Do subsidized nursing homes and home care teams reduce hospital bed-blocking? Evidence from Portugal

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This version: July 9, 2021.

Abstract

Excessive length of hospital stay is among the leading sources of inefficiency in healthcare. When a patient is clinically fit to be discharged but requires support outside the hospital, which is not readily available, they remain hospitalized until a safe discharge is possible —a phenomenon called bed-blocking. I study whether the entry of subsidized nursing homes (NH) and home care (HC) teams reduces hospital bed-blocking. I use individual data on emergency inpatient admissions at Portuguese hospitals during 2000-2015. My empirical approach exploits two sources of variation. First, variation in the timing of entry of NH and HC teams across regions, originating from the staggered implementation of a policy reform. Second, variation between patients in their propensity to bed-block. I find that the entry of HC teams in a region reduces the length of stay of individuals at increased risk of bed-blocking by 4 days relative to regular patients. Reductions in length of stay upon the entry of NH occur only for patients with high care needs. The reductions in length of stay do not affect the treatment received while at the hospital nor the likelihood of a readmission. The beds freed up by reducing bed-blocking are used to admit additional elective patients. I also provide evidence on the mechanisms preventing the complete elimination of bed-blocking.

Keywords: nursing home; home care; hospital bed-blocking; delayed discharges.
JEL codes: H51; I10; I18; J14.

*Tilburg University. E-mail: a.c.moura@tilburguniversity.edu. I am thankful to Jan Boone and Martin Salm for extensive advice and support. For thoughtful discussions, comments, and suggestions, I thank Mara Barschkett, Joan Costa-Font, Pilar García-Gómez, Martin Gaynor, James Gaughan, Ludovica Gazze, Judite Gonçalves, Shan Huang, Tobias Klein, Rebecca Leber, Maarten Lindeboom, Giuseppe Moscelli, Pedro Pita Barros, Marianne Tenand, and seminar participants at Tilburg University, CHE Monash, Health Economics Bristol, the EuHEA PhD Conference, the IZA Workshop on Long-Term Care, the Essen Health Conference, and the Portuguese Health Economics Workshop. Access to the individual hospital data is possible under the data-sharing agreement between Administração Central do Sistema de Saúde, I.P. (ACSS) and the Health Economics & Management Knowledge Center at Nova School of Business and Economics, with which I am affiliated. I thank Hugo Lopes for providing me the data on the entry dates of nursing homes and home care teams.

1 Introduction

A significant, growing share of resources in developed countries is allocated to the healthcare sector. This has raised concerns about waste and inefficiency in healthcare among economists and policy-makers. However, identifying specific sources of inefficiency and potential improvements is challenging (Einav et al., 2019). The World Health Organization considers excessive length of hospital stay as one of the leading sources of inefficiency in healthcare (WHO, 2010).

One reason for excessive length of hospital stay is lack of alternative care arrangements following a hospitalization. When a patient is clinically fit to be discharged but requires some form of support outside the hospital, such as a stay at a nursing home facility or home-help, which is not readily available, they cannot be safely discharged. The patient remains hospitalized until a safe discharge is possible, resulting in a longer length of stay —a phenomenon referred to as bed-blocking (Holmås et al., 2013).

Bed-blocking is not inconsequential. It is associated with higher hospital costs, has potentially detrimental impacts on patients' health originating from increased risks of mobility loss, hospital-acquired infections, and loneliness, and can create delays for patients awaiting elective care (Mur-Veeman and Govers, 2011).[1]

Bed-blocking is a growing policy concern in developed countries. During the last decades, there was a significant increase in life expectancy and, consequently, a rising share of the elderly in the population. Elderly people are more likely to need support following a hospitalization. Moreover, chronic diseases became the leading cause of illness, disability, and death. While largely manageable outside the hospital, chronic diseases limit patients' ability to live independently. These demographic and epidemiological trends put pressure on existing institutional arrangements within the health system (Harper, 2014). Social trends, such as the rise in female labor force participation and the decline of multi-generational households, in turn, threaten existing informal care arrangements (Lakdawalla and Philipson, 2002).

I investigate whether, and to what extent, the availability of publicly subsidized nursing homes (NH) and teams providing home care (HC) reduces hospital bed-blocking in Portugal. Existing estimates for Portugal suggest that, on a random day in 2019, 4.7% of beds in public hospitals were occupied with patients who were ready to be discharged but were awaiting support outside the hospital. These estimates amount to over 80,000 delayed bed-days and imply a cost burden of €M83 for public hospitals throughout the course of 2019.[2,3]

[1] In the specific case of Portugal, waiting lists for elective care are a major concern for the healthcare system (Simões et al., 2017). Moreover, a substantial share of hospitals has annual inpatient bed occupation rates over 90% (Figure A.1 in the Appendix).

[2] Results from a snapshot-census carried out by the Portuguese Association of Hospital Managers (APAH) in collaboration with EY. See `https://apah.pt/portfolio/barometro-de-internamentos-sociais/`.

[3] In Sweden, the share of bed-blockers was 7% in 1992 (Styrborn and Thorslund, 1993). In 2006, 6.1% of

My empirical analysis relies on a difference-in-differences framework. I compare the length of stay of patients at increased risk of bed-blocking and the length of stay of regular patients, before and after the entry of NH and HC teams in their region of residence. This identification strategy exploits two distinct sources of variation. First, it exploits plausibly exogenous variation across regions and time in the availability of NH and HC teams. Second, it exploits variation between patients who live in the same region and are admitted to the hospital in the same time period, but have different propensities to bed-block.

Variation in the availability of NH and HC teams across regions and time originates from the staggered implementation of a policy reform. Before 2006, such services were not within the scope of the Portuguese National Health Service and individuals relied almost exclusively on informal care provided by family members. In 2006, the government introduced a network of publicly subsidized NH and teams providing HC, to fill in this gap in service coverage. NH and HC teams belonging to the network operate in coordination with hospitals to ease patients' transition out of the hospital. The network was introduced in a staggered fashion, so that different regions experienced the entry of NH and HC teams at different points in time, as centrally determined by the government.

