Lorenz et al., 2020; Zweifel et al., 1999)

[67] In particular, TTD-0 is equal to 1 in the year of death, TTD-1 in the year before, and so on, up to TTD-5, which is equal to 1 at five or more years from death and for those who survive during the observed period.

[68] As further demographic characteristics, we also control for the area of residence, which indicates if individuals live in urban areas, and the presence of the income-related exemption. The latter is included as an absorbing-state variable (it is equal to 1 when the exemption is released and for each subsequent period) which provides the static before-after effect of the economic status on individual healthcare expenditures.

[69] Each additional condition being thus identified as a co-morbidity. Therefore, one co-morbidity corresponds to two conditions, while individuals with zero co-morbidities are those who do not present any disease or those who are affected by one disorder.

trend[70]. It allows us to estimate the coefficients γ_s net of any unobserved pre-trends, like those generated by the occurrence of planned first admissions. Indeed, while we are able to separately identify hospital services for acute cases (overall hospitalizations) from those required for a scheduled rehabilitation (day hospital services), data does not provide any information on different types of hospital access, i.e., planned or emergency admissions. The former are usually preceded by several preparatory specialist visits or therapies and are thus associated with increased health expenditures in the periods before the admission. These features make the occurrences of such hospitalizations an issue for the estimation, as the event would be no longer as good as random. Indeed, individuals would be able to anticipate or have discretion on the exact time of the first admission. Note that, with c_{it}, each γ_s represents the deviation of y_{it} from the pre-event linear trend[71] (Dobkin et al., 2018; Freyaldenhoven et al., 2019).

2.5 Results

To carry out our analysis, we first estimate Equation 2.1 on the whole sample to evaluate the effects of hospitalization on total HCE and expenses for hospital and day hospital admissions, outpatient services, and pharmaceuticals. Next, we briefly focus on the impact of individual characteristics on total HCE to identify the main determinants of healthcare expenditures. The relative findings then help drive further investigations on the impact the event exerts on distinct groups of individuals, an exercise that allows us to delve into the mechanisms underlying the observed trend in expenditures around the admission.

For each estimation, we plot the estimated coefficients on event time (γ_{A-}, γ_s, and γ_{B+}) from Equation 2.1, along with their 95% confidence intervals (indicated by a blue vertical line). Our relative event time function s ranges from -3 years before the event up to 4 years after. The first hospitalization timing is indicated by a dashed vertical red line plotted at $s = 0$[72].

[70]The linear functional form is motivated by the results from the simple non-parametric event study reported in Table 2.B.2 in Appendix 2.B (fourth column), which suggest that a linear trend captures any pre-trends quite well.

[71]With the inclusion of the linear trend c_{it}, the identifying assumption is that, conditional on the included controls, the timing of the admission is uncorrelated with deviations of the outcome from a linear trend in event time. An implication of this assumption is that, while individuals may be on a secular trend before the admission, they are not able to anticipate or have discretion over the exact timing of the hospitalization (Dobkin et al., 2018).

[72]For all the estimations, standard errors are clustered at individual level to account for the within-individual correlation in HCE over time.

2.5.1 Total HCE and spending categories

We first analyze the impact of hospital admissions on total HCE according to different specifications (Table 2.B.2 and Figure 2.B.2 in Appendix 2.B). Each control is found to reduce the event's effect at the time of the admission and, even more, in the post-event period. By comparing the specification saturated by all the regressors with the one where only the event study function is included, we note that the impact of the first admission decreases by about 5% in $s = 0$ and by 30% four years after the event. At that time, the largest reduction is observed when health-related characteristics are included in the regression, underlining the central role of such traits in estimating unbiased admission effects. The estimated coefficients on the pre-event period also decrease in absolute terms and are even no longer statistically significant when the linear pre-trend is added. This finding points out the importance of controlling for unobserved trends for the discussed identifying assumption to be met. Indeed, without such a factor, the HCE gap between treated and never-treated individuals, normalized to zero in $s = -1$, would not be constant over time, indicating the presence of pre-event trends. In the absence of treatment, the HCE of the two groups would not evolve in parallel, violating the assumption of common-trends assumption. Hence, the result reported in the sixth column of Table 2.B.2 in Appendix 2.B supports the assumption that the first hospitalization is as good as random, conditional on the included controls, indicating our preferred specification.

The coefficients on the event time estimated according to our preferred specification are shown in Figure 2.2. Not surprisingly, the long-term statistically significant impact of the first admission reflects the fact that the first hospitalization is associated with substantial future medical expenses for inpatient and outpatient services and pharmaceuticals. However, the contribution of this analysis is that it provides the precise magnitude and evolution over time of average expenditures for different services.

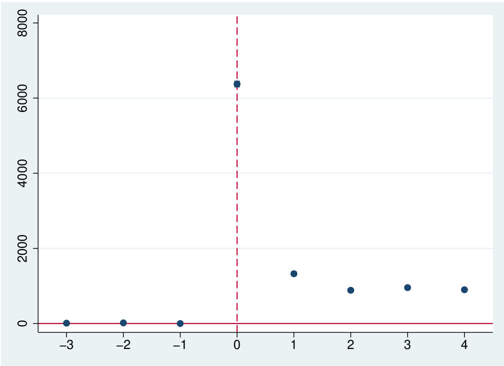
In $s = 0$, total expenditures rise by 7,000€ with respect to HCE of never-admitted (Figure 2.2e). Then, they rapidly decrease by about 73% one year after the hospitalization and by 85% four years after, without ever returning to the pre-event level[73]. To give an idea of the magnitude of the effect in absolute terms, we calculate the average unconditional total HCE for never-treated individuals, which amount to about 385 € . It follows that overall expenditures of the treated amount to almost 1,400€ four periods after the admission, a figure that shows the full extent of the economic burden of the first health shocks.

As suggested by Figure 2.2a, the evolution of total expenditures after the first

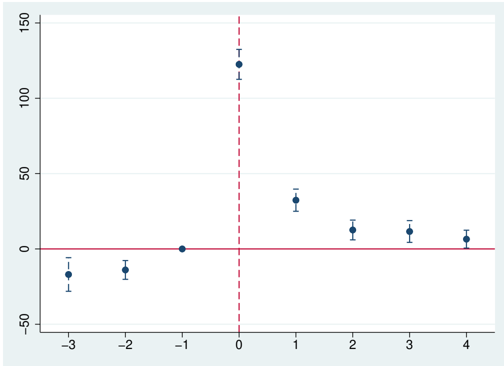
[73] Percentages reported in this section are derived by looking at the estimated coefficients in Table 2.B.3 (Appendix 2.B) and are calculated with respect to the relative time $s = 0$.

Figure 2.2: Total HCE and expenses for different services by event time.

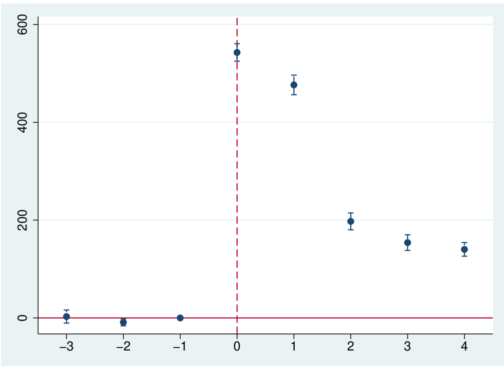
(a) Hospital



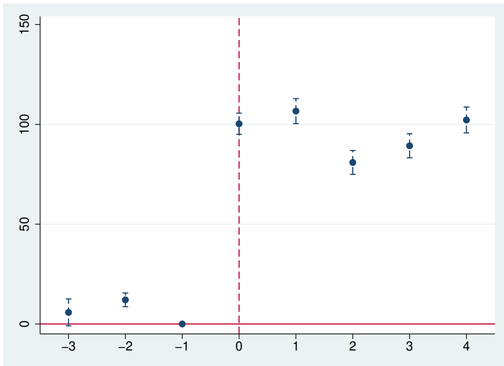
(b) Day Hospital



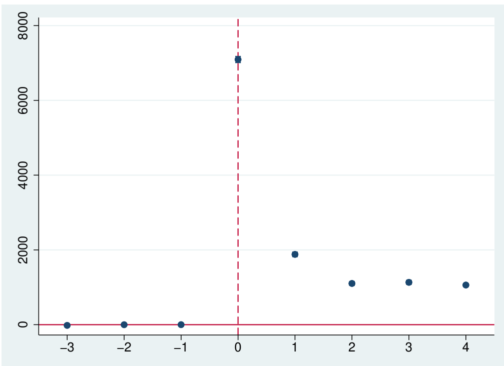
(c) Outpatient services



(d) Pharmaceuticals



(e) Total HCE



hospitalization is mainly driven by the effect of hospital admissions on HCE[74]. Indeed, even after $s = 0$, hospital expenditures are found to be considerably higher than the pre-event level. This result indicates the occurrence of future admissions, whose effects will be extensively examined in Section 2.5.2, where we discuss several heterogeneity effects.
The other panels of Figure 2.2 illustrate the results from the estimates on the remaining spending categories, which reveal an immediate and long-term effect of the first admission on the expenses for all the other services. At the time of the access, expenses for day hospital admissions increase by about 120€ (140€ in absolute terms) with respect to the pre-event period, and then rapidly decline, approaching their pre-admission level[75]. Those for outpatient services, instead, decrease relatively slowly. In particular, when hospitalized, individuals spend for outpatient services about 540€ more than the never-treated (about 750€ in absolute terms) and then experience a gradual drop in the following years. One year after the admission expenses decrease by 12%, 64% two years after, and 74% in the fourth year. Regarding pharmaceutical expenditures[75], after the increase of 100€ in $s = 0$ (about 250€ in absolute terms), expenses seem to follow a cyclical pattern and come back to the event-level after four years.

Determinants of total HCE

Although the main focus is on the evolution of expenditures around the event, it is worth briefly analyzing also the effect, in some cases even quite large, that some individual characteristics have on total HCE for individuals aged 50-70[76].

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[74]Since individuals in the control group do not incur any hospital expenses, the estimated coefficients reported in Figure 2.2a represent absolute means for the individuals in the treatment group.

[75]Note that the estimation of the coefficients on the event time for day hospital expenses should be interpreted with caution, as the statistically significant pre-trend shows that the common trend assumption is not met. It is probably due to the fact that the pre-event trend in HCE estimated without the term c_{it} presents a non-linear shape that the linear term c_{it} is not completely able to capture. The same is true for pharmaceutical expenses. In this case, the higher expenditures of the admitted compared to the never admitted observed in s=-2 is driven by individuals who, at the time of the first hospitalization, already present a chronic disease or disability (the results on this specific population are not reported).

[76]Note that the model might suffer from multicollinearity, due to a high correlation among health-related traits and between those variables and the first admission. To test for the presence of multicollinearity, we report a correlation matrix for all the variables used in the model (Table 2.B.4 in Appendix 2.B) and the centered variance inflation factors (VIF) for the independent variables specified in a linear regression model, along with their reciprocals (Table 2.B.5 in Appendix 2.B). By looking at the correlation matrix, we observe that no couplet of independent variables are highly collinear. The only exception is the coefficient of the correlation between income-related exemption and age (0.4156), probably reflecting the fact that many classes of this type of exemption are ensured beyond a certain age threshold (65 years for low-income households and 60 for individuals with minimum pensions). However, such a correlation is rejected by the VIF. Indeed, by using the rule of thumb on which most analysis rely (Chatterjee et al., 1986), we do not observe strong evidence of multicollinearity in our model, as the mean of all the VIFs is not considerably larger than 1 and only the VIF associated to the event time

The effect of age and TTD is statistically significant and large in magnitude (Figure 2.B.3 in Appendix 2.B), a result in contrast with the so-called red herring hypothesis (Breyer and Lorenz, 2019; Costa-Font and Vilaplana-Prieto, 2020; Lorenz et al., 2020; Werblow et al., 2007; Zweifel et al., 1999). According to the latter, the observed positive correlation between age and healthcare expenditures is exclusively due to the fact that mortality rises with age, and a large share of HCE is caused by proximity to death; consequently, the effect of age on expenditures is found to be no longer statistically significant when proximity to death is also controlled for. In this analysis, instead, the age profile of HCE is increasing, with individuals aged 70 spending about 500€ more than 50-years-old individuals. Expenditures by TTD instead take an S-shaped curve. They linearly increase up to three years before the demise; then, in the two last years of life, they sharply rise, with dying individuals spending almost 8,000€ more than those who survive or are at five or more years from death ($TTD = 5+$, the omitted category). Although the red herring hypothesis is not confirmed for individuals aged 50-70, the result about end-of-life patterns still shows that a large share of HCE is incurred in the last years of life as a result of deteriorating health status and increased use of health services.

Regarding health-related characteristics, we note that the morbidity profile of expenditures (Figure 2.B.3b in Appendix 2.B) is increasing and convex, indicating a marginally increasing growth of HCE in the number of additional health conditions. Estimations show that an individual affected by three or more co-morbidities spends on average almost five times more than the healthiest person (about 2,000€).

2.5.2 Heterogeneous effects on total HCE

Demographic characteristics, number of co-morbidities and TTD

The existing literature documents that females generally tend to use significantly more outpatient services and pharmaceuticals and spend more for such services than men, with the greatest disparity in expenditures noted in the population aged 45-64 years (Gabriele et al., 2006; Owens, 2008; Williams et al., 2017). Consequently, given the higher demand for the continuity of care, we expect women to use less acute hospital treatments[77] and spend less when they

$s = 0$ is greater than 10. From further investigations, we observe that this result is given by the correlation between the linear pre-trend and the year of the admission, probably due to the occurrence of planned hospitalizations which are usually associated to an increase in expenditures before the admission. However, the reciprocal 1/VIF, which shows tolerance, is lower than 0.1, indicating a low degree of collinearity between these two terms. Hence, overall, we estimate a quite parsimonious model.

[77]It is confirmed by the results reported in Table 2.B.6 in Appendix 2.B, reporting the marginal effects of individual characteristics on the probability of future admissions.

are needed; in contrast, we expect men to make greater use of inpatient care and to spend more when this types of services are required. Heterogeneous effects by gender (Figure 2.B.4a in Appendix 2.B) shows that, when admitted, men aged 50-70 spend about 600€ more than women. Since total expenditures are found to be mainly driven by expenses for hospital services, the evidence provided by the literature seems to be confirmed, although the gender gap reduces over time after the hospitalization.

Concerning life-cycle patterns, we analyze the effects of hospitalization by age, surviving status, and time to death at the first admission[78] (Figure 2.B.4b and Figure 2.B.4c in Appendix 2.B). As previously shown, even after controlling for health-related traits and TTD, age is still one of the most important factors of HCE and plays a significant role in defining the evolution of expenditures around the first access. At each relative time, total HCE is systematically increasing in age, with the oldest spending about 1,500€ more than the youngest in $s = 0$. Then, as expected, the increase in HCE among those who die is remarkably larger than the expenditures growth of survivors, even when death occurs several years after the admission. In particular, while HCE of survivors settle on a stable horizontal path after the event, expenditures of those dying after four years move following a U-shaped curve[79]. After a gradual drop in expenditures, HCE start growing again from the third year from the event, suggesting a heavy use of hospital services during the last years of life. It is confirmed by our additional estimations, which show that being one year from death ($TTD = 1$) increases the probability of hospitalization by 24.53% while being in the year of death ($TTD = 0$) by as much as 51.59% (Table 2.B.6 in Appendix 2.B). Such a result is also in line with the existing literature on healthcare expenditures and time to death. Geue et al. (2015) find an exponential increase in the probability of accessing hospital care from the penultimate to the last quarter of life relative to the 12$^{\text{th}}$ quarter before death. They also document significantly higher costs in the last eight quarters of life, as illustrated in our figure for individuals at three and four years form death in $s = 0$ and by the effect of time to death on total HCE (Figure 2.B.3c in Appendix 2.B).

As an additional exercise, we also analyze the event effects by the number of co-morbidities at the access (Figure 2.B.4d in Appendix 2.B). Given a more severe health condition and consequently greater need for medical assistance, individuals affected by three or more additional diseases face the highest increase in expen-

[78]Heterogeneous effects are analyzed between survivors and those who, at the time of the first admission, are one (TTD-1), two (TTD-2), three (TTD-3), or four (TTD-4) years from death. Note that those who die in the year of the first access are not included in the sample.

[79]Note that the reduction in total HCE for those who are one year or two distant from death at the time of first access is probably due to the fact that the demise occurs at the beginning of the year. Total expenditures are therefore composed only of expenses incurred from January 1 to death.

ditures at the first access and in following periods. They spend approximately 6,200€ more than individuals who do not present any co-morbidity in $s = 0$, and 2,200€ more in the fourth year from the event.

Number of accesses

Almost 30% of individuals experience multiple admissions in the first access year, and 40% are admitted in future years (Table 2.B.1 in Appendix 2.B). Hence, we analyze the heterogeneous effects of the event by the number of accesses in $s = 0$ and the number of subsequent years with admissions (Figure 2.B.4e and Figure 2.B.4f in Appendix 2.B).

Not surprisingly, at the time of the access, total HCE is increasing in the number of admissions, with those who experience 4+ accesses spending 30,000€ more than the pre-event level and almost eight times more than those who are hospitalized only once. Then, the trends observed for all groups gradually approach over time until they almost match up in $s = 4$. To the extent that healthcare expenditures are a good approximation for the underlying health status, it suggests that, after some periods, the same health level (although lower than the pre-admission one) is ensured to all hospitalized individuals aged 50-70, whatever the initial condition is.

To investigate the effects of future hospitalizations, we estimate a specification where the occurrence of additional admissions after $s = 0$ is controlled for and find that they account for 63% of the high level of total HCE observed in $s = 4$ (Figure 2.5c in Section 2.6). To analyze how the evolution of total HCE changes when additional hospitalizations occur, we compare individuals by the number of years individuals experience additional admissions (Figure 2.B.4f in Appendix 2.B). As expected, after the event, HCE of individuals admitted in one period only ($s = 0$) approach their pre-event level, while expenditures of those who experience multiple accesses during the observed period settle on a considerably higher amount. However, what is interesting is the cross-sectional profile of HCE. For each event time, the latter is increasing in the number of years with hospitalizations, suggesting that the more the individuals are admitted over time, the more the average annual total HCE increases. A possible explanation is that the number of years with accesses is positively correlated with the number of admissions per year or with the cost of hospital services. Whatever the reason is, both cases seem to be strictly related to the individual health status.

To identify the most responsible factors of further admissions, we carry out a probit model on the probability of being readmitted in subsequent years conditional on several individual characteristics (Table 2.B.6 in Appendix 2.B, first column). The marginal effects show that being male slightly increases the probability of being additionally hospitalized, as well as presenting a worse health condition. Interestingly, we do not find any difference in the probability of additional hospitalizations among individuals of different age; it suggests that, once health-related traits and time to death are controlled for, aging is no longer a determinant factor for the use of hospital services after the first admission.

By looking at the heterogeneous effects reported here, we note that the average total HCE evolution shown in Figure 2.2e reflects the one estimated for survivors and lies between the patterns of expenditures estimated for males and females, for those admitted at age 56-60 and 61-65, and for those presenting one and two co-morbidities. Total HCE is also mainly driven by those with one and two accesses in $s = 0$ and those who are admitted in one ($s = 0$) and two years during the observed period.

2.5.3 Major Diagnostic Categories

A large variation in healthcare expenditures by disease is well documented. OECD shows that the major non-communicable diseases groups covering circulatory, digestive (including oral health), muscular, cancer, endocrine, and mental health account for nearly 60% of health spending in OECD countries (OECD, 2013a, 2016). In particular, circulatory diseases (including stroke and heart attack) account for the largest share of health spending (from 11% to 15% of HCE across countries) and, along with cancer, for a high share of expenses in the inpatient and pharmaceutical sector (around 18% and 20% on average, respectively). Regarding outpatient spending, 25% relates to the digestive system (again including oral health), while between 6 and 10% to musculoskeletal, respiratory, and genitourinary systems. Instead, infectious diseases represent a small share of spending (from 1% to 6% of total health spending).

To better understand such variations, as well as differences in medical practice for specific conditions, we examine how expenditures for different spending categories evolve around the first admission by medical specialty or, equivalently, Major Diagnostic Category (MDC). They are aggregations of Diagnostic Related Groups (DRGs) and represent epidemiologically relevant groups of patients with similar problems and treatment patterns. In particular, these categories are related to the specialty for which a hospital or day hospital admission is required. To carry out our analysis, we focus on MDCs that are found to be the leading causes of the first admission. Since individuals may be hospitalized more than once during the year of the event, the leading cause is represented by the MDC related to the highest hospital expenses in the same year, which is considered the primary or most responsible diagnosis. Such a definition of the leading cause of hospital admission, however, gives rise to several issues. First, although it allows expenditures to be allocated to different disease groups in a mutually exclusive manner, when multiple admissions occur for different underlying diseases, we cannot exactly know whether the most expensive MDC is the true cause of the hospitalization. In the case of co-morbidities, we may incur an overestimation of the medical care costs of the primary diagnosis if part of the expenditures is linked to secondary conditions. Second, in terms of comparison among diseases, similar issues arise with pathologies that can be considered sequelae of other health conditions. Indeed, we cannot link multiple hospital stays, as no information is provided about re-admissions; links between hospital admissions, day hospital services, outpatient visits, or pharmaceuticals are not available either. Although the exact estimates of the cost-per-case for each particular disease cannot be provided, analyzing heterogeneous effects by disease still offers interesting evidence and allows us to identify the conditions requiring greater medical assistance after the admission.

For each diagnostic category, Figure 2.3 and Figure 2.B.5 (Appendix 2.B) show the estimated effects of the first admission on total HCE and expenses for the different spending categories[80].

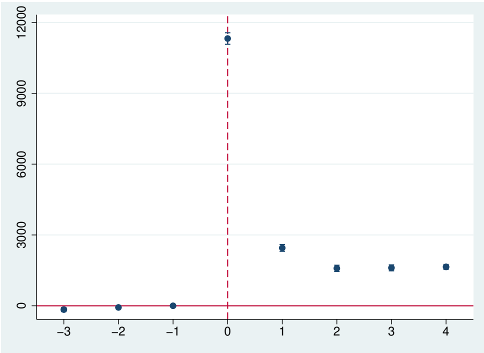
Circulatory diseases and tumors cause the highest increase in total HCE and hospital expenditures at the time and after the first access. By looking at the results for hospital expenditures, we note that the large and persistent long-term effect of the admission on total expenditures is mainly due to the occurrence of additional accesses after $s = 0$. Cardiovascular diseases account for 21% of total future hospitalizations, while cancer for 17%. The predicted probabilities of being further admitted for these two conditions, conditional on the leading causes of the first access, are found to be the highest in case of re-admission, i.e., the leading cause of the additional hospitalization is the same as the first access, and higher than 10% for almost all the other diagnostic categories (Table 2.B.7 in Appendix 2.B). Regarding cardiovascular diseases, this result indicates a high frequency of complications related to the circulatory system, not only when the first access is due to disorders of this type, but also when the primary disease at $s = 0$ belongs to other diagnostic categories (for example, infectious and nervous system diseases, COPD, digestive system and musculoskeletal diseases). It is probably driven by the fact that such conditions, often called 'silent killers', develop slowly over time and rarely show early symptoms (WHO, 2013). Regarding tumors, our result suggests that many of the pathologies diagnosed at first access have a significant probability of leading to a new onset of cancer.

Cardiovascular diseases and tumors also generate a considerable need in terms

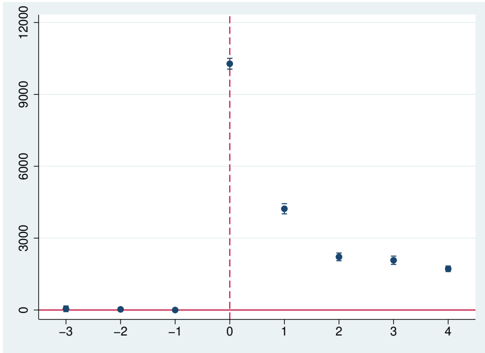
[80]Figure 2.B.5 (Appendix 2.B), the MDCs are divided into two groups. The first group combines disorders (cardiovascular diseases, tumors, Chronic Obstructive Pulmonary Disease (COPD), and disorders of the digestive system) that can be more effectively prevented and controlled within the outpatient and primary care setting (OECD, 2019). Moreover, these conditions together affect more than half of the population included in the treatment group (as reported in Table 2.B.1) and are related to roughly 50% of hospital admissions and expenditures recorded in our dataset. The second group includes all the other MDCs (Infectious diseases, Musculoskeletal diseases, mental disorders, and nervous system diseases), except the residual category 'Other'. The latter is not included because it combines diseases that are not related each other.

Figure 2.3: Total HCE by event time and MDC.

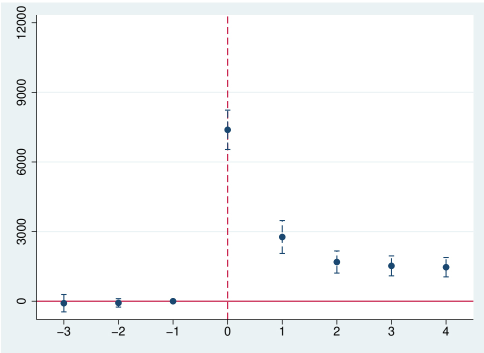
(a) Circulatory disease



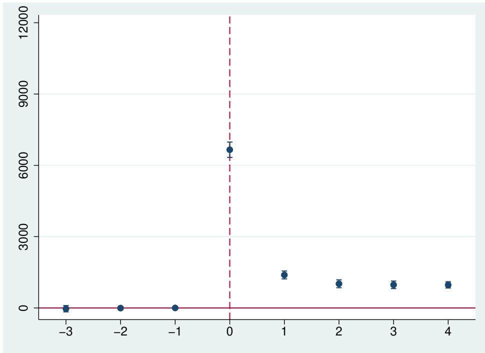
(b) Tumor



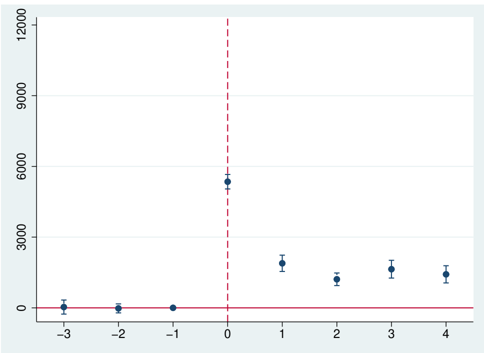
(c) Infectious disease



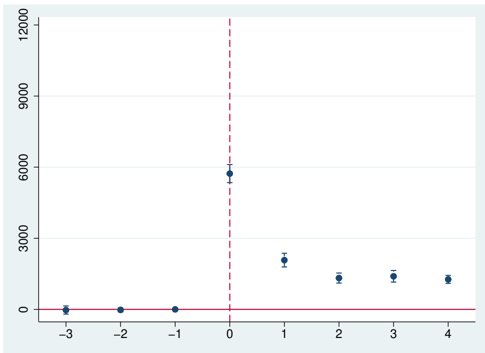
(d) Musculoskeletal disease



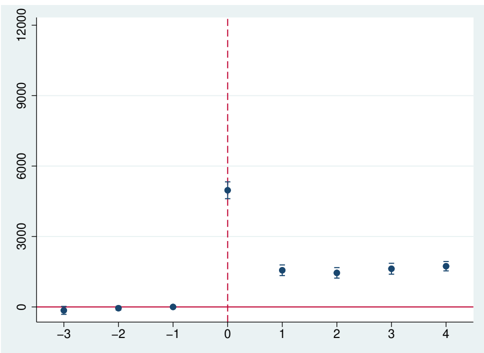
(e) Mental disorder



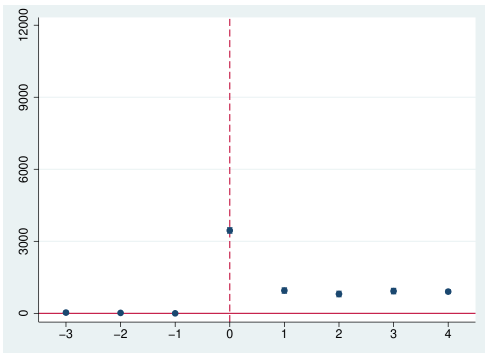
(f) Nervous System disease



(g) COPD



(h) Digestive System disease



of post-admission assistance outside the hospital, especially regarding outpatient services and pharmaceuticals. In particular, outpatient (for an individual admitted for tumor) and pharmaceutical expenditures (for both the MDCs) present the same post-event evolutions as those estimated for the entire population, although a considerable difference in level is observed. For example, at the time of the event, an individual affected by cancer spends on outpatient services about four times more than the average hospital patient.