Using individual data on the universe of emergency inpatient admissions at public hospitals in Portugal for the years 2000 to 2015, I identify patients at increased risk of bed-blocking from the presence of social factors that might hinder a timely discharge. These social factors include, for example, the lack of informal support in the community or inadequate housing conditions (i.e. lack of home adaptations). The presence of these social factors is associated with longer hospital stays, even after controlling for demographics, comorbidities, and medical diagnoses. Throughout the paper, I refer to patients who exhibit these social factors as bed-blockers, as opposed to regular patients, who exhibit no social factors.

My baseline results show that the entry of HC teams in a region reduces the length of stay of bed-blockers relative to regular patients by 4 days. Reductions in the length of stay of bed-blockers relative to regular patients following the entry of NH occur only for patients with high care needs, such as those with a stroke diagnosis. This finding is consistent with NH admissions requiring higher levels of disability and dependence. The entry of NH and HC teams has a precise zero impact on the length of stay of regular patients. Thus, reductions in the length of stay of bed-blockers relative to regular patients originate only from reductions in the length of stay of bed-blockers. Using an event-study, I typically find no differential trends between the length of stay of bed-blockers and regular patients in the three years prior to the entry of NH and HC teams in a region.

hospital days in the Netherlands were bed-blocking days (Mur-Veeman and Govers, 2011). In Canada during 2008-09, 5% of all hospitalizations (13% of hospital days) corresponded to patients awaiting a discharge (CIHI, 2010). During 2014-15 in England, 3% of hospital days were delayed transfers of care (NAO, 2016).

Consistent with the longer length of stay of bed-blockers being wasteful, I find no reduction in the intensity of treatment received by bed-blockers during their hospital stay after the entry of NH and HC teams. I also find no increase in the likelihood of a hospital readmission. Finally, the beds freed up by bed-blockers do not remain unoccupied: I find evidence of an increase in the number of programmed admissions upon the entry of HC teams in a region. This finding makes clear that I am identifying bed-blocking and not simply excessive length of stay at the hospital.

The event-study plots convey that reductions in bed-blocking upon the entry of NH and HC teams get larger over time, thought bed-blocking is never fully eliminated. I examine two potential explanations for these time dynamics. First, capacity expansions of NH and HC teams over time. Second, the accumulation of experience from interactions between hospitals and the regional teams responsible for finding vacancies in NH and HC teams. Both channels play a role in explaining the observed time patterns.

Related Literature. This paper relates to several strands of the economics literature.[4] First and foremost, it relates to a growing literature studying the impacts of NH and HC availability on hospital bed-blocking (Forder, 2009; Holmås et al., 2013; Gaughan et al., 2015, 2017a,b; Walsh et al., 2020). I make several contributions to this literature. First, I use exogenous variation to identify the causal effects of NH and HC teams on bed-blocking. Existing studies often lacked a clean source of exogenous variation. The policy reform that I exploit allows analyzing the effects of both NH and HC teams, whereas existing studies focused on a single type of provider (usually NH). My findings show that HC teams are a more successful policy tool to reduce bed-blocking than NH. Second, I identify individuals at increased risk of bed-blocking using information on social needs. Medical scholars have noted that bed-blocking does not only affect the elderly or those with complex clinical conditions (Pellico-López et al., 2019) and emphasized the role of social needs (McDonagh et al., 2000). However, existing studies in economics often restrict their analysis to specific populations (e.g. the elderly, stroke patients), and neglect the role of social needs. Third, I assess the impact of reducing bed-blocking on the intensity of care received and readmissions. Due to data limitations, existing studies were not able to investigate these effects.

A related literature focuses on the substitutability of acute hospital care and care provided by NH or HC teams. Most of this literature examines if care provided by NH and HC teams can delay or avoid the need for hospital care and finds little to no substitution between these settings of care (McKnight, 2006; Gonçalves and Weaver, 2017; Bakx et al., 2020; Costa-Font

[4]Outside economics, medical scholars have studied the causes of bed-blocking, characterized the affected population, and quantified the associated monetary losses (Bryan et al., 2006; Hendy et al., 2012; Costa et al., 2012). In operations research and healthcare management, the optimization of patient flows has been well studied (McClean and P., 2006; El-Darzi et al., 1998; Katsaliaki et al., 2005; Osorio and Bierlaire, 2007).

et al., 2018; Kümpel, 2019). I contribute to this literature by studying an alternative form of substitution between acute care and care provided by NH or HC teams. I am interested on whether care provided by NH and HC teams can be used in lieu of (the last days of) a hospital stay, particularly for patients who do not seem to need acute care anymore.

My finding that reductions in bed-blocking lead to increases in programmed admissions relates to a discussion on the internal allocation of resources within a hospital, which dates back to Harris (1977). I provide empirical evidence of a shift in the allocation of beds from emergency to elective care, following reductions in bed-blocking. This shift could take place via a reduction of waiting times for patients who are on waiting lists for elective care, as suggested in Johar et al. (2013).

I also provide insights on the factors preventing the complete elimination bed-blocking. Different settings of care are organized and funded separately in many countries (Siciliani, 2014), making coordination difficult (Cebul et al., 2008). Fernandez et al. (2018) study the role of coordination frictions in driving bed-blocking. Consistent with the idea of reducing coordination frictions through the accumulation of experience, I show that a large number of interactions between hospitals and the regional teams responsible for finding vacancies in NH and HC providers is needed to generate meaningful reductions in bed-blocking. This can explain why larger hospitals, with a high number of admissions, seem to manage discharges more efficiently and have less delayed discharges (De Volder et al., 2020).

Finally, and more broadly, this paper relates to recent work zooming in on specific aspects of the healthcare sector to identify sources of waste and inefficiency. A large part of this literature focuses on interactions between the acute care and the nursing home settings (Doyle Jr et al., 2017; Einav et al., 2018; Eliason et al., 2018; Jin et al., 2018; Einav et al., 2019; Kümpel, 2019). By and large, this literature points to the nursing home sector as a source of inefficiency in the healthcare system. My paper offers a different perspective, investigating whether the entry of NH and HC teams helps reducing inefficiencies associated with bed-blocking in the acute-care setting. My baseline estimates suggest that the availability of HC teams generates a 28% reduction in annual bed-blocking costs incurred by hospitals.

The remainder of this paper is organized as follows. Section 2 provides an overview of the institutional setting. Section 3 describes the data and Section 4 describes the empirical approach. Section 5 presents the results and Section 6 elaborates on potential mechanisms. Finally, Section 7 concludes.

2 Institutional Setting

2.1 Inpatient care

In Portugal, most inpatient care is provided by public hospitals belonging to the National Health Service (SNS). The SNS is predominantly financed through general taxation and access to care is mostly free at the point of use (Simões et al., 2017).

Inpatient care provided by public hospitals belonging to the SNS is paid based on Diagnosis-Related Groups (DRGs). A DRG groups patients who have similar consumption of resources based on their medical diagnosis, treatment received, and demographic characteristics. There are over 600 distinct groups in the current DRG system and each has an associated price that is unilaterally determined by the government. DRGs are used to set an annual prospective global budget for inpatient care provided by each hospital, which is the main source of inpatient revenues for public hospitals (Mateus, 2011).

Hospitals have no financial incentive to keep patients for longer than necessary. Since hospitals are paid according to the number and the DRG of patients they treat, DRG-based funding provides incentives for hospitals to treat more patients and to cut costs, possibly by reducing length of stay. To account for complicated patients whose length of stay might be extraordinarily long, hospitals get an additional daily payment for each day in excess of an upper trim-point defined by law for the patient's DRG until discharge. While the trim-point is DRG-specific, the daily amount for days in excess of the trim point is not.

2.2 Entry of nursing homes and home care teams

Some individuals need support outside of the hospital following a hospitalization. For example, they might need nursing care and rehabilitation, or they might need help with personal care (i.e. personal hygiene) and activities such as housework or meals.

Before 2006, the SNS provided no such support. Individuals relied almost exclusively on informal care provided by relatives or friends. Alternatively, individuals could purchase these services from private providers, namely non-profit religious institutions (*Misericórdias*) (Simões et al., 2017), but had to pay for them out of pocket. This took a financial toll on many users and likely priced some potential users out of the market (Santana, 2010).

To fill in this gap in service coverage, in 2006 the Portuguese government established the National Integrated and Continuous Care Network (RNCCI), as a joint effort of the Ministry of Health and the Ministry of Labor and Social Security (Decree-Law 101/2006). The RNCCI was not explicitly aimed at reducing bed-blocking, which is a recent topic in the public debate.

The RNCCI comprises two distinct settings of care provision: home care services (HC)

Table 1: Overview of the organization of the RNCCI

	Nursing home (NH)	**Home care** (HC)
Start of roll-out	2006	2008
Providers	Private	Public
Funding	Public	Public
Set-up	Government contracts with existing providers	Teams created in primary care centers
Price	Highly subsidized (means-tested) co-payments	Free
Services	24-hour medical care, rehabilitation, food, personal hygiene, accommodation, etc.	Preventive care, food, personal hygiene, medication, etc.

and nursing homes (NH). Table 1 provides an overview of these two settings.

The NH setting operates in a model of public funding and private provision in which the government contracts with private providers. In the earlier years of the RNCCI, the vast majority of contracts was signed with the *Misericórdias*, who had been active in care provision for several decades.[5,6] The services contracted include around-the-clock medical care, rehabilitation, accommodation, meals, personal hygiene, etc. There are different types of NH facilities that cater to patients with different care needs. Some target individuals who no longer need acute hospital care but still require intensive medical, nursing, and rehabilitation care for a relatively short period of time. Other NH facilities offer less intensive medical, nursing, and rehabilitation components, mainly catering to individuals with chronic illnesses and high functional dependency. NH providers receive an administratively set daily price for the care provided to individuals in the RNCCI, which is either fully paid or highly-subsidized by the government.

The HC setting operates in a model of public funding and public provision. The government established specialized teams in primary care centers that visit patients in their homes. HC teams provide services such as preventive care or help with activities of daily living. They cater to individuals with dependency who need a lower frequency and intensity of medical

[5] *Misericórdias* were historically the main healthcare providers in Portugal. They operated many small hospitals aimed at serving the population within a municipality. Their role was substantially diminished upon the creation of the SNS in 1979, and most of these small hospitals were closed down.

[6] More recently the government started contracts with private, for-profit providers and also established some public-owned facilities. These amounted to, respectively, 16% and 2% of NH providers contracted as of 2015, the end of my study-period.

and rehabilitation care and are still able to live in the community. Care provided by HC teams is free of charge to users.

The contracting of NH units started in 2006, whereas the first HC teams were established in 2008. Figure 1 shows the entry year of the first NH facility (on the left panel) and the first HC team (on the right panel) across ACES regions. ACES is the Portuguese acronym for Primary Care Center Groups and these regions are relevant for organizing primary care delivery.[7] The majority of ACES regions experienced the entry of the first NH in 2006 and 2007 and the entry of the first HC team in between 2008 and 2010.

The timing of NH entry across regions was mainly determined by the availability of buildings that could be converted into nursing homes with minimal adaptation and cost —these were often buildings that had been used as small municipal hospitals in the past, and had not yet been repurposed. The entry timing of HC teams was largely determined by the availability of human resources in primary care centers to be allocated to the new team.[8]

Patients need a referral to access the RNCCI. The referral can be made either by a hospital if they are hospitalized, or by their general practitioner if they live in the community. My analysis focuses on patients who are hospitalized so I focus on the former channel, which amounts to 65-70% of referrals during my study-period (UMCCI, 2011, p. 47). Every hospital has a discharge planning team, whose main job is to timely prepare and manage hospital discharges. This is a multidisciplinary team composed of physicians, nurses, and social assistants that flags patients in need of support outside the hospital either due to their health condition and degree of transitory or prolonged functional dependency or to social factors that might be preventing a safe discharge. The discharge planning team refers patients to the RNCCI. Upon referral, a local coordination team based in the ACES region where the patient lives validates the assessment made by the discharge management team and finds an adequate vacancy for the patient, preferably within its region of influence. Figure 2 summarizes the admission process to the RNCCI.

[7] There are 55 ACES regions in Portugal. ACES are defined so that they have about the same population size. In urban areas, ACES borders often coincide with municipal ones, but in less dense, rural areas ACES typically group a few neighboring municipalities. The dense municipalities of Lisbon, Porto, and Vila Nova de Gaia have more than one ACES. Because patient locations are recorded at the municipality level in the inpatient data, I collapse these ACES at the municipality level. Thus, there are 52 ACES in my analysis.