Respiratory diseases and digestive system diseases are instead the two least expensive leading causes of admission in terms of total expenditures at the access. Although they represent one of the categories with the highest percentages of related first admissions (Table 2.B.1), at $s = 0$ and after, they show the lowest increase in hospital expenditures, as well as in outpatient services and pharmaceuticals (the first access is found not to affect day hospital expenditures). Regarding digestive system diseases, a possible explanation is that their treatments are mainly related to oral health, which is often financed through out-of-pocket payments, with the latter not included in our dataset as it records only expenditures covered by the Italian healthcare system. Regarding respiratory disorders, instead, the low increase in total expenditures in $s = 0$ may be related to the fact that it is mainly represented by COPD, a disease that can be effectively prevented and controlled within the outpatient and primary care setting (OECD, 2019). This explanation is also confirmed by the post-event evolution of pharmaceuticals. At the time of the admission, it presents a relatively lower growth than other diseases, but then linearly increases over time up to reach and exceed, in $s = 4$, cancer patients' expenses.

Results concerning mental disorders also provide interesting evidence. The OECD study (OECD, 2016) documents a high prevalence and burden of mental health diseases. However, the proportion of total public spending allocated to mental health care is often small across OECD countries[81], with differences in level reflecting healthcare systems organization and specific policies for the treatment of mental disorders. In Italy, for example, efforts have been made to reduce inappropriate use of inpatient services for patients with mental disorders, and re-admissions are monitored to improve the organization and clinical effectiveness of mental healthcare outside the hospital (OECD, 2013b). Hence, the high expenses for hospital services detected in our chapter (Figure 2.B.5 in Appendix 2.B) probably reflect a rise in the threshold for admission to primarily ensure inpatient services to the most complex and resource-intensive care episodes[82]. The efforts

[81] In terms of hospital care, spending on mental illness accounts for between 5% and 19% of total in-patient expenditures (typically behind circulatory diseases and cancer).

[82] An example is provided by severe mental illnesses such as schizophrenia, which, given their higher symptom severity and chronic nature, tend to account for a dominant proportion of acute mental health spending (OECD, 2013a).

to improve care after discharge are also shown by the persistent effect of the first access on expenditures for outpatient services and pharmaceuticals[83]. However, individuals whose first hospitalization is related to mental disorders still show a high probability of future re-admissions (49%) and admissions for other diagnostic categories, such as cardiovascular diseases (10%), tumors (9.5%), COPD (7%), digestive system diseases (8%) and musculoskeletal diseases (7%) (Table 2.B.8 in Appendix 2.B).

2.5.4 Disease and disability exemptions

The previous section shows that, whatever the cause of admission, hospitalization is associated with substantial future medical expenses in both out-of-hospital and inpatient settings. This evolution of HCE is typical of all those long-term conditions, such as chronic diseases or disabilities, that have a permanent effect on individual health and require continuity of care. To investigate the impact of such conditions, we study the effect of chronicity and disability on individual HCE, replicating our model by including in the regression binary variables for the release of disease- and disability-related exemptions[84], used here as proxies for the onset of the underlying disease. The latter are added as time-absorbing variables[85] so that their coefficients show the before-after effect of the occurrence of the related conditions on individual HCE (Figure 2.B.6 in Appendix 2.B). In line with the existing literature (OECD, 2019; Sambamoorthi et al., 2015), we find that their impact is extensive in magnitude. Indeed, once exempted, individuals spend each year 650€ more if chronic (960€ in absolute terms) and 1,900€ more if disabled (2,480€ in absolute terms).

As important determinants of HCE, we expect such conditions to largely impact expenditures around the admission, especially for the individuals in the age window 50-70, where the first long-lasting diseases arise. To better capture their influence, we compare the evolution of HCE of never-exempted with the one of those affected by chronicity or disability and verify whether the timing of diagnosis plays a role in defining the pattern of expenditures around the event.

Not surprisingly, individuals who have never been exempted experience the lowest growth in HCE at the admission time for all the spending categories (Figure 2.4). Also, the long-term effect of the first hospitalization is small in magnitude. The coefficients on relative time in the post-event period are even not-statistically significant for day hospital and outpatient expenditures, meaning that expenditures come back to their pre-event level after the admission. It shows that the

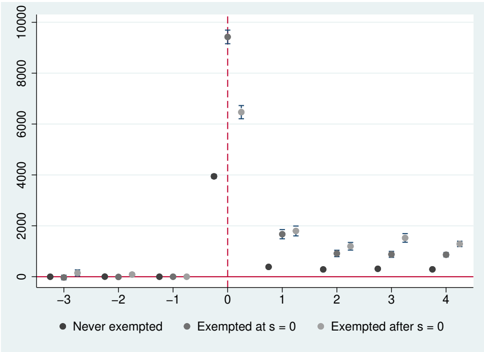
[83]The coefficients on event time of day hospital expenses for mental disorder show large confidence intervals, probably because of a very low number of individuals affected by these types of conditions with positive values for day hospital expenditures.

[84]And by excluding the variable indicating the number of co-morbidities for collinearity issues.

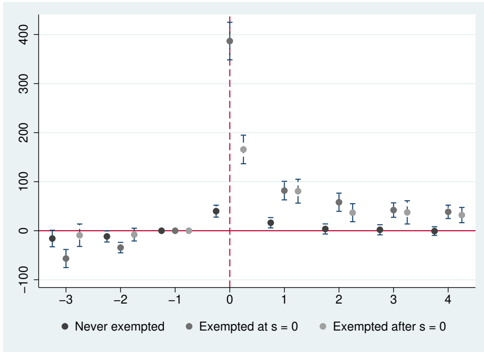
[85]They are equal to 1 when the exemption is released and for all subsequent periods.

Figure 2.4: Total HCE and expenses for different spending categories by event time and exemption timing.

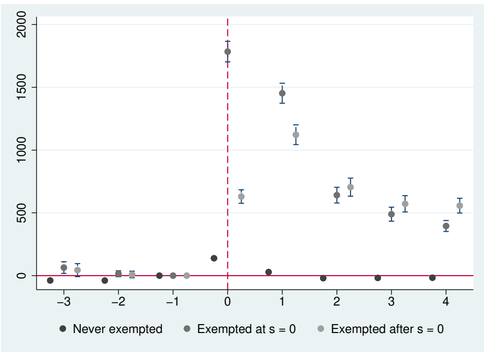
(a) Hospital



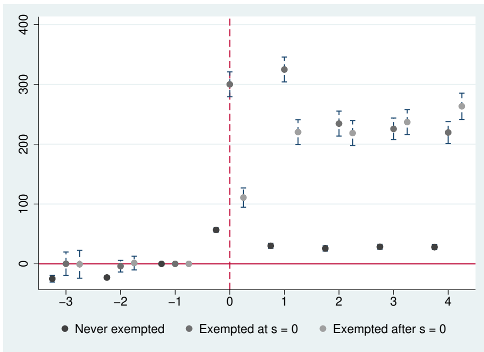
(b) Day Hospital



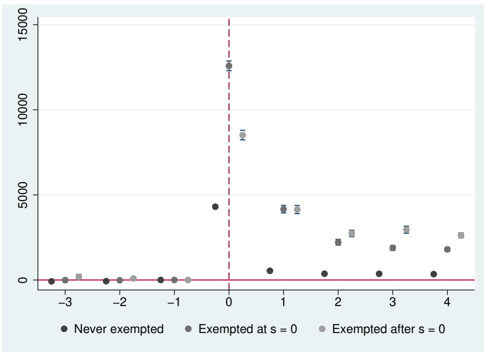
(c) Outpatient



(d) Pharmaceuticals



(e) Total HCE



first hospitalization does not lead to further diagnostic tests and specialist visits and that we are dealing with temporary health shocks that the required hospital admission can promptly and successfully treat. We also note that, in these cases, the first admission is likely to be planned in advance. Elective hospitalizations represent 45% of total hospital admissions in Italy (Pietrantonio et al., 2016) and are usually preceded by increased use of medical tests and treatments preparatory to the admission, as shown by the statistically significant upward pre-event trend for pharmaceutical and outpatient expenses. Such a pattern reflects an increase of expenditures starting from the year before the access[86], probably when individuals begin to undergo these treatments. Indeed, if the admission is planned to be provided at the beginning of the year, preparatory care probably starts in the previous year, contributing to the increase of health expenses in that period.

Regarding exempted individuals, as expected, the effect on HCE is always large in magnitude at the time of the admission and persistent in the following periods. However, this analysis shows some interesting results.
First, for those exempted at $s = 0$ or after, the admission represents the realization of the very first health shock with permanent effects on the health status. To analyze how the estimates change in this case, we replicate our model by comparing such population with those who are never hospitalized and never affected by long-lasting conditions during the whole period. Estimates show that the hospitalization has less large effects on HCE than the one exerted on expenditures of the whole population of individuals aged 50-70. Indeed, the increase in total HCE reduces by 10% in $s = 0$, primarily due to the decrease in hospital expenses (-10%) at the admission time. Four years later, the reduction in hospital expenses (-55%) is also accompanied by a substantial decline in expenditures for outpatient services (-71%) and pharmaceuticals (-64%), resulting in a decline in total HCE of 54%. This minor effect of the hospital admission both at the time of the admission and subsequent periods is probably due to the better health status of the considered population with respect to the whole sample, as demonstrated by its lower mortality rate (4.68% against 5.55% in the baseline sample). Even when this healthier population is analyzed, however, the effect of hospitalization on individual HCE is large in magnitude and persistent in subsequent periods for all spending categories, emphasizing, even more, the role of long-lasting conditions in the definition of future individual HCE.
Second, the expenditures evolution of individuals affected by cardiovascular diseases and cancer reflects the HCE trend of those exempted at $s = 0$, indicating a considerable incidence of admitted individuals diagnosed with a chronicity or disability individuals among those affected by these two MDCs. According to our data, they are 27.71% among those hospitalized for cancer and 17.03% among

[86]It is confirmed by testing the equality between the coefficients on event time -2 and -3.

inpatients with cardiovascular disease, the highest percentages among all MDCs considered[87].

Third, we observe a large difference in HCE increase at $s = 0$ between those diagnosed at and after the first hospitalization. For all spending categories, expenditures in $s = 0$ are higher for those exempted contemporary with the first admission, reflecting the greater severity of the health condition given by the underlying presence of chronicity or disability. However, such a difference is no longer detected in the post-event period, at least for day hospital admissions, outpatient services, and pharmaceuticals. In these cases, expenses of later-diagnosed individuals reach the expenditures level of earlier-exempted individuals after some periods from the first hospitalization, probably when the condition also emerges for the former group. It indicates that, once a chronic disease or disability is diagnosed, healthcare expenditures follow defined patterns independently of the onset timing. Such a trend is not detected, instead, for hospital expenses. In this case, the post-event pattern for individuals diagnosed in $s = 0$ is always below the HCE trend of those exempted later. To better understand this result, we calculate the frequencies of the first admission by MDC and find that the highest share of those diagnosed later is hospitalized the first time for cardiovascular diseases (17%) and cancer (18%), i.e., for conditions likely to be or to lead to long-lasting disorders. Furthermore, individuals diagnosed later are more likely to be additionally hospitalized (Table 2.B.6 in Appendix 2.B, second column). Hence, their higher increase in hospital expenditures in the post-event period suggests that, for these individuals, the hospital discharge is not followed by the continuous care required by long-lasting conditions, resulting in subsequent hospitalizations for the treatment of a worsened health status.

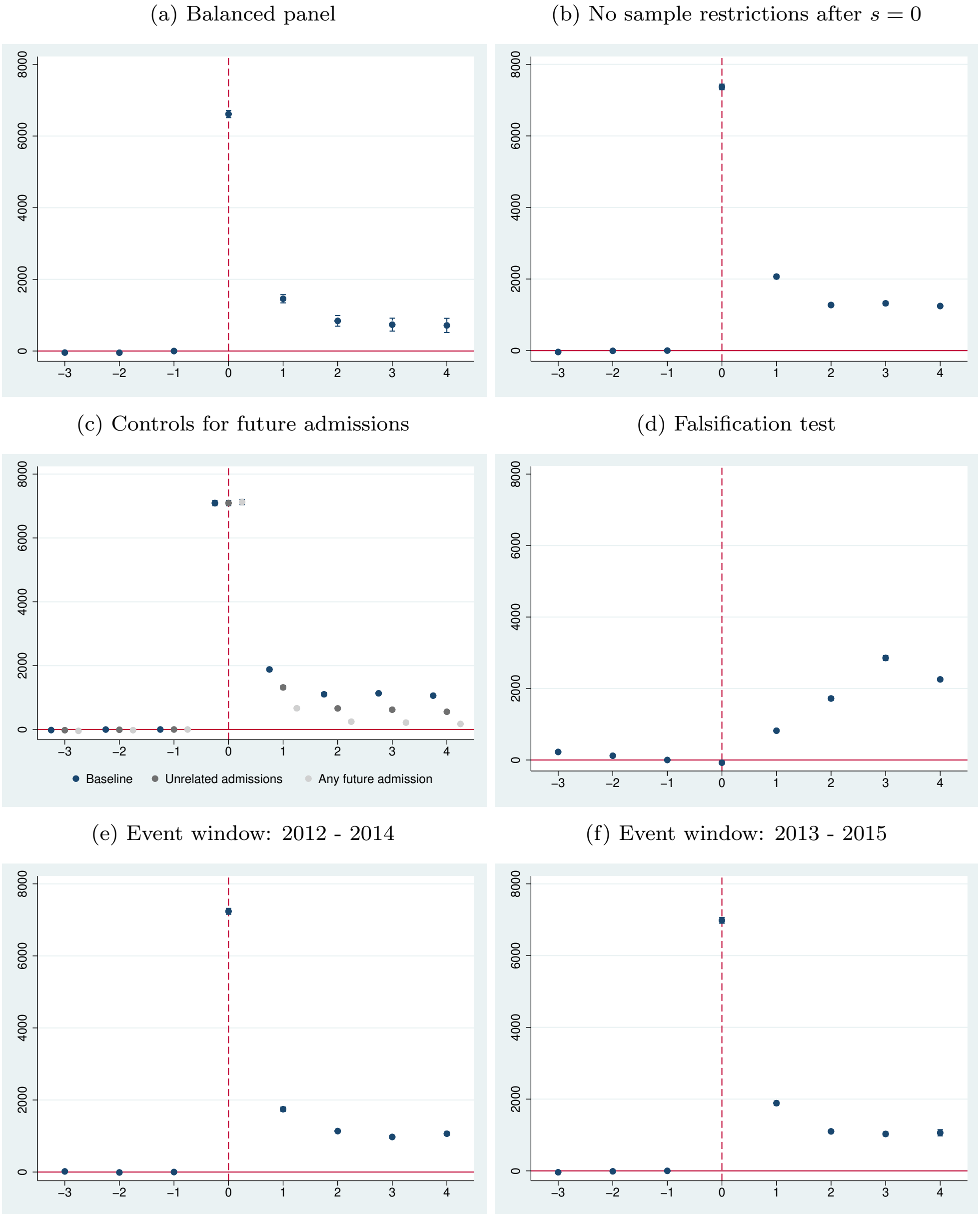
2.6 Robustness checks

2.6.1 Attrition and selection bias

In the following sections, we perform several checks to verify whether the estimations are robust to different specifications and alternative samples.

[87]The third highest percentage involves those affected by infectious diseases, with 9.85% diagnosed with a chronicity or disability in the year of admission (results are not reported). Regardless of the timing of diagnosis, the group of individuals with cancer or cardiovascular disease generally presents the highest percentage of chronic and disabled individuals. This is likely due to the fact that those who survive an acute form of cardiovascular disease, such as acute myocardial infarction and angina pectoris, become chronically ill (della Salute, 2014); moreover, when the tumor cannot be completely eliminated, it can be transformed into a chronic disease through immunotherapy (Crombet and Lage, 2016; Phillips and Currow, 2010). Hence our result is not that surprising, given that the percentage of decedents in our sample is very low, 1.42% (Table 2.B.1 in Appendix 2.B)

Figure 2.5: Total HCE by event time - Robustness checks.



First, our estimates may be biased due to attrition[88]. In our sample, the share of individuals who exit the sample after the admission for non-construction reasons is 3.89% among the never-hospitalized and 9.45% among the treated (Table 2.B.9 in Appendix 2.B). Among the latter, 5.55% die, while 3.90% drop the sample for unknown reasons. At the bottom of the table, we also report individual characteristics and average total HCE for individuals who exit and who continue. Regarding the control group, no substantial differences are found between leaving and staying individuals, while, within the treatment group, the percentage of the unhealthy is higher among those who drop, as well as average expenditures. It suggests that, for the admitted, dropping the sample is strictly correlated with the first hospitalization and that, if anything, the selection induced by attrition should bias results upward. Attrition bias is further shown by the probability of leaving the sample for non-construction reasons at t, conditional on the first access timing (Table 2.B.10 in Appendix 2.B). The results show that the probability of exiting is always correlated with being hospitalized, even if admission occurs four years earlier.

A standard solution to attrition bias is the inclusion of individual fixed effects, as within-individual estimates should not be affected by individuals exiting the sample. However, if the treatment effect is heterogeneous across individuals, results may still be affected by compositional changes within the group of individuals used to identify a given relative time coefficient (Dobkin et al., 2018). To verify how and to what extent attrition bias influences our baseline results, we drop individual fixed effects and the control group and balance the sample around the event. In particular, we carry out the estimation on the group of individuals observed three years before and four years after the first hospitalization, occurring between 2011 and 2013. In this way, each unit is observed for the same number of periods before and after the event, allowing us to examine the time pattern of HCE without concerns about the potential effects of compositional changes. Results are reported in Figure 2.5a and confirmed our baseline event study. Indeed, the effect of the first admission on total HCE is large in magnitude at the time of the access and persistent in the following years. However, as expected, attrition biases the results upward, as the coefficients on the event time estimated on the balanced panel are always lower in magnitude than our baseline estimates. In particular, the increase in total HCE reduces by 6.78% in $s = 0$ and 32.55% in $s = 4$ with respect to the estimation performed on the baseline sample. This result is not surprising. Indeed, differently from the baseline sample, the balanced one is composed only of those who survived at least until the fourth year after

[88] In particular, in this setting, the identification strategy is violated if individuals leave the sample after the first hospitalization because of non-random mortality or other causes related to the admission (for example, individuals choose another care facility outside the dataset coverage area).

admission. The latter are healthier and, consequently, spend less. One solution to avoid attrition bias could be to use a sample that includes only those who survive. However, death represents a potential and important outcome of hospitalization, which cannot be ignored when the focus is on the short- and long-term effects of hospital admission. Hence, we keep all the deceased, except those who die in the same year of hospitalization. In this way, we can observe the post-event effect of the admission even for those who die very early.

Another issue for our estimates is selection bias, which may be generated by the restrictions on the minimum number of years (three) individuals are observed before the event. Such a limitation is imposed to focus only on those who have not had a prior hospitalization for several years preceding the first access. To analyze how selection bias influences our results, we replicate our event study on the original sample without any restrictions and report the coefficients' estimates in Figure 2.5b. The results are extremely close to those from our baseline empirical strategy, suggesting that, even with sample restrictions, our main results are not biased by selection into treatment[89].

2.6.2 Multiple events

To obtain a clean effect, we should estimate the impact of the first hospitalization on the population of individuals admitted only once during the observed period. However, since, in that case, the sample would be restricted to the population of the healthiest, selection would bias downward the results. Therefore, the HCE evolution in such an ideal setting could be replicated by including all hospitalized individuals and adding a dummy variable for any subsequent admission to our regression. The findings are reported in Figure 2.5c, where the light grey dots represent the coefficients on event time from this alternative specification. After the event, the pattern of HCE reflects the one reported in Figure 2.B.4f related to the group of individuals admitted in only one period ($s = 0$). As expected, after the first admission, total expenditures come back to their pre-event level.
However, as discussed in Section 2.4, in our baseline specification we chose not to control for additional accesses to avoid endogeneity issues caused by the occurrence of planned or unplanned re-admissions and analyze the effectiveness of treatments and the definition of the care path in the post-admission period among the different services. Therefore, the estimation strategy is based on the whole population of inpatient individuals, independently on the number of accesses they undergo after the first one. Consequently, the estimated long-run impacts of the first admission

[89]Since the non-restricted sample also includes those who died in the year of hospitalization and those who may have already had hospitalization in the previous three years (which are all individuals with a potentially lower level of health), our results are slightly underestimated. In particular, the increase in expenditures is lower by 3.91% in $s = 0$ and 17.64% in $s = 4$.

are interpreted as capturing the total impact of all hospital accesses, according to the assumption that all future accesses are re-admissions, i.e., they are strictly related to the first one. It means that, if independent hospital admissions occur, the post-event estimates we obtain from our baseline specification are upward biased. Therefore, to explore the implications of non-linked accesses, we replicate the event study by including in the regression a dummy variable for unrelated hospitalizations after $s = 0$. Since data does not provide any information on the link between the first admission and the consecutive ones, the latter are defined as those occurring for different MDCs with respect to the leading cause of the first hospitalization.

Results are shown in Figure 2.5c. While dark gray dots describe the effect of non-linked hospitalizations, the impact of re-admissions is represented by the distance between the latter and the coefficients on event time from the baseline specification (blue dots). Both types of access are found to contribute to the increase in total HCE for nearly the same amount after the event, suggesting that about half of the effect estimated according to Equation 2.1 represents overestimation. However, defining future unrelated admissions based on MDCs does not take into account the fact that many of the complications from hospitalization do not belong to the category of the primary disease, as reported in Table 2.B.8 (Appendix 2.B). For each diagnostic category, the predicted probabilities are found to be the highest in case of re-admissions. However, future admissions for unrelated health conditions are also likely to occur. For example, individuals admitted for the first time for infectious diseases present a high predicted probability of being further hospitalized for several other conditions (cardiovascular diseases, tumor, digestive system diseases). Despite this, according to our definition of unrelated (and, consequently, related) hospitalizations, future accesses for cardiovascular diseases, for instance, can be considered re-admissions only when they represent the leading causes of the first hospitalization, but not when they occur as a consequence of infections. Given such an over-representativeness of the group including non-linked accesses, the true pattern of total HCE should lie between the baseline estimation and the specification in which unrelated admissions are controlled for. Unfortunately, the extent to which it approaches the baseline estimation is a measure that cannot be determined in this analysis. Since we cannot provide a more accurate definition of unrelated hospital admissions, we chose not to include the related variable in our specification to avoid potential endogeneity issues.

2.6.3 Falsification test and external validity

Finally, we carry out a falsification test and replicate our estimation on different event windows to verify the external validity of our analysis on the population of individuals aged 50-70. For the first exercise, we select individuals hospitalized for the first time in the years 2014-2017. Then, we randomly assign to this group a first admission within the time window 2011-2013. Results are shown in Figure 2.5d. As expected, the coefficient on the event time $s = 0$ is not statistically significant, while the upward increase in HCE observed in the following periods reflects the impact of the true first accesses. For the second exercise, we select individuals who experience the first hospitalization in the years 2012-2014 and 2013-2015. Results are shown in Figure 2.5e and Figure 2.5f and confirm the patterns found from our main event study. For the population of individuals aged 50-70, the effect of the first admission on total HCE is positive, large, and persistent over time.

2.7 Discussion

Hospitalization rates represent relevant policy outcomes in terms of population health. Indeed, as shown by our results, hospital admissions significantly affect the individual health status in the short and long run. In this section, therefore, we look at our results to draw some policy implications.

Our main findings show that the first hospital admission is associated with substantial future medical expenditures, accounted for the largest part by inpatient expenses caused by the frequent occurrence of additional hospitalizations. We calculate that, for the individuals hospitalized between 2011 and 2013, the re-admission rate is 39% over the post-event period, meaning that about one person over three is hospitalized at least one more time in the four years following the first hospitalization[90]. To the extent that such additional hospitalizations are mainly required for unplanned re-admissions rather than for adherence to defined care paths, this result suggests that neither the first hospitalization nor the follow-up ensures an effective rehabilitation to a health condition that can be treated successfully within the outpatient or primary care setting. Services offered outside the hospital also show a significant increase in expenditures, especially for chronic conditions such as cardiovascular disease and cancer. In particular, the use of outpatient services appears to be intensive in the first few years after the admission, while pharmaceutical treatments seem to support the patients continuously during post-hospitalization. Despite their more intensive use after the admission, however, territorial treatments do not seem to effectively prevent and treat further health complications, leading to additional hospital access.
This evidence shows the need for a rethinking of the Lombardy healthcare system. Although the latter excels in acute care, a strengthening of territorial care seems

[90]The rate of readmission is calculated as the ratio between those who experience additional hospitalizations and the total number of treated individuals, independently on the effective number of hospitalizations

necessary to increase population health. Indeed, within out-of-hospital settings continuity of care, essential for the population of chronic and disabled individuals, can be provided more effectively, improving health outcomes (Berchet, 2008; Cabana et al., 2004; for Economic Co-operation and Development, 2017; Guthrie et al., 2008; Hofmarcher et al., 2007). To analyze how the different services play a role in the post-hospitalization treatment of patients, we investigate the changes in the contribution of spending categories to total HCE between the year of the event and subsequent periods; since care paths are heterogeneous among the different pathologies, we carry out our analysis by MDC. The first two column of Table 2.2 report the percentages of total HCE covered by each service at the time of the first access ($S_{s=0}$) and four years later ($S_{s=4}$) by primary diagnosis, i.e., by leading cause of first admission; the third column shows instead the difference in shares between the two periods ($S_{s=4} - S_{s=0}$). By looking at the table, we note that, although considerable increases in the share of out-of-hospital treatments and reductions in the incidence of acute inpatient care are observed for all diseases, after four years from the first admission, hospital expenditures still cover a considerable part of total HCE.

The enhancement of territorial care requires a different prioritization of policies to be implemented. In countries where the health system is publicly funded, hospitalization rates also represent important policy outcomes in terms of economic performances (Depalo, 2019). Indeed, cost-containment policies targeting the inpatient setting represent the fastest way to cut healthcare costs, as it accounts for 38% of healthcare expenditures (OECD, 2019). However, the existing literature documents that such policies may lead to deteriorating health outcomes (Calabro, 2016; Depalo, 2019), making the simultaneous pursuit of the objectives related to population health and economic performances the major challenge for policy-makers. In this scenario, the Lombardy Region is a very interesting case. As described in Section 2.2, it has implemented a substantial downsizing of the hospital supply in recent years, accompanied by an increase of the offer of outpatient services. Such a 'de-hospitalization' phenomenon aims to reduce unjustified and inappropriate hospital admissions and consequent costs through a progressive shift from the hospital to the territory. It has been mainly achieved through a reduction in the number of beds and, consequently, hospitalizations. This intervention has significantly reduced healthcare costs, an impact that is observed even when the treated population alone is considered. Between 2011 and 2013, first hospitalizations were reduced by 44%, from 27,891 to 15,593 (Table 2.B.1 in Appendix 2.B), allowing the Lombardy Region to save a total amount of about 79 million euros[91]. However, this intervention alone is not adequate to simultaneously

[91] The unconditional average hospital expenditures at the time of the admission, 6400€, has been multiplied for the number of reduced accesses.

Table 2.2: Share of predicted total HCE covered by the spending categories at $s = 0$ and $s = 4$ and differences.

	$S_{s=0}$	$S_{s=4}$	$S_{s=4} - S_{s=0}$
Infectious disease			
Hospital	73	49	-24
Day Hospital	3	2	-1
Outpatient services	15	28	13
Pharmaceuticals	9	21	12
Mental disorder			
Hospital	79	56	-23
Day Hospital	3	2	-1
Outpatient services	9	17	8
Pharmaceuticals	9	25	16
Nervous System disease			
Hospital	80	49	-31
Day Hospital	3	3	0
Outpatient services	11	24	13
Pharmaceuticals	6	24	18
Cancer			
Hospital	69	39	-30
Day Hospital	2	2	0
Outpatient services	24	36	12
Pharmaceuticals	5	23	18
Cardiovascular disease			
Hospital	87	49	-38
Day Hospital	1	2	1
Outpatient services	7	23	16
Pharmaceuticals	5	26	21
COPD			
Hospital	78	49	-29
Day Hospital	1	2	1
Outpatient services	12	25	13
Pharmaceuticals	9	24	15
Digestive System disease			
Hospital	80	47	-33
Day Hospital	1	2	1
Outpatient services	12	28	16
Pharmaceuticals	7	23	16
Musculoskeletal disease			
Hospital	82	48	-34
Day Hospital	3	3	0
Outpatient services	10	28	18
Pharmaceuticals	5	21	16

increase population health, the true goal of any health policy. For example, to align the supply of hospital services to the demand of a continuously growing population of the elderly, the reduction in hospital admissions is usually accompanied by an increase of the rotation rate of the single hospital bed, obtained by decreasing the number of hospital days[92]. Such a strategy may induce hospitals to discharge patients earlier than necessary, with negative consequences on the individual's health status and the output quality of the system (Rizzo and Secomandi, 2020). It could increase the occurrence of frequent additional hospitalizations, resulting in increased costs actually incurred for each patient and making the efforts made to keep hospital spending under control ineffective. In addition, even if these policies do not have adverse effects on health, they are inadequate for creating a structurally less expensive system. For example, the downsizing of the hospital supply accompanied only by an increase in outpatient services does not lead, on its own, to an increase in the quality of territorial care, leading to a temporary reduction in costs but not to an improvement of health outcomes.