[8] Figure A.2 in the Appendix shows that the entry timing of NH and HC teams is unrelated with the share of bed-blockers in a region and the occupancy rates of hospitals prior to the introduction of the RNCCI. In the empirical analysis I formally test for pre-treatment trends.

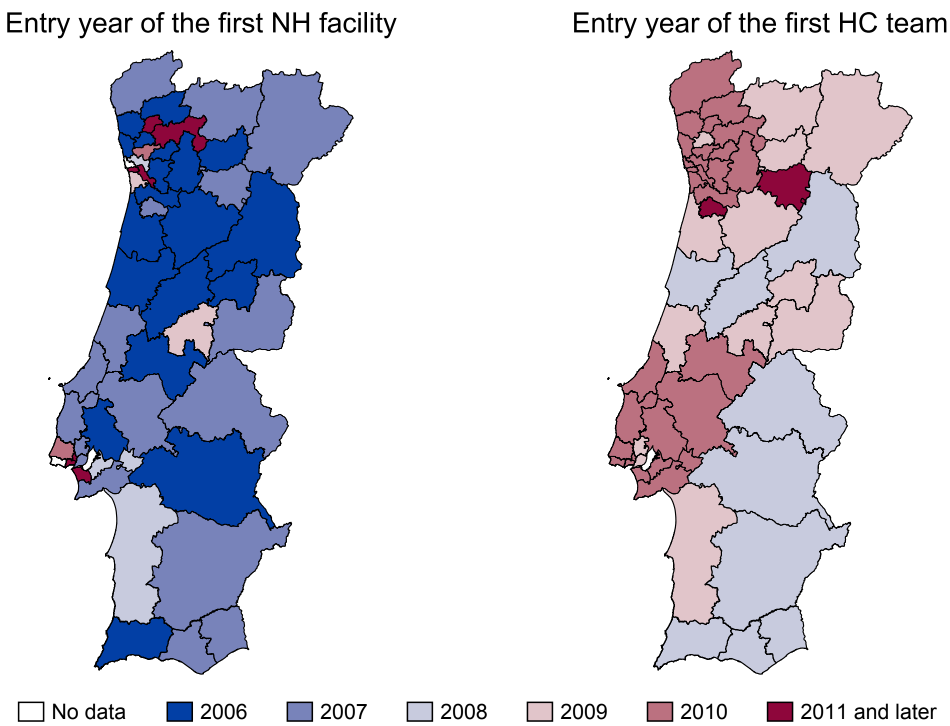


Figure 1: Entry year of the first NH unit and the first HC team across ACES regions

3 Data

3.1 Data sources and variable definitions

The main dataset used for the analysis contains individual information on the universe of inpatient stays at public hospitals located in mainland Portugal between the years 2000 and 2015. The data are maintained by Administração Central do Sistema de Saúde, I.P. (ACSS).

Throughout most of the analysis, I focus on emergency inpatient admissions. There are two main reasons why I do this. First, as opposed to programmed admissions, they are unpredictable.[9] This minimizes the concern that individuals might make their own care arrangements in advance when they know they will be hospitalized on a certain date. Second, over 90% of patients at increased risk of bed-blocking are admitted to the hospital as emergency admissions. In robustness checks I show that my results are unchanged when including programmed admissions in the sample.

[9] Inpatient admissions imply that the patient spends at least one night at the hospital. They can be programmed or emergency admissions. Programmed inpatient admissions (also called elective care) are for pre-arranged health care services, including scheduled operations, and usually involve a referral to the hospital by a primary care physician or a specialist, a waiting period, and an appointment for an admission date. Emergency inpatient admissions, in turn, include patients with urgent or life-threatening conditions that require immediate medical assistance.

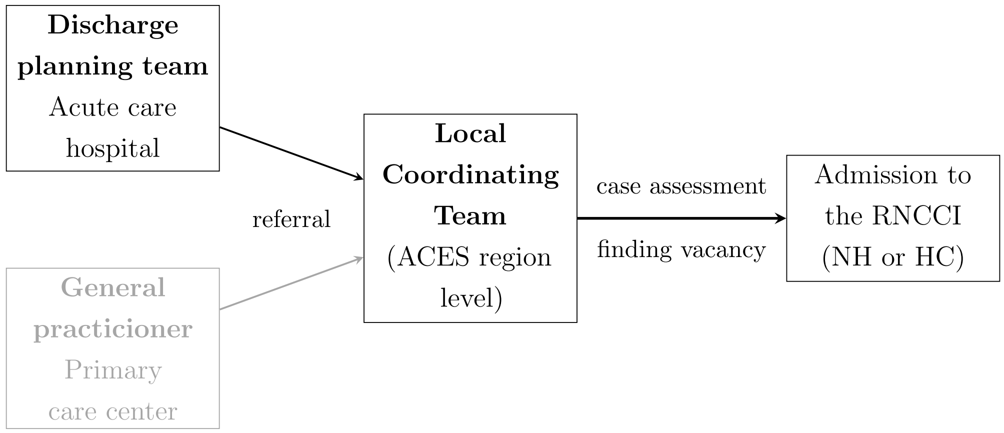


Figure 2: Process of admission to the RNCCI

I exclude admissions into specialized hospitals[10] and admissions of individuals under 18 years old, thus focusing on adult patients admitted to general acute care hospitals. My final dataset comprises over 7.5 million complete emergency hospital admissions over 16 years.

In my baseline specification, the outcome variable is the length of hospital stay of patient i (in days), who is admitted to the hospital in month t. This measure is the sum of the appropriate length of hospital stay and the bed-blocking period.

I identify individuals at increased risk of bed-blocking using the ICD-9-CM secondary diagnosis codes capturing underlying social factors influencing a patient's health status and contact with health services. I focus on factors such as living alone, lacking family support, and having inadequate housing conditions or an unfavorable economic situation because these have been previously associated with the use of NH and HC (Lopes et al., 2019; Diepstraten et al., 2020) and bed-blocking (Costa et al., 2012; Bryan et al., 2006; McDonagh et al., 2000).[11]

Social needs are assessed for all patients by the hospital discharge planning team. When social needs are expected to affect the discharge process, information on the most relevant social factor is added to the patient's file and coded in the data.[12]

How do social factors put patients at increased risk of bed-blocking? Take two clinically

[10]Specifically, I exclude three cancer hospitals and two psychiatric hospitals because they do have specific long-term beds targeting the needs of their patients.