Therefore, what emerges from our analysis is that interventions strictly aimed at reducing costs should be accompanied by those aimed at improving treatments for the groups of individuals who mainly need assistance, such as chronic and disabled patients (Tognetti, 2020). An example of such targeted policies is the improvement of tertiary prevention approaches (Kisling and Das, 2020). The increase in the share of total HCE related to pharmaceuticals and outpatient services after the admission offers some assurance in favor of care continuity, but further efforts could be made to soften the impact of ongoing illnesses and, in particular, of those with long-lasting effects (Walker et al., 2018). On the one hand, it would improve patients' health by preventing complications and acute cases; on the other hand, it would also generate significant savings by preventing avoidable additional hospitalizations. Our main results show that subsequent hospitalizations are associated with substantial spending incurred by the healthcare system for the inpatient setting, which decreases in the post-admission period. After four years from the first access, average hospital cost decrease by 16% with respect to the one observed at the time of the first access (Figure 2.2a) and is associated with hospitalization days about one-fifth of those at the first hospitalization[93]. Despite that, for such additional admissions, the Lombardy Region spent a total of 300 million euros, three times more than the savings obtained by reducing the number of first hospitalizations between 2011 and 2013. An idea of the expenditures incurred due to the lack of adequate

[92]In the decade 2007-2017, in Italy beds were reduced by 45 thousand units, the admissions dropped by 3.4 million and the days of hospitalization by 16.6 million (OECD, 2020).

[93]Given an average cost per bed day of 175€ (Stenberg et al., 2018), individuals stay in hospital for about 30 days at the time of the first access and 6 days when admitted in the following periods, independently on the number of hospitalizations.

tertiary prevention is also given by the evidence shown by comparing individuals by onset timing of chronicity and disability (Figure 2.4). The amount spent for late diagnoses is roughly 20 million euros[94], about one-third of the savings.

2.8 Conclusions

Using a DID event study approach, we investigate how total HCE and expenses for different healthcare services evolve around the first admission for individuals aged 50-70. As this lifespan is the period in which the first health shocks occur, for such a group of individuals inpatient care represents a response to acute conditions with temporary effect on the health status or the treatment of ongoing or new chronic diseases. Consequently, the hospital admission can lead to the complete recovery of the admitted individuals, the onset of a chronic condition or disability, future hospitalizations, and premature death. Whatever the scenario is, it is expected to significantly affect the individual health status in the short and long run.

Our main findings confirm the existence of a large effect of the first hospitalization on HCE that, in many cases, persists over time. At the first access, total expenditures rise by 7,000€ with respect to HCE of never-admitted; four years after the admission, total HCE of treated individuals amount to almost 1,400€ in absolute terms, showing the full extent of the economic burden of the first health shocks. Such substantial future medical expenses are observed for all healthcare settings. For example, after the increase of 100€ in $s = 0$ (about 250€ in absolute terms), pharmaceutical expenses seem to follow a cyclical pattern and come back to the event-level after four years. Inpatient care, instead, account for the largest part of post-admission expenditures, indicating the occurrence of subsequent hospitalizations.

Regarding the analyses by disease, the largest effect on HCE is found for individuals affected by cardiovascular disease and cancer, the conditions requiring greater medical assistance in both inpatient and out-of-hospital settings. It is probably driven by the occurrence of frequent complications, as shown by the high percentage of additional admissions faced by individuals affected by such diseases. Cardiovascular diseases account for 21% of total future hospitalizations, while cancer for 17%. Moreover, we find that the persistence of the effect is specifically distinctive for the broader group of individuals suffering from long-lasting conditions, i.e. chronic diseases and disability.

As admissions significantly affect the health condition, hospitalization rates

[94] It is calculated by multiplying the number of individuals diagnosed later by the difference between the coefficients on post-event time estimated for such a population and those estimated on the group of those diagnosed at the first access.

represent relevant policy outcomes. The occurrence of additional admissions suggests that neither the first hospitalization nor the follow-up ensures an effective rehabilitation to a health condition that can be treated successfully within the outpatient or primary care setting, with territorial treatments not effective in preventing and treating further health complications. It shows the need for a rethinking of the healthcare system and the policies to be pursued as a priority to reduce costs while improving health outcomes. Where the health system is publicly funded, hospitalization rates are also important policy outcomes in terms of economic performances, as cost-containment policies targeting the inpatient setting represent the fastest way to cut healthcare costs. However, for an effective improvement of health outcomes, such policies should be accompanied by interventions aimed at improving the quality of the territorial setting. An example is the strengthening of tertiary prevention approaches, aimed at reducing the occurrence of complications and the need for further hospitalizations. For additional admissions, indeed, the Lombardy Region spent a total of 300 million euros, three times more than the savings obtained by reducing hospitalizations. Late diagnosis, instead, cost the system about 20 million euros.

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Appendices

2.A Data handling and variables description

The original sample included in the dataset drawn from the Health Information System of the ATS of the Province of Milan consists of about 820,000 individuals per year, recorded over the period 2006-2017, for a total of 10,031,350 observations. However, some manipulations of the sample are needed to obtain a clean and reliable dataset. The underlying criterion is to eliminate individuals only when dropping observations would generate time gaps in individual records.

First, 1,596,701 observations recorded for the first two years in the dataset are excluded because information on the number of co-morbidities and survival status per individual is absent in, respectively, 2006 and 2007. Moreover, health expenditures and volumes in these periods are much lower than in the following years.

Second, information on individuals is analyzed. Some observations (69) are also recorded for years following the individual demise. Therefore, they are dropped from the sample for the period in which they should not have been observed. Moreover, observations presenting null costs but positive volumes for hospital and day hospital admissions, outpatient visits, and pharmaceuticals are excluded (110,616). Then, we drop individuals when they are arbitrarily considered as outliers (527 observations).

Finally, individuals with gaps in years of observation (83,726), as well as individuals observed for only one year (123,155), are eliminated.

Table 2.A.1: Variables used for the analysis.

Dependent variables			
Name	Type	Min-Max	Description
Total expenditures	Continuous		Sum of expenses for hospital and day hospital admissions, outpatient services and pharmaceuticals.
Hospital expenditures	Continuous		Expenses for elective and emergency admissions.
Day Hospital expenditures	Continuous		Expenses for day hospital admissions.
Outpatient expenditures	Continuous		Expenses for outpatient services.
Pharmaceutical expenditures	Continuous		Expenses for pharmaceuticals.
Exit_t	Binary	0 - 1	Exit of the individual from the sample because of death or other reason.
Independent variables			
Name	Type	Min-Max	Description
Linear pre-trend	Continuous		Linear pre-trend extrapolated from the four years before the admission.
Relative time	Categorical	-4 - 4	Number of years the individual is distant from the admission
Years	Categorical	2008 - 2017	Years of observations. Omitted categories: 2016, 2017.
Age	Categorical	50 - 70	Individual's age. Omitted category: 50.
Income exemption	Binary	0 - 1	Income-related exemption. Time absorbing variable.
Co-morbidities	Categorical	0 - 3+	Number of co-moribidities.
TTD	Categorical	0 - 5	Time to death, with TTD-0 indicating the year of death. Omitted category: TTD-5.
Unrelated future admissions	Binary	0 - 1	Admissions after $s = 0$ required for a different MDC with respect to the one causing the first access.
Future admissions	Binary	0 - 1	Any type of admissions after $s = 0$.
Other variables			
Name	Type	Min-Max	Description
First access	Binary	0 - 1	First year with at least one access.
Male	Binary	0 - 1	Individual's gender.
Number of accesses at $s = 0$	Categorical	1 - 4+	Number of accesses in the year of the first admission.
Number of accesses after $s = 0$	Categorical	1 - 4+	Number of years following the first admission with at least one access.
Disease exemption	Binary	0 - 1	Disease-related exemption. Time absorbing variable.
Disability exemption	Binary	0 - 1	Disability-related exemption. Time absorbing variable.
MDCs	Categorical		Major Diagnostic Categories for which the individual is hospitalized.
Deceased	Binary	0 - 1	Death.

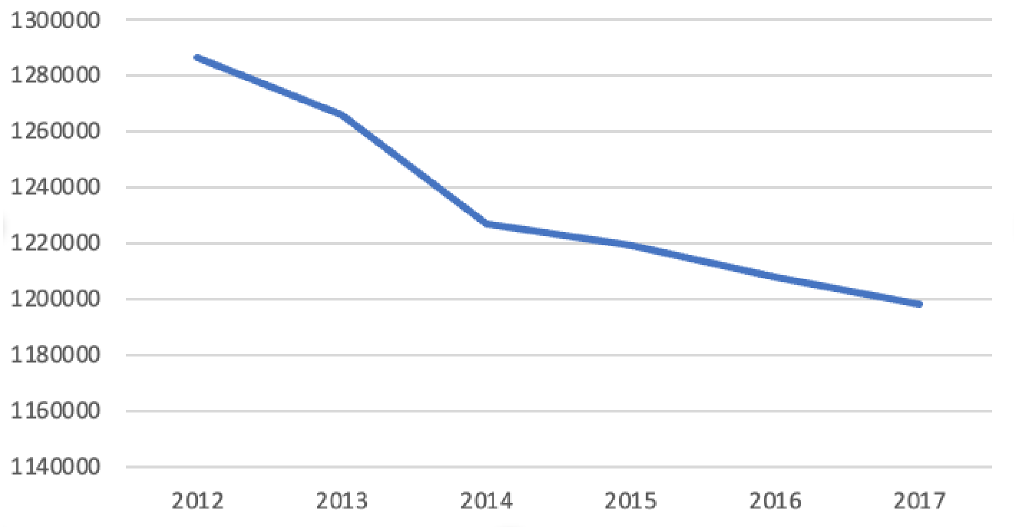
2.B Additional tables and figures

Table 2.B.1: Descriptive statistics - First access and subsequent health events.

First access	
First access in:	
2011	27,891
2012	22,488
2013	15,503
Total HCE [a]	
Mean	8,316
SD	10,560
Number of accesses: (%)	
One	70.31
More than one	29.69
Age	62
Income exemption (%)	12.26
Disease exemption (%)	14.22
Disability exemption (%)	2.05
Number of co-morbidities (%)	
0	27.77
1	34.21
2	23.54
3+	14.47
MDC (%)	
Infectious disease	0.97
Mental disorders	1.55
Nervous System	5.58
Tumor	16.13
Cardiovascular Disease	18.77
Chronic Obstructive Pulmonary Disease (COPD)	5.03
Digestive System	14.07
Musculoskeletal disease	7.11
Other	30.79
Subsequent health events	
Hospitalizations (%)	
1 re-admission	26.51
2+ re-admissions	14.02
Disease exemption (%)	2.24
Disability exemption (%)	1.62
Deceased (%)	1.42

Note:
Yearly statistics.
[a] Expenditures data is deflated by dividing current expenditures by the Italian consumer price index for the health sector provided by the OECD. The reference year is 2015.

Figure 2.B.1: Number of ordinary hospitalizations between 2012-2017.



Source: Lombardy Region Open Data.

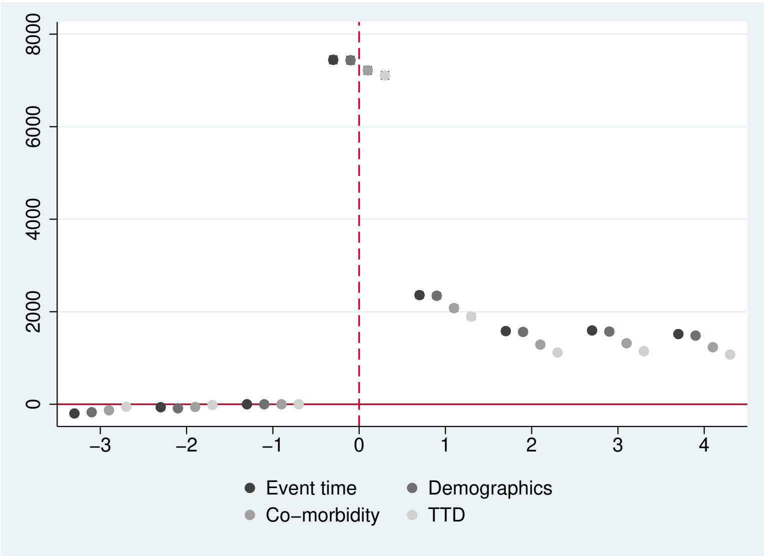
Table 2.B.2: Impact of the first access on total HCE according to different specifications.

	Event time	**Demographics**[a]	**Co-morbidities**	**End of life**	**Linear pre-trend**
Linear pre-trend					15
					(1.48)
Event time function					
-3	-199***	-172***	-134***	-55***	-18
	(-23.17)	(-19.87)	(-15.81)	(-5.98)	(-0.87)
-2	-64***	-88***	-60***	-16**	-1
	(-13.31)	(-18.31)	(-12.44)	(-2.76)	(-0.12)
0	7,446***	7,436***	7,213***	7,108***	7,093***
	(183.69)	(183.39)	(181.97)	(181.02)	(171.16)
1	2,360***	2,345***	2,075***	1,896***	1,881***
	(72.57)	(72.03)	(66.36)	(62.99)	(60.18)
2	1,582***	1,563***	1,286***	1,117***	1,103***
	(59.70)	(59.00)	(50.64)	(45.92)	(41.11)
3	1,595***	1,571***	1,316***	1,147***	1,133***
	(58.68)	(57.85)	(50.39)	(45.77)	(40.41)
4	1,518***	1,484***	1,231***	1,075***	1,060***
	(73.47)	(72.31)	(63.44)	(58.50)	(50.18)
Controls	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓	✓
N. periods	10	10	10	10	10
N. observations	4,189,603	4,189,603	4,189,603	4,189,603	4,189,603
N. individuals	459,760	459,760	459,760	459,760	459,760
R^2	39.92	39.95	40.73	41.90	41.90

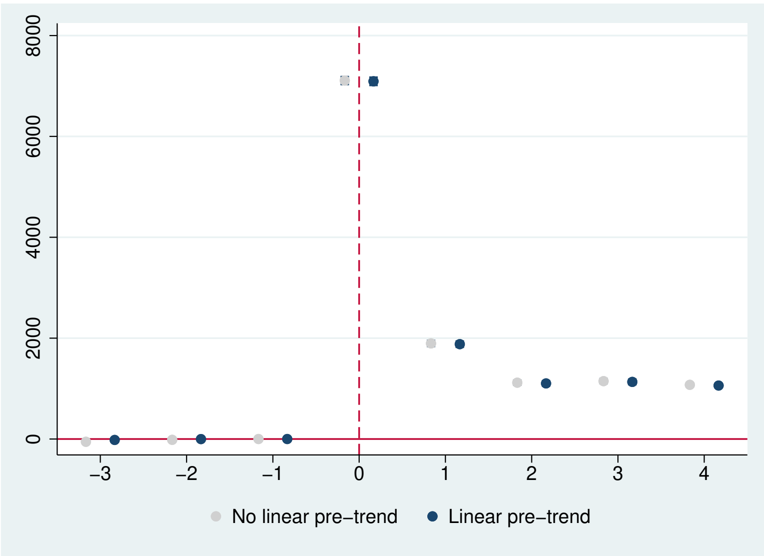
Note:
t-statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Standard errors clustered at individual level.
[a] Demographics characteristics include age, area of residence and income-related exemption.
Controls: age dummies; living in urban areas; income-related exemption; number of co-morbidities; time to death.
Categorical variables in italics. Omitted category: $S_{it} = -1$.

Figure 2.B.2: Total HCE by event time according to different specifications.

(a) Demographic and health-related traits



(b) Linear pre-trend



Note: Demographics include age, income-related exemptions and residence area.

Table 2.B.3: Impact of the first access on expenses for different services.

	Hospital		Day Hospital		Outpatient		Pharmaceuticals	
	No pre-trend	Pre-trend	No pre-trend	Pre-trend	No pre-trend	Pre-trend	No pre-trend	Pre-trend
Linear pre-trend		-23		6**		18***		11***
		(-3.07)		(-3.27)		(5.53)		(7.36)
Event study function								
-3	65***	9	-1	-17**	-41***	3	-22***	6
	(10.41)	(0.61)	(-0.37)	(-2.98)	(-12.69)	(0.41)	(-15.89)	(1.69)
-2	40***	17	-7***	-14***	-27***	-9*	1	12***
	(13.17)	(2.26)	(-3.29)	(-4.38)	(-13.08)	(-2.43)	(0.88)	(6.92)
0	6,351***	6,374***	116***	123***	561***	543***	112***	100***
	(176.52)	(169.02)	(25.95)	(24.17)	(62.78)	(59.52)	(49.06)	(37.07)
1	1,302***	1,324***	26***	32***	495***	477***	118***	107***
	(51.11)	(50.72)	(7.81)	(8.62)	(50.44)	(46.65)	(39.74)	(33.60)
2	862***	885***	6*	13***	216***	198***	92***	81***
	(41.41)	(39.76)	(2.16)	(3.76)	(28.72)	(22.56)	(31.43)	(26.52)
3	932***	955***	5	12**	172***	154***	101***	89***
	(42.88)	(40.21)	(1.62)	(3.14)	(24.51)	(18.84)	(35.24)	(29.06)
4	877***	899***	0	6*	158***	140***	113***	102***
	(59.97)	(54.54)	(0.05)	(2.15)	(25.16)	(19.54)	(39.85)	(30.98)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
N. periods	10	10	10	10	10	10	10	10
N. observations	4,189,603	4,189,603	4,189,603	4,189,603	4,189,603	4,189,603	4,189,603	4,189,603
N. individuals	459,760	459,760	459,760	459,760	459,760	459,760	459,760	459,760
R^2	31.97	31.97	17.11	17.11	36.15	36.15	66.59	66.59

Note:
t-statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Standard errors clustered at individual level.
Controls: age dummies; living in urban areas; income-related exemption; number of co-morbidities; time to death.
Categorical variables in italics. Omitted category: $S_{it} = -1$.

Table 2.B.4: Correlation matrix for the variables included in the preferred specification.

Correlation matrix							
	First access	Pre-trend	Age	Residence area	Income exemption	Co-morbidities	TTD
First access	1.0000	-	-	-	-	-	-
Linear pre-trend	0.3682	1.0000	-	-	-	-	-
Age	0.0347	0.1456	1.0000	-	-	-	-
Area	0.0097	0.0229	0.0019	1.0000	-	-	-
Income exemption	0.0172	0.1060	0.4156	−0.0570	1.0000	-	-
Co-morbidities	0.0922	0.2385	0.2560	−0.0453	0.2556	1.0000	-
Time to death	−0.0614	−0.1360	−0.0396	−0.0059	−0.0274	−0.0838	1.0000

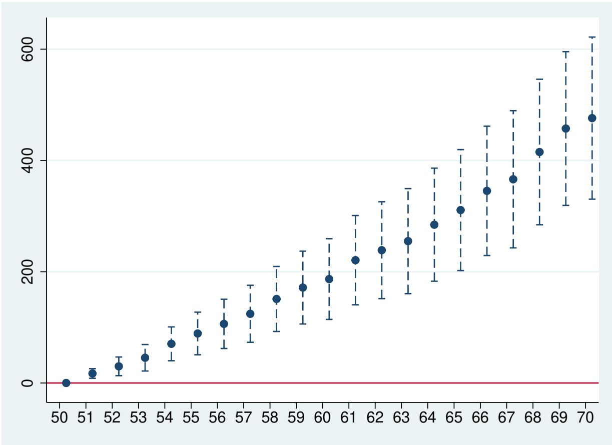
Note: All the coefficients are significant at 1% level.

Table 2.B.5: Variance Inflation Factor.

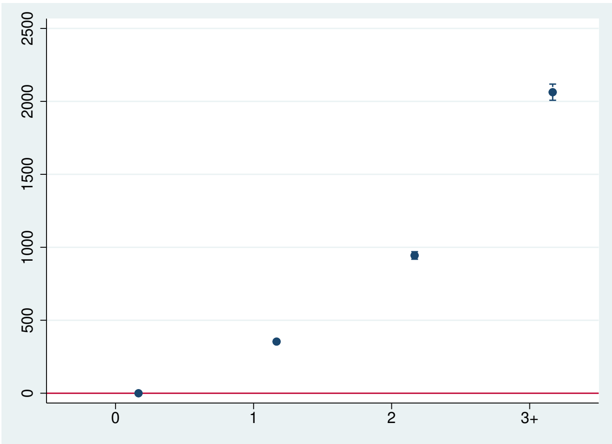
	VIF	1/VIF		VIF	1/VIF
Linear pre-trend	6.14	0.1628	*Age*		
Event time			51	2.20	0.4539
-3	3.02	0.3313	52	2.43	0.4120
-2	2.03	0.4928	53	2.64	0.3785
0	11.86	0.0843	54	2.85	0.3513
1	2.10	0.4764	55	3.04	0.3287
2	2.03	0.4919	56	3.22	0.3105
3	1.95	0.5126	57	3.14	0.3187
4	2.75	0.3632	58	3.06	0.3264
Area	1.01	0.9919	59	3.00	0.3332
Income exemption	1.51	0.6638	60	2.97	0.3368
Number of co-morbidities			61	2.94	0.3403
1	1.17	0.8573	62	2.93	0.3415
2	1.16	0.8645	63	2.89	0.3459
3+	1.12	0.8892	64	2.87	0.3482
TTD			65	2.78	0.36
TTD_0	1.01	0.9879	66	2.65	0.3772
TTD_1	1.01	0.9886	67	2.51	0.3983
TTD_2	1.01	0.9897	68	2.35	0.4256
TTD_3	1.01	0.99	69	2.15	0.4641
TTD_4	1.01	0.9922	70	1.94	0.5157
Year					
2010	1.45	0.6441			
2011	1.64	0.6092			
2012	1.70	0.5868			
2013	1.73	0.5769			
2014	1.76	0.5689			
2015	1.76	0.5692			
2016	1.76	0.5690			
2017	1.73	0.5770			
Mean VIF			2.36		

Figure 2.B.3: Effects of individual characteristics on total HCE.

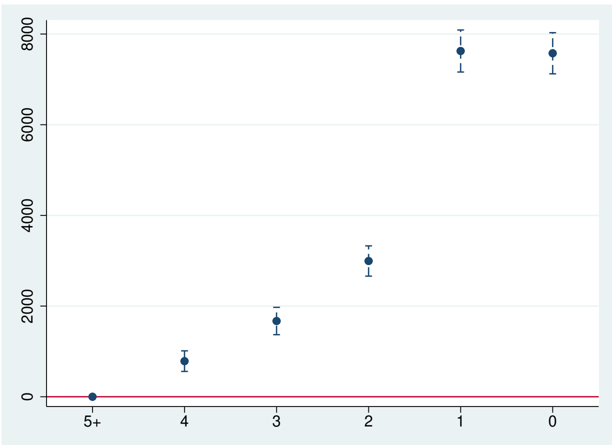
(a) Age



(b) Number of co-morbidities



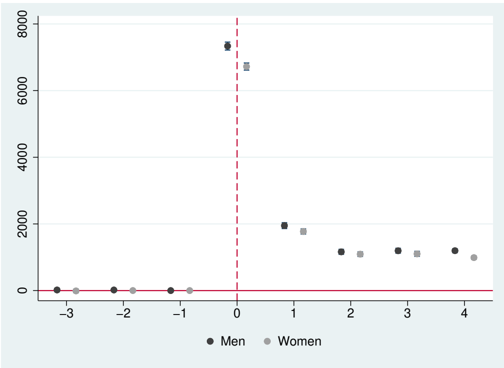
(c) Time to death



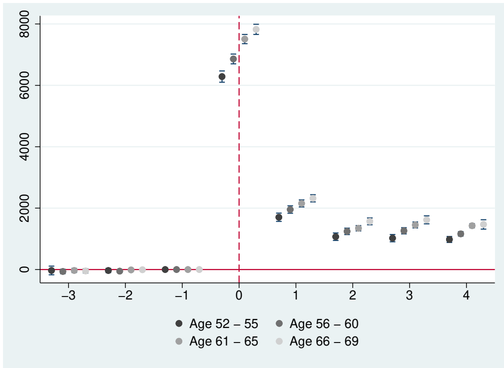
Note:
Coefficients estimated from the preferred specification where age, area of residence, income-related exemption, number or co-morbidities, time to death and the linear pre-trend, time and individual fixed effects are controlled for.
Figure (c): $TTD = 5+$ is equal to 1 for individuals at 5 or more years from death and for survivors.

Figure 2.B.4: Total HCE by event time - Heterogeneous effects

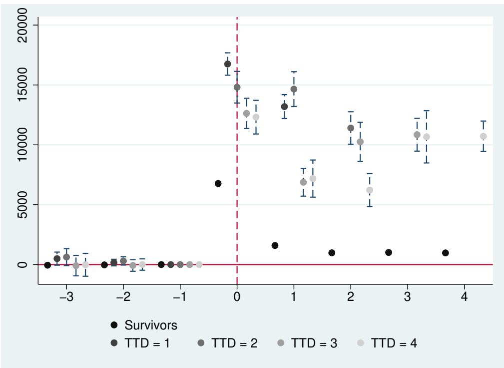
(a) Gender



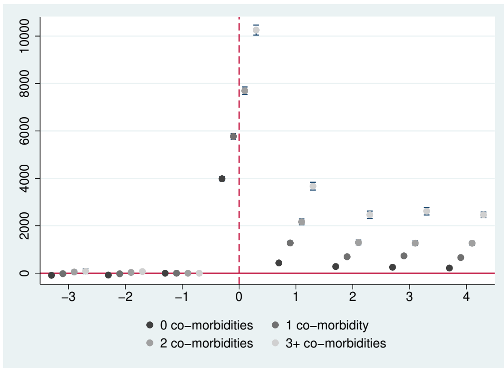
(b) Age in $s = 0$



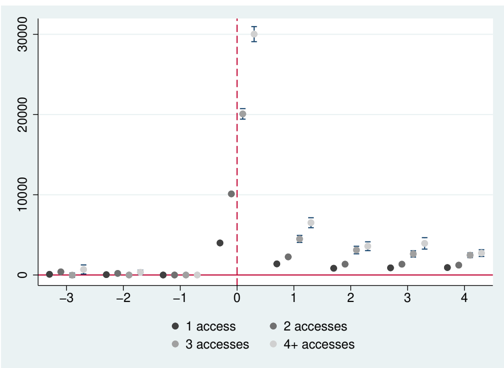
(c) Time to death in $s = 0$



(d) Number of co-morbidities in $s = 0$



(e) Number of accesses in $s = 0$



(f) Admission timing

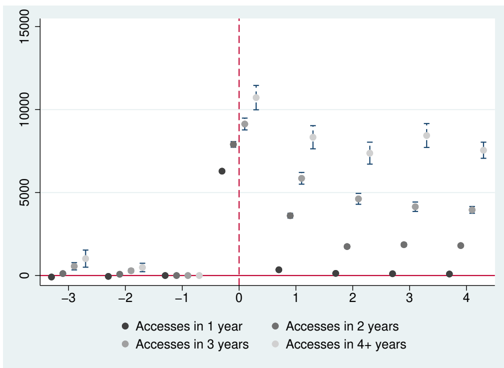


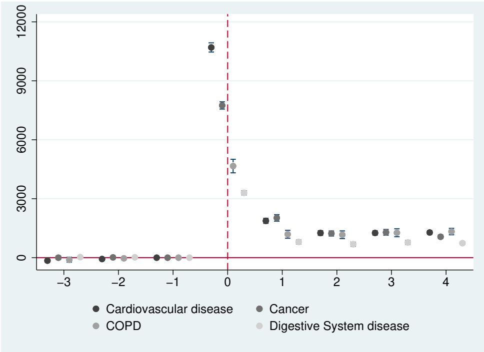
Table 2.B.6: Marginal effects of individuals characteristics on the probability of future admissions.