[11]The codes for underlying social factors influencing a patient's health status and contact with health services can be found at `https://www.hcup-us.ahrq.gov/toolssoftware/ccs/AppendixASingleDX.txt` under the header "Administrative/social admissions". For individuals living alone, I use code V603; for individuals with no family to care, I use codes V604 and V605; for individuals with unfavorable housing conditions and economic situation, I use codes V600, V601, V602, V608, V6081, V6089, and V609. The unused codes refer to various situations that are either not associated with bed-blocking (i.e. living in a residential home for elderly people), not related to care needs (i.e. legal matters), or associated with services and populations outside of the scope of the Network (i.e. mental health, children).

[12]Since hospitals hospitals only code what they perceive to be the most relevant social factor affecting the discharge process, social factors are mutually exclusive.

identical patients who need help with activities of daily living, such as personal hygiene, for some weeks following a hospital stay. One has a partner at home who can help with such activities and the other does not. While the former can be safely discharged home without additional support, the latter cannot. The existence of, for example, teams providing home care services is then crucial for his timely discharge. A similar reasoning applies for patients who lack the necessary home adaptations to safely carry out their daily routines by themselves.

One possible concern is that hospitals change the coding frequency of the social factors used to identify patients at increased risk of bed-blocking following the entry of NH and HC teams. In Appendix B, I show that this is not the case.

I complement the inpatient dataset with monthly data on the roll-out of the RNCCI. For most of my analysis, I measure the availability of NH and HC teams in the patient's region of residence using two binary indicators for months after the entry of the first NH and the first HC team in the region. In robustness checks I use continuous measures, such as the monthly number of NH facilities and HC teams in a region and their capacity.

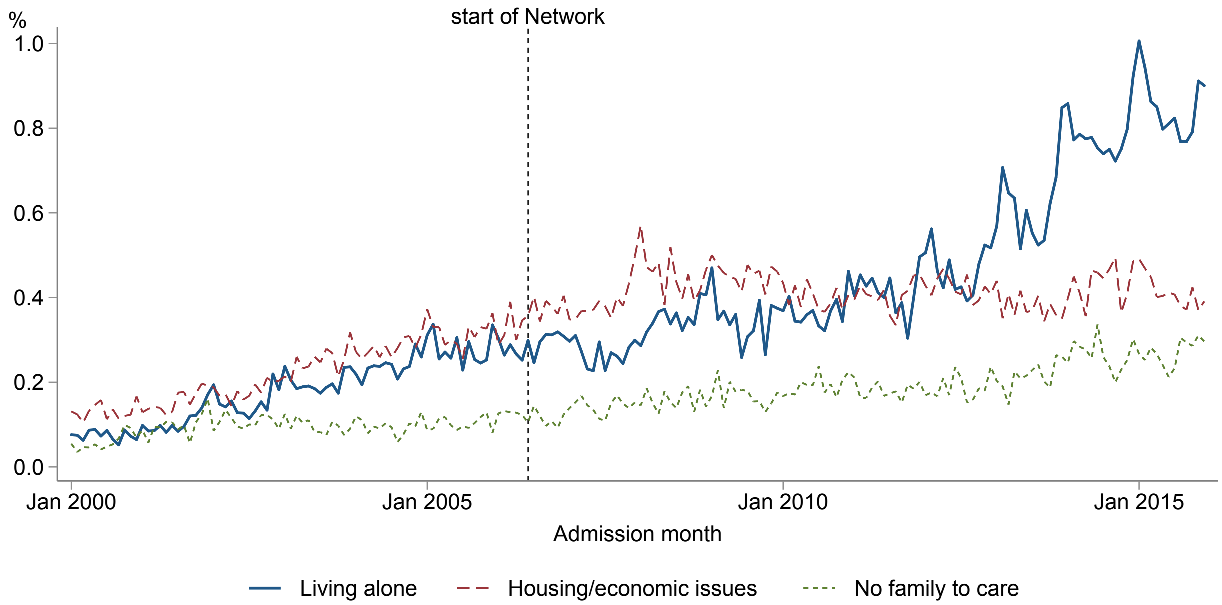
In the baseline analysis, I define the relevant region as the ACES. As mentioned in Section 2, these are relevant because the local coordination teams that find vacancies for patients referred to the RNCCI are established at the ACES level and preferably search for vacancies within that region. In robustness checks I use alternative region definitions.

Figure A.2 in the Appendix shows that the entry timing of NH and HC teams across ACES regions is unrelated to the share of individuals at increased risk of bed-blocking and hospital occupancy rates in 2005, the year prior to the introduction of the RNCCI. Figure A.3, in turn, shows that the entry timing of NH and HC teams across regions is largely unrelated with the degree of political alignment with the party in power (the Socialist Party) and the political marginality of a region. To rule out further concerns about the potential endogeneity of treatment timing, in robustness checks I formally test for pre-treatment trends using an event-study design.

Throughout the empirical analysis, I control for demographics, comorbidities, DRG group, admission month-by-year, and occasionally the hospital where the patient was admitted to. I also use information on medical diagnosis and procedures. All this information is available from the inpatient dataset. For some of my analyses, I use information on DRG trim-points, which I collected from the laws passed by the Government.[13]

[13]In particular, I use information on DRG trim-points from Portaria 189/2001 published on March 9; Portaria 132/2003 published on February 5; Portaria 567/2006 published on June 12; Portaria 110-A/2007 published on January 23; Portaria 132/2009 published on January 30 and updated by Portaria 839-A/2009, published on July 31; Portaria 163/2013, published on April 24; and Portaria 20/2014, published on January 29. I did not find information on DRG trim-points prior to 2001, so I exclude admissions in 2000 from the estimations using trim-points as dependent variable.

Figure 3: Share of patients at increased risk of bed-blocking



NOTES: The figure shows the monthly evolution of the share of patients at increased risk of bed-blocking on total emergency admissions. The vertical dashed line marks the start of the RNCCI. Entry of nursing homes and home care teams occurred in a staggered way after the start of the RNCCI.