	Probability of multiple hospitalizations	
	Co-morbidities	**Disease and disability ex.**
Male	0.0170***	0.0225***
	(12.10)	(16.14)
Residence area	0.0230***	0.0204***
	(16.19)	(14.41)
Income-related exemption	0.0167***	0.0218***
	(10.77)	(14.15)
Number of co-morbidities		
1	0.0427***	
	(28.58)	
2	0.0874***	
	(46.55)	
3+	0.1562***	
	(61.38)	
Disease-related exemption		
Before $s = 0$		0.0511***
		(31.50)
At $s = 0$		0.0461***
		(20.56)
After $s = 0$		0.0797***
		(30.98)
Disability-related exemption		
Before $s = 0$		0.0644***
		(19.29)
At $s = 0$		0.0709***
		(10.89)
After $s = 0$		0.1312***
		(34.49)
Time to death		
TTD_4	0.0817***	0.0510**
	(4.77)	(3.25)
TTD_3	0.0824***	0.0611***
	(6.93)	(5.35)
TTD_2	0.1475***	0.1289***
	(14.21)	(12.63)
TTD_1	0.2852***	0.2826***
	(29.32)	(28.39)
TTD_0	0.5217***	0.5273***
	(64.50)	(63.80)
Age dummies [a]	✓	✓
Number of observations	281,901	

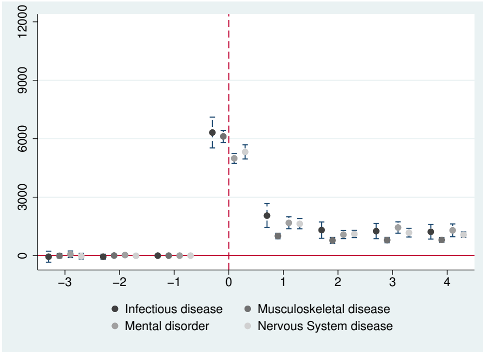
Note:
t-statistics in parentheses.
Standard errors clustered at individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Probit model carried out for years following the first admission on over-52 treated individuals.
Categorical variables in italics. Omitted category: age 52, Living in Milan, Never exempted for income, 0 co-morbidities, Never exempted for disease, Never exempted for disability, TTD_5.
[a] No single age dummy is found to be statistically significant.

Figure 2.B.5: Expenses for different spending categories by event time and MDC.

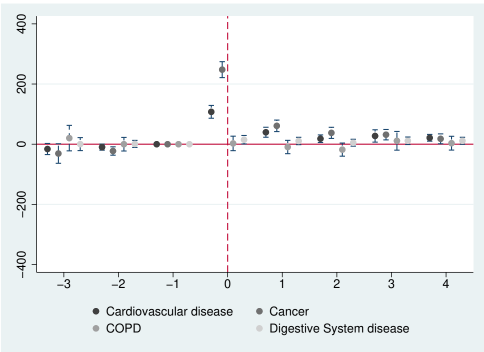
(a) Hospital: Outpatient/Primary Care diseases



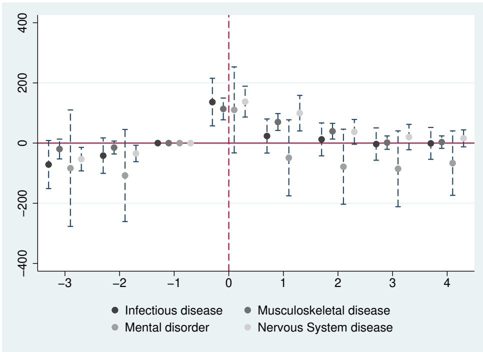
(b) Hospital: Other diseases



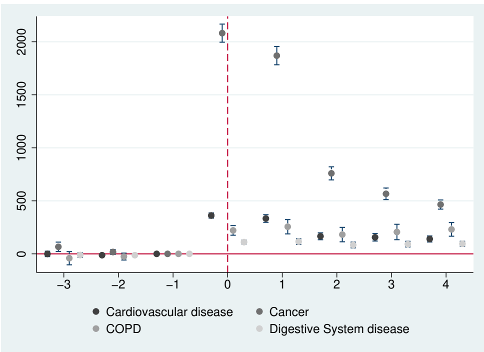
(c) Day Hospital: Outpatient/Primary Care diseases



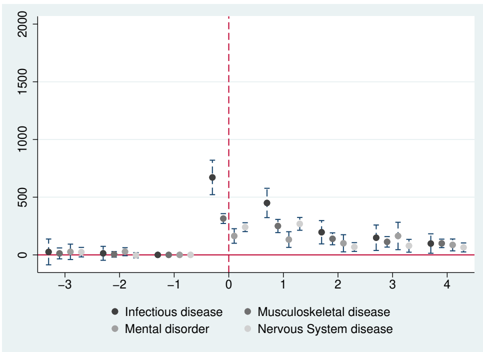
(d) Day Hospital: Other diseases



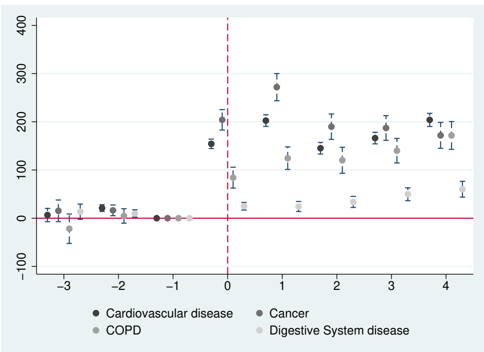
(e) Outpatient: Outpatient/Primary Care diseases



(f) Outpatient: Other diseases



(g) Pharma.: Outpatient/Primary Care diseases



(h) Pharma.: Other diseases

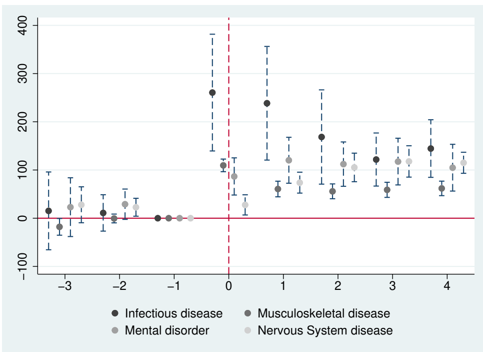


Table 2.B.7: Predicted probability of future admissions for specific diseases conditional on the leading cause of the first hospitalization.

	Infectious	**Mental**	**Nervous**	**Cancer**
Percentage of additional accesses	1.72	2.32	6.88	17.42
Infectious disease	0.1760***	0.0168**	0.0577***	0.1261***
	(8.14)	(2.72)	(4.85)	(7.38)
Mental disorder	0.0194**	0.4939***	0.0534***	0.0950***
	(3.21)	(22.66)	(6.05)	(7.73)
Nervous System disease	0.0187***	0.0149***	0.3915***	0.1069***
	(5.95)	(5.05)	(30.92)	(14.00)
Cancer	0.0157***	0.0095***	0.0468***	0.3217***
	(10.20)	(6.38)	(16.68)	(48.20)
Cardiovascular disease	0.0146***	0.0097***	0.0505***	0.0886***
	(10.32)	(7.23)	(18.54)	(25.67)
COPD	0.0208***	0.0138***	0.0622***	0.1408***
	(6.42)	(4.71)	(10.48)	(16.46)
Digestive System disease	0.0199***	0.0110***	0.0543***	0.1703***
	(8.94)	(6.19)	(14.75)	(26.63)
Musculoskeletal disease	0.0210***	0.0108***	0.0584***	0.1308***
	(6.13)	(4.53)	(10.19)	(16.42)
Other	0.0174***	0.0073***	0.0550***	0.1585***
	(13.06)	(7.76)	(22.64)	(39.68)
Number of observations	36,469	36,469	36,469	36,469

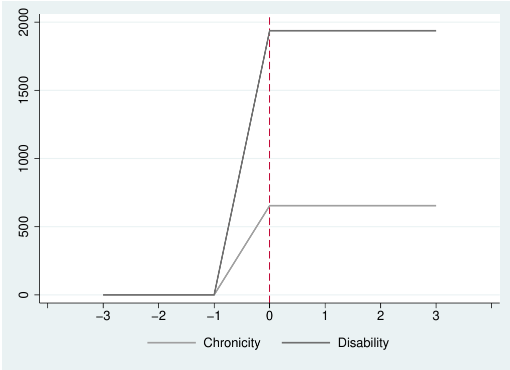
Note:
Probit model carried out for years following the first admission on over-53 treated individuals. Only observations associated to multiple hospitalizations are taken into account. Predicted probability calculated at the means of the other covariates.
t-statistics in parentheses.
Standard errors clustered at individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Controls: male, age dummies, residence area, income-related exemption, number of comorbidities, time-to-death dummies, year fixed effects.

Table 2.B.8: Predicted probability of being additionally admitted for specific conditions conditional on the leading causes of the first hospitalization.

	Cardiov.	**COPD**	**Digestive**	**Musculosk.**
Percentage of additional accesses	20.73	6.85	12.71	6.92
Infectious disease	0.1732***	0.0909***	0.1254***	0.1023***
	(8.67)	(5.93)	(7.02)	(7.01)
Mental disorder	0.1008***	0.0709***	0.0764***	0.0723***
	(8.64)	(6.76)	(7.24)	(8.00)
Nervous System disease	0.1533***	0.0727***	0.0885***	0.0815***
	(17.33)	(11.93)	(13.75)	(13.38)
Cancer	0.0981***	0.0520***	0.1417***	0.0610***
	(24.87)	(18.18)	(30.29)	(19.09)
Cardiovascular disease	0.4290***	0.0594***	0.1042***	0.0694***
	(64.96)	(20.82)	(28.26)	(21.91)
COPD	0.1597***	0.3298***	0.1072***	0.0650***
	(16.71)	(25.62)	(14.98)	(11.54)
Digestive System disease	0.1767***	0.0642***	0.3004***	0.0644***
	(26.89)	(15.38)	(38.80)	(16.89)
Musculoskeletal disease	0.1719***	0.0597***	0.0983***	0.2135***
	(19.04)	(10.56)	(15.04)	(23.69)
Other	0.1623***	0.0549***	0.1043***	0.0798***
	(40.59)	(22.92)	(33.44)	(28.53)
Number of observations	36,469	36,469	36,469	36,469

Note:
Probit model carried out for years following the first admission on over-53 treated individuals. Only observations associated to multiple hospitalizations are taken into account. Predicted probability calculated at the means of the other covariates.
t-statistics in parentheses.
Standard errors clustered at individual level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Controls: male, age dummies, income-, disease- and disability-related exemption, number of co-morbidities, time-to-death dummies, year fixed effects.

Figure 2.B.6: Before-after average unconditional total HCE of chronicity and disability on total HCE.



Note: The figure is constructed by assigning to each period lower than 0 (baseline period) the value 0 and to period 0 and each subsequent period the value of the coefficient found in the regression where disease- and disability-related exemptions are controlled for.

Table 2.B.9: Descriptive statistics - Individuals who leave and those who continue.

Share of individuals who leave the sample				
	Treatment group		**Control group**	
	%	Individuals	%	Individuals
For sample construction	90.55	59,656	96.12	378,584
Age 70	30.46	20,067	18.03	71,000
Year 2017	60.09	39,589	78.09	307,584
Other reasons	9.45	6,226	3.89	15,294
Death	5.55	3,656	0.31	1,203
Other	3.90	2,570	3.58	14,091
Characteristics of those who leave and those who continue				
	Treatment group		**Control group**	
	Continue	Leave	Continue	Leave
Total HCE [a]	1,952	5,876	385	364
Age	61	61	59	59
Disease-related exemption	56.63	65.96	34.38	30.76
Disability-related exemption	9.59	23.36	3.29	5.02
0 co-morbidities	38.91	30.27	62.61	67.14
1 co-morbidity	31.51	27.63	25.75	22.44
2 co-morbidities	18.69	22.36	8.73	8.10
3+ co-morbidities	10.90	19.74	2.92	2.31

Note:
[a] Expenditures data is deflated by dividing current expenditures by the Italian consumer price index for the health sector provided by the OECD. The reference year is 2015.

Table 2.B.10: Probability of leaving the sample conditional on being hospitalized.

$\boldsymbol{Exit_t}$	$\mathbf{Hosp_{t-1}}$	$\mathbf{Hosp_{t-2}}$	$\mathbf{Hosp_{t-3}}$	$\mathbf{Hosp_{t-4}}$	$\mathbf{Hosp_{t-5}}$	$\mathbf{Hosp_{t-6}}$
First hospitalization	0.0062***	0.0220***	0.0510***	0.0847***	0.1287***	0.1896***
	(4.40)	(14.01)	(28.10)	(39.84)	(50.25)	(59.55)
Time fixed effect	✓	✓	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓	✓	✓
N. periods	10	10	10	10	10	10
N. observations	586,435	586,435	586,435	586,435	586,435	586,435
N. individuals	65,882	65,882	65,882	65,882	65,882	65,882

Note:
t-statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Standard errors clustered at individual level.
Individual fixed effects models. Controls: age, area of residence, income-related exemption, number of co-morbidities.

Thesis Appendix
Theoretical Model for Variations in HCE

Under the Italian healthcare system, GPs are salaried through capitation-based payments and work in a setting where the coverage for medical treatments is largely free at the point of access. Co-payments in charge to the patients also play a role for non-exempted individuals, but these types of economic forces are generally supposed to barely affect the demand and supply of healthcare, leading to an equilibrium that is presumably placed at the point where the quantity defined by the practitioner is located. To provide a conceptual framework for this equilibrium, we present a theoretical model that follows those of Chandra and Skinner (2012) and Cutler et al. (2019)[95], with some modifications introduced to adapt it to the Italian institutional setting. It aims at identifying the drivers that, leading to shifts of healthcare demand and supply curves, cause variations in individual volumes and expenditures for medical treatments. In particular, each side of the market in the Italian context is characterized in order to understand how individual and GP-specific characteristics work in defining the equilibrium in the provision of healthcare.

The demand side is represented by a simplified two-periods individual utility function defined as $V = U(C_1) + \frac{s(x)U(C_2)}{1+\delta}$, where δ is the discount rate. Such a utility function depends on consumption in the two periods (C_1 and C_2) and individual's perceived quality of life[96] $s(x)$, influenced by individual health status and hence by utilization of medical services x. $s(x)$ is assumed to be concave, so that $s'(x) \geq 0$ and $s''(x) < 0$.
The individual utility function is then maximized under the budget constraint $Y_1 + \frac{Y_2}{1+r} - P = C_1 + px + \frac{C_2}{1+r}$, where Y_i is the income in period $i = 1, 2$, P the amount of income-based taxes for public healthcare coverage, p the co-payment per unit of treatment in charge to the patient, and r is the interest rate[97].
Solving the individual's problem yields to the following optimality condition:

$$\Psi s'(x) = \frac{U(C_2)}{(1+\delta)\frac{\partial U}{\partial C_1}} = p, \tag{TA.1}$$

where Ψ is the demand for an extra quality-adjusted year of survival. Therefore, the individual will require healthcare up to the point where marginal benefits

[95] The former explicate a model of patient demand and supplier behavior to explain trends in cost growth, while the latter develop an equilibrium model that specifies health care intensity (as measured by expenditures) as a function of a variety of factors specific to health care providers' and patients' preferences.

[96] For example, as measured by quality-adjusted life years (QALY).

[97] For more complex models involving investments in health capital, see (Grossman, 1972).

equal the co-payment in charge to the patients.
Given the assumption of concavity for the perceived quality of life function $s(x)$, patients would demand a potentially infinite number of medical treatments in the absence of financial constraints[98]. However, even if individual financial resources were extremely high or individuals were totally exempted from co-payments ($p = 0$), and patients could afford a considerable use of healthcare services, they still could be constrained by their GPs, who could decide to deny a referral to further medical care[99]. Indeed, as described below, the supply side is modeled under the assumption that GPs seek to maximize their patient's perceived health but may deviate from this goal because of financial incentives, ethical judgment, and clinical ability.

The supply-side utility function is defined as $Z = \Psi s(x) + (nB + \omega x)$, where $\Psi s(x)$ is the patient's perceived health status and the terms in brackets specify GP's own income. The latter comprises the GP's total salary (salary per patient B times number of patients n), and a factor including intensity of care (ωx). GP's income is expressed as a function of x for two reasons[100]. First, given that GP's total salary (nB) depends on the number of patients treated, each practitioner could attract more patients by satisfying the individual demand and increasing the number of referrals provided even when they are judged not to be medically appropriate. Also, GPs may increase the number of referrals to avoid malpractice concerns that may reduce their financial resources. ω, therefore, captures the trade-off between the GP's willingness to act professionally and his or her own income.
In maximizing the utility function, the first constraint the practitioner faces is the individual demand, with GPs unable to treat their patients if they do not attend medical consultations. Once the contact with patients has taken place, the practitioners' treatment decisions may also be influenced by their ability in evaluating each case and condition or by professionalism, intended as the effort employed in the evaluation. It is shown by the first term of the supply-side constraint, defined as $\phi(|x - x^d|) + \mu(|x - \bar{X}|) = 0$. ϕ represents

[98]Moreover, note that the typical utility function is $U = \frac{C_2^{1-\gamma}}{1-\gamma}$, where γ is the Arrow-Pratt constant relative risk aversion. In this case, a rise in income and consumption will imply a more-than-proportional decline in the marginal utility of non-medical consumption. In fact, if the constant relative risk aversion $\gamma = 2$, a doubled income in the second period would reduce the marginal utility of consumption to $2^{-2} = 0.25$ times its previous level. Therefore, willingness to pay for healthcare will rise, stimulating demand for additional medical treatments.

[99]Note that GP's treatment decisions about referrals do not limit the access to healthcare, but may restrict patient's purchasing power. In fact, referrals are strictly required for medical treatments to be at least partially covered by the healthcare system and its absence forces individuals to pay the entire cost to satisfy their own request. In many cases it may imply the inability for the patients to obtain the care demanded.

[100]Here, x can be thought as the number of additional referrals provided by the practitioner for each patient.

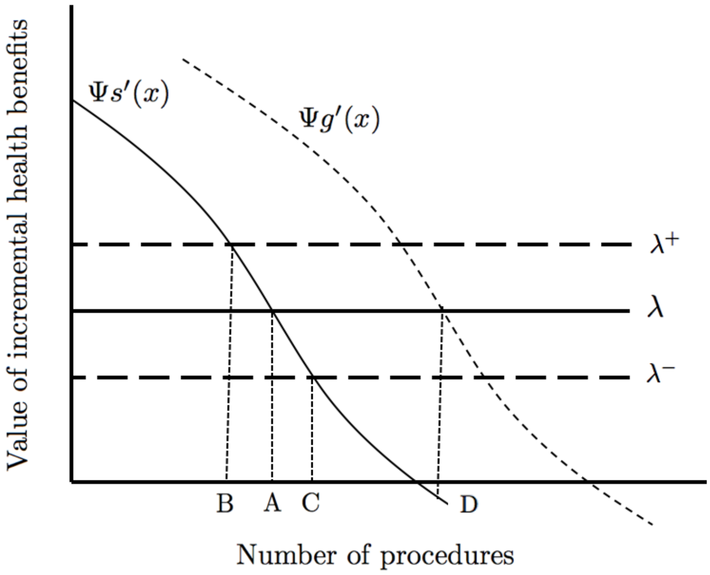
the weight of a possible deviation between the quantity of referrals provided by the practitioner (x), and the amount of care patient's clinical needs require (x^d). Other non-economic factors that could also play a role are summarized by the term $\mu(|x - \bar{X}|)$. μ indicates the importance of deviations from the average intensity of care. It reflects ethical judgments about both the social cost of using unnecessary resources and the cost for patients when $\Psi s'(x)$ is small or even null and out-of-pocket expenses are high.
Solving the GP's problem for the intensity of care leads to:

$$\Psi s'(x) + \omega = \phi + \mu = \lambda \tag{TA.2}$$

Equation TA.2 implies that GPs refer patients up to the point where the combination of the marginal value of health and the importance of financial rewards is limited by ethical and ability constraints. The extent to which financial incentives are offset by other factors is described by the constant λ, which represents the supply curve depicted in Figure TA.1. Its flat shape derives from the fact that the parameters related to the practitioner's behavior (i.e., ϕ, μ and ω) reflect GP-specific traits that are independent of the number of referrals provided. On the other hand, the downward sloping curve $\Psi s'(x)$ reported in the figure represents the set of points where individuals maximize the perceived quality of life and is constructed by sorting patients by health status and, consequently, appropriateness of treatment. Indeed, the model assumes that GPs are able to allocate treatments to those who would benefit most and work down the distribution so that the marginal patient is the one with a lower incremental benefit. Therefore, it is not a demand curve per se but instead reflects diminishing returns to treatment by moving further into the population of patients less likely to benefit from additional medical care.

The optimum level of medical care provided by the average practitioner is given by the intersection of the supply curve and the marginal benefit curve, at point A in Figure TA.1. However, different equilibria may exist. While changes in individual health status lead each patient to move along the marginal benefit curve, the intensity of treatment in equilibrium also depends on shifts of the $\Psi s'(x)$ curve, the shape and location of which are observed through movements of the λ curve. The latter are induced by deviations of physician-specific characteristics from the average behavior. It follows that higher levels of ability or professionalism (ϕ) and greater importance for ethical factors (μ) shifts the curve λ^+ along the $\Psi s'(x)$ curve and define an equilibrium, point B, where volumes of healthcare are lower and marginal benefits are higher than point A. On the contrary, when the weight given to additional earnings or aversion to malpractice risk (ω) is considerable, practitioners are inclined to satisfy the patients' requests for medical care even when the latter are believed not to be medically appropriate. In those cases, the

Figure TA.1: Marginal productivity of health treatments for different production functions and constraints



Source: Skinner, 2011.

corresponding supply curve is λ^- and the equilibrium is at point C, where the intensity of care is higher, but the value of incremental treatment is reduced[101]. While factors included in λ affect the intensity of treatment via movements of the respective curve, other factors may influence the perception of the return to treatment causing shifts of the $\Psi s'(x)$ curve and different equilibria. The first factor is represented by population aging, which leads to a decline in individuals' health conditions. It will shift downward the marginal benefit curve (from $\Psi g'(x)$ to $\Psi s'(x)$), leading to a lower value of incremental health benefits for a given number of procedures. The opposite movements (from $\Psi s'(x)$ to $\Psi g'(x)$) is instead observed, for example, with the introduction of new medical technologies and drugs, which increase the marginal benefit of healthcare. Another element is professional uncertainty, for which imperfect information may drive practitioners to base their decisions on misperceptions that differ from the true return to treatment. This situation is shown in the figure, where $\Psi s'(x)$ represents the true medical benefit curve and $\Psi g'(x) = \alpha_p + s'(x)$ describes the perception of GP p, with α varying across practitioners. In particular, the curve $\Psi g'(x)$ is related to a practitioner that is overly optimistic about a given treatment ($\alpha_p > 0$). In that case, although the practitioner incorrectly believes to be placed at point A, the equilibrium is at point D. There, the intensity of treatment corresponds

[101] Note that in this case the minimum value of $s'(x)$ cannot be lower than zero for the assumption that practitioners, in absence of restrictions seek to maximize the perceived health of their patient and therefore would not harm them.

to negative values of the true marginal benefit, implying that the additional treatment harms the patient as a result of excessive care.

This model offers important insights about heterogeneity across individuals and practitioners that, leading to different equilibria, causes variations in individual healthcare volumes and expenditures. In particular, if all practitioners faced the same marginal returns, these variations would lead to different points along the same benefit curve, and the cross-sectional association across GPs would trace out the $\Psi s'(x)$ curve and the marginal return of HCE. On the other hand, if practitioners also differ about the perceived marginal benefit curve or the real one (for example, as a result of different patients' age or different decisions about the use of new drugs), then these comparisons across GPs will trace out some combination of both variations in the marginal benefit of healthcare and variations in λ. Hence, separating shifts in λ and shifts in $\Psi s'(x)$ allows us to understand how different elements contribute to the HCE variation across individuals.

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Conclusions

In this thesis, we model the life-cycle evolution of healthcare expenditures (HCE), expressed as a function of the aging process, health shocks and conditions, and distance to death for the young-old population.

The first chapter is devoted to examining the effect of age, morbidity, and time to death (TTD) on individual HCE and investigating how individual and GP components contribute to the variability in expenditures among individuals. Our main results show that age, morbidity, and TTD are all important determinants of HCE and, along with unobserved individual-specific factors and idiosyncratic shocks, are the elements that contribute most to generating variability in expenditures among individuals. However, they play different roles in shaping healthcare costs according to the spending component examined, with out-of-hospital and inpatient expenses showing opposite features. When total HCE are analyzed, we observe a positive gradient in age that is mainly driven by expenditures for out-of-hospital services, while no difference in hospital costs is observed over the considered lifespan once the number of co-morbidities and proximity to death are taken into account. On the other hand, inpatient expenses mainly drive the morbidity and end-of-life profiles of total HCE, a result indicating a progressive shift towards more complex and expensive inpatient treatments as the severity of the health condition increases. Such a substitution is confirmed by the different end-of-life evolution of HCE among the services considered: while hospital costs continue their growing trend over the last period of life, those incurred for all other services fall sharply in the year of death. Heterogeneous effects are also analyzed, with interesting results emerging especially when different diseases are compared. The effect of age on HCE is never statistically significant when disease-specific hospital expenses are considered, including the broader group of chronic conditions. Instead, the impact of the number of co-morbidities is always statistically significant, with the largest effect found for individuals affected by cancer, especially on outpatient expenses. Finally, the effect of TTD presents significant differences in HCE evolutions in the end-of-life period with respect to the type of the underlying disease. For acute conditions, end-of-life costs evolve rapidly; on the contrary, for long-lasting conditions, the HCE pattern begins to grow exponentially many years before death, suggesting a slow disease progression. The analyses carried out in this chapter are crucial from a policy perspective, as they allow to identify the critical point where the health shocks start to have permanent effects on the individual health status and expenditures and, hence, when preventive interventions should be undertaken. Such a critical point corresponds to the interval where the HCE pattern starts to marginally increase due to worsening health conditions of the population and, in particular, chronic and disabled individuals. For some of the latter, the condition is more easily kept under control even without relying on intensive and costly hospital treatments. Others, instead, more often suffer from acute shocks requiring hospitalization and are those who place the greatest burden on the expenditures borne by the Italian healthcare system. It suggests that the enhancement of primary and secondary prevention approaches before such a critical point is a priority goal to reduce the incidence of long-lasting diseases and prevent them from deteriorating to the point of exacerbation in acute cases requiring hospital admissions, associated with a greater need for medical care and higher expenditures.

Given the results obtained in the first chapter, in the second one, we analyze the effect of the first health shocks requiring hospitalization on HCE and expenses for different services. Our main findings confirm the existence of a large effect of the first hospitalization on HCE and show that the first admission is associated with substantial future medical expenses in all healthcare settings, accounted for the largest part by acute inpatient care. Indeed, the analysis of hospital expenditures indicates the occurrence of subsequent hospitalizations, mainly required for complications of cardiovascular diseases and cancer. These two diagnostic categories are responsible for the highest increase in inpatient expenditures and also present a persistent post-admission increase of outpatient and pharmaceutical expenses. In particular, the use of outpatient services appears to be intensive in the first few years after the admission, while pharmaceutical treatments seem to support the patients continuously during post-hospitalization. This result is driven by the high incidence of chronic and disabled individuals within the group of those affected by these two conditions. Indeed, while non-chronic/non-disabled individuals are admitted for temporary health shocks that the hospitalization can promptly and successfully treat, individuals affected by long-lasting disorders require greater post-admission assistance within both the inpatient and outpatient setting. We also note differences in the HCE evolution between those diagnosed at the first admission and those diagnosed later. For the latter, the post-admission expenditures for hospital services are always above those of the earlier-diagnosed individuals, suggesting that, in these cases, the hospital discharge is not followed by a care continuity path, resulting in subsequent hospitalizations for the treatment of a worsened health state.

Summing up, these findings show a significant rate of re-admission over the post-event period. To the extent that such additional hospitalizations are mainly required for unplanned re-admissions rather than for adherence to defined care paths, they suggests that neither the first hospitalization nor the follow-up ensures an effective rehabilitation to a health condition that can be treated successfully within the outpatient or primary care setting. From a policy perspective, this result raises questions about the quality of the healthcare system. Indeed, hospitalization rates represent relevant policy outcomes in terms of both population health and economic performances. On the one hand, hospital admissions affect the population's health status in the short and long run. On the other hand, cost-containment policies focused on the inpatient setting, such as those aimed at reducing hospitalization days, are the fastest way to cut costs. However, if not accompanied by interventions aimed at improving the quality of territorial care, they only increase the risk of future re-hospitalizations and, consequently, costs. Hence, the strengthening of territorial care, to be implemented alongside cost-containment policies, seems necessary to reduce costs while improving population health. Indeed, continuity of care, essential for the population of chronic and disabled individuals, can be provided more effectively within out-of-hospital settings, improving health outcomes and reducing costs. In particular, while the first chapter indicates the enhancement of primary and secondary prevention approaches to reduce the incidence of long-lasting diseases and prevent them from further complications, the second chapter reveals the need for tertiary prevention improvements to soften the impact of ongoing illnesses with lasting effects. If, on the one hand, it would improve patients' health by preventing complications and acute cases, it would also generate significant savings due to the prevention of avoidable additional hospitalizations.