3.2 Summary Statistics

Figure 3 shows the relative frequency of monthly emergency admissions in each of the three groups of patients at increased risk of bed-blocking over my study-period. Despite the upward trend over time, each of these groups amounts to a small share of total emergency admissions in a month. Throughout my study-period there are 67,262 individuals at increased risk of bed-blocking, corresponding to 0.85% of total emergency admissions in the sample.[14]

Table 2 shows summary statistics for regular patients, i.e. patients who do not exhibit social factors, as well as each group of patients at increased risk of bed-blocking. It conveys that individuals at increased risk of bed-blocking have longer length of stay than regular patients and are more likely to have a length of stay beyond their DRG trim-point. However, they are also older and have more comorbidities as measured by the Charlson score.

To understand whether social factors such as living alone, having no family to care, and having inadequate housing and other economic difficulties are associated with longer length of stay, I estimate the following equation:

[14]This share is lower than that suggested by the APAH Census in footnote 1. There are several reasons for this. First, the APAH Census was done in 2019 and my data goes only until 2015. My data shows an upward trend in the share of potential bed-blockers over time, so one would expect a larger share in future periods. Second, the sample of hospitals in the APAH Census does not include all public general acute-care hospitals (the Census was not mandatory). Third, the APAH Census includes psychiatric hospitals.

Table 2: Summary statistics

	Regular patients		Living alone		No family to care		Housing/econ. issues	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Female (%)	58.2	49.3	57.1	49.5	52.2	50.0	46.7	49.9
Age (years)	58.6	22.5	74.2	14.2	71.0	16.5	64.9	19.8
Length of stay (days)	8.8	12.7	18.5	33.0	36.5	53.2	27.4	50.6
No. days over trim-point	0.4	6.6	2.8	25.6	10.3	41.6	6.9	42.6
Over DRG trim-point (%)	2.3	14.9	7.5	26.4	21.8	41.3	15.0	35.7
Charlson score	1.2	1.9	1.9	2.1	2.2	2.5	2.0	2.4
Number of procedures	5.9	3.8	8.1	4.3	8.2	4.8	7.5	4.5
Number of diagnoses	4.5	3.7	8.9	5.1	8.6	5.3	7.8	4.5
Observations	7,883,374		28,499		12,013		26,750	

NOTES: The table shows the mean and standard deviation of the main variables used in the empirical analysis, for regular patients as well as each of the groups at increased risk of bed-blocking. *Abbreviations:* DRG: diagnosis-related group.

$$y_{it} = \beta BB_i + \delta X_i + \lambda_d + \lambda_h + \lambda_t + \varepsilon_{it}, \tag{1}$$

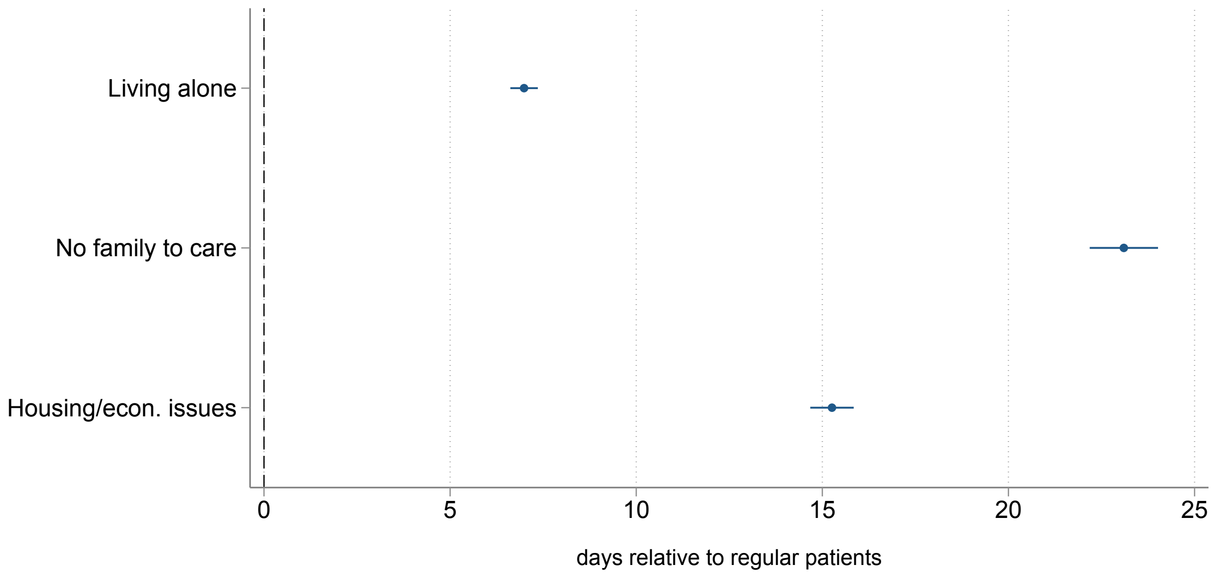
where the dependent variable y_{it} is the length of stay (in days) of patient i, who is admitted to the hospital in period t. BB_i is a vector containing three binary indicators for each group of patients at increased risk of bed-blocking (living alone, no family to care, and housing/economic issues); X_i is a vector containing 10-year age bins separately by gender and a set of dummies for the comorbidities included in the Charlson index (Charlson et al., 1987); λ_d, λ_h and λ_t are DRG, hospital,[15] and month-by-year of admission fixed effects, and ε_{it} is an error term. Vector β contains the parameters of interest, which measure the additional length of stay of each group at increased risk of bed-blocking relative to regular patients, averaged throughout my study-period.

Figure 4 shows the estimates of β from equation (1) and their 95% confidence intervals. Individuals living alone have hospital stays that are, on average, a week longer than regular patients. Individuals with no family to care and those with inadequate housing stay at the hospital, on average, 23 and 15 days longer than regular patients, respectively.

I conclude that these social factors appropriately proxy bed-blockers in the sense that the longer length of stay of patients exhibiting these factors cannot be explained by differences in

[15]During my study-period there were several hospital mergers. These were purely administrative, but the hospitals involved change their identifiers in the dataset (when hospitals A and B merge they start sharing an identifier and their old identifiers are no longer used). I follow Chandra et al. (2016) and treat hospitals A and B as one synthetic hospital throughout the analysis.

Figure 4: Estimates of β from equation (1)



NOTES: The figure shows the estimates of β from equation (1) and their corresponding 95% confidence intervals. The dependent variable is length of stay in days. The model includes individual demographics and comorbidities and admission month-by-year, diagnosis-related group, and hospital fixed-effects. The sample consists on 7,950,636 emergency inpatient episodes between the years 2000 and 2015.

their clinical status. To ease the exposition, I henceforth refer to patients exhibiting these social factors as bed-blockers.

In the empirical analysis, I assess whether the gap in the length of stay of bed-blockers and regular patients decreases after the entry of NH and HC teams in a region.

4 Empirical Strategy

4.1 Baseline Model

My baseline specification is a difference-in-differences model comparing the length of stay of each group of bed-blockers and the length of stay of regular patients, before and after the entry of nursing homes and home care teams in a region:

$$\begin{aligned} y_{it} =& \alpha_1 BB_i + \alpha_2 PostHC_{mt} + \alpha_3 PostHC_{mt} \times BB_i + \alpha_4 PostNH_{mt} + \\ & \alpha_5 PostNH_{mt} \times BB_i + \delta X_i + \lambda_d + \lambda_m + \lambda_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

where $PostNH_{mt}$ is an indicator variable taking value 1 after the first NH provider is contracted in region m. Similarly, $PostHC_{mt}$ is an indicator variable taking value 1 after the first HC team is created in region m. λ_m is a vector of region fixed-effects. All remaining notation is as previously defined.[16]

The parameters of interest are α_1 to α_5. The estimates of α_1 are informative about differences in length of stay between each group of bed-blockers and regular patients, prior to the entry of NH and HC teams in a region. The estimates of α_2 and α_4 capture changes in the length of stay of regular patients following the entry of the first HC team and the first NH in a region, respectively. The estimates of α_3 and α_5, in turn, capture changes in the length of stay of each group of bed-blockers relative to regular patients, following the entry of the first HC team and the first NH in a region, respectively. Since most ACES regions experience the entry of several HC teams and NH facilities over time, the estimates of α_2 to α_5 are informative about the effect of having *at least one* HC team and one NH facility in the region of residence on length of stay. Because I do not observe individual take-up of the services provided by the RNCCI, the estimates have an intent-to-treat flair.

One feature of my specification is that it includes two distinct treatments: the entry of the first NH and the first HC team in a region. Crucial for disentangling the effects of NH and HC entry, the first NH and HC team never enter a region in the same period. Additionally, regions which were among the first to have a NH facility were not necessarily among the first to have a HC team (Figure A.4 in the Appendix). The correlation between the rankings of regions with respect to the entry of their first NH and their first HC team is fairly low, at 0.29. Consequently, there is quite some variation across regions in the number of months between the entry of the first NH and the entry of the first HC team (Figure A.5 in the Appendix). These are all essential for separately identifying the effects of NH and HC entry.

Another feature of equation (2) is that it includes both bed-blockers and regular patients. The inclusion of regular patients helps controlling for general region and time specific trends in length of stay. For example, suppose that the entry of HC teams in a region decreased length of stay for all patients due to some unobserved factor. Then, estimating the model among bed-blockers only (thus only exploiting variation in treatment timing) would overestimate the effect of HC teams. Additionally, because there are relatively few bed-blockers in the sample, including regular patients helps pinning down the estimates of the covariates in the model.

However, including both regular patients and bed-blockers in the estimation requires assuming that these groups are comparable. This is a strong assumption as regular patients and bed-blockers might be different in aspects that I am not able to control for in the estimation. To alleviate this concern, I estimate an alternative model specification only among bed-blockers in Section C.1 of the Appendix. This specification focuses on each group of

[16]This specification includes many covariates. Table A.1 in the Appendix shows that the estimation results are stable when using different subsets of these covariates.

bed-blockers separately and exploits only variation in treatment timing. Because it compares the length of stay of bed-blockers at different points in time, it does not require any assumption on the comparability of regular patients and bed-blockers.

It is possible that the presence of social factors is not a good proxy for bed-blockers. For example, there might be some option value in keeping some patients for longer at the hospital, even if they do not exhibit any social factors. Or, as discussed above, the presence of social factors might reflect a lower underlying (unobserved) health status and thus require longer hospital stays, without these being bed-blocking days. This would bias the estimates of interest from equation (2) towards zero. My estimates can thus be interpreted as a lower bound of the true effects of the entry of NH and HC teams on bed-blocking.

The inclusion of DRG fixed-effects, λ_d, is also worth of discussion. My dependent variable does not allow separating the appropriate length of stay and the length of the bed-blocking period. Since DRGs group patients with similar medical conditions and demographics, who undergo similar treatments, patients in the same DRG are expected to have similar length of appropriate stay. The DRG fixed-effects therefore capture the time-invariant, DRG-specific component of length of stay corresponding to the appropriate duration of the stay because the majority of individuals do not experience delays related to bed-blocking.

Due to the large number of DRG groups, I estimate equation (2) using the Stata package `reghdfe` (Correia, 2016), which allows for high dimensional fixed-effects. I exclude the month of entry of the first NH and HC team in a region from the estimation because I do not observe the exact day of the month when entry took place. Additionally, I follow Abadie et al. (2017) and cluster standard errors at the level of treatment assignment, which is the region.[17]

4.2 Parallel trend assumption

The core identifying assumption of my empirical approach is that, in the absence of the entry of NH and HC teams, any trends in length of stay of each group of bed-blockers and regular patients would have been similar across regions. This is the so-called parallel trend assumption. The parallel trend assumption is untestable because I do not know how length of stay would have evolved, had NH and HC teams not entered a region. To inform about the plausibility of the parallel trend assumption, it is standard practice to examine pre-treatment trends: if these evolved similarly, it does give some confidence that the post-treatment would have, too.

I examine pre-trends using an event-study approach. There are two events of interest, the entry of the first NH in a region and the entry of the first HC team in a region. The

[17] Alternative clustering options, for example at the region-month or region-DRG level, yield smaller standard errors, but do not qualitatively change my findings.

event-study framework allows the effect of the entry of NH and HC teams on the length of stay of each group of bed-blockers and regular patients to vary over time. I estimate the following event-study equation separately for each event:

$$y_{it} = \sum_{j=1}^{3} \sum_{\substack{r=-4 \\ r \neq -1}}^{6} \theta_r^j BB_i^j f(r) + \sum_{\substack{r=-4 \\ r \neq -1}}^{6} \theta_r f(r) + \sum_{j=1}^{3} \theta^j BB_i^j + \delta X_i + \lambda_d + \lambda_m + \lambda_t + \varepsilon_{it}, \tag{3}$$

$$f(r) = \begin{cases} \sum_{r<-3} I_r & \text{if } r < -3 \\ I_r & \text{if } -3 \geq r \leq 5 \\ \sum_{r>5} I_r & \text{if } r > 5 \end{cases}$$

where BB_i^j is a binary indicator for individual i being coded in bed-blocking group j (that is, BB_i^j is the j^{th} component of BB_i); r indexes time in years relative to the event; and $f(r)$ is a function of relative time. Specifically, $f(r)$ includes binary indicators for each relative year inside the event-window $(I_{-3}, I_{-4}, ..., I_5)$, a binary indicator for relative years prior to the event-window $(r < -3)$, and a binary indicator for relative years after the event-window $(r > 5)$. That is, I assume that outside of the event-window effects are constant in relative time. The advantage of specifying $f(r)$ in this way is that it allows me to still use observations outside of the event-window to pin down the fixed effects, demographics, and comorbidities. I normalize the year before the event to zero, $f(-1) = 0$. All remaining notation is as before.

I am interested in the estimates of both θ_r and θ_r^j. The estimates of θ_r capture the evolution of the length of stay of regular patients in the years around the event. The estimates contained in θ_r^j, in turn, convey the evolution of the length of stay differential between each group of bed-blockers j and regular patients around the event. I normalize $f(-1) = 0$, so the common trend assumption requires the estimates of θ_r^j for the remaining years prior to the event to be zero. This would mean that the length of stay differential between bed-blockers and regular patients is constant before the entry of NH and HC teams in a region, confirming the plausibility of the common trend assumption.

I estimate equation (3) separately for the two relevant events, the entry of the first NH and entry of the first HC team in a region. When estimating the event-study for the entry of the first NH (HC team), I control for the presence of HC teams (NH units) in the region.

4.3 Intensity of care, readmissions, and other health outcomes

One concern is that reductions in the length of stay of bed-blockers upon the entry of NH and HC teams might be accompanied by reductions in the treatment received while at the hospital. To assess this possibility, I estimate equation (2) using the number of medical procedures patients receive during their hospital stay as dependent variable. This is a typical measure of the intensity of care received by a patient (Kleiner, 2019).

Reductions in the length of stay of bed-blockers upon the entry of NH and HC teams might also impact their future consumption of acute care. If these individuals have now a form of support outside the hospital, they might be able to avoid a readmission. But if their longer stay at the hospital was beneficial in some way that is not captured by the number of procedures, then reducing length of stay might increase the probability of a readmission.

To investigate this question, I estimate equation (2) using a binary indicator for readmission as dependent variable. Unfortunately, the structure of the dataset in the earlier years does not allow to follow patients across years and across hospitals. I therefore focus on readmissions to the same hospital, within 30 and 60 days of the discharge date.[18] To capture admissions within the same calendar year, I exclude admissions in December of each year when assessing the likelihood of readmission within 30 days. Similarly, I exclude admissions between October and December when assessing the likelihood of readmission within 60 days.

Hospital-acquired infections are a potential consequence of longer hospital stays. In an attempt to capture reductions in hospital-acquired infections upon the entry of NH and HC teams in a region, I use a binary indicator for having a diagnosis code for serious infection as outcome variable in equation (2).[19] I alternatively focus on serious infection as main diagnosis and as secondary diagnosis. The former are more likely to refer to an infection that was present at admission and was the reason for the hospitalization, whereas the latter are more likely to represent a complication that occurred during the hospitalization.[20]

Finally, I assess changes in mortality. For in-hospital mortality I use a binary indicator for whether the patient died during his hospital stay as outcome variable in equation (2). I do not observe out-of-hospital mortality at the individual level, so I use regional mortality data to assess potential effects on out-of-hospital mortality upon the entry of NH and HC teams.

4.4 Programmed admissions

Reductions in the length of stay of bed-blockers might raise concerns about decreased hospital occupancy, given the costs of empty hospital beds (Pauly and Wilson, 1986; Gaynor and Anderson, 1995; Keeler and Ying, 1996). However, waiting lists (and times) for elective care are a major challenge for public hospitals in Portugal (Simões et al., 2017). Provided some flexibility in the allocation of resources (ie. beds, physicians' time) within the hospital, the

[18] In the last years of my study-period, over 92% of readmissions occur in the same hospital as the initial admission. Thus, restricting the analysis to readmissions to the same hospital is a good approximation.

[19] I used the list of diagnosis codes for serious infection in Wiese et al. (2018).

[20] The medical literature has highlighted the limitations of administrative data for distinguishing between hospital-acquired infections and infections that were present at admission, see Jhung and Banerjee (2009).

resources freed up by bed-blockers can be devoted to elective care.

To examine whether a reallocation of hospital activity occurs, I make use of the full inpatient dataset, which includes both emergency and programmed admissions at public hospitals in Portugal. First, I estimate the following equation:

$$Programmed_{it} = \phi_1 PostHC_{mt} + \phi_2 PostNH_{mt} + \lambda_m + \lambda_t + \lambda_h + \varepsilon_{it}, \tag{4}$$

where $Programmed_{it}$ is a binary indicator taking value 1 if the episode of patient i was scheduled and value 0 if it was an emergency. As before, λ_m, λ_t, and λ_h are region, admission month-by-year, and hospital fixed-effects. The estimates of ϕ_1 and ϕ_2 are informative about changes in the share of programmed admissions in hospital h originating from region m, following the entry of HC teams and NH providers in that region, respectively.

The share of programmed admissions can increase due to increases in the number of programmed admissions and to reductions in the number of emergency admissions. The number of programmed admissions can go up if hospitals are able to reallocate their resources to elective care. The number of emergency admissions could go down if, for example, the availability of NH and HC teams has some kind of protective effect in terms of avoiding a hospitalization.

To ensure that the increase in the share of programmed admissions is being driven by increases in the number of programmed admissions and not by a reduction in emergency admissions, I collapse my data at the region-hospital-month level and estimate:

$$NumberAdm_{hmt} = \varphi_1 PostHC_{mt} + \varphi_2 PostNH_{mt} + \lambda_m + \lambda_t + \lambda_h + \varepsilon_{hmt}, \tag{5}$$

where $NumberAdm_{hmt}$ is alternatively the monthly number of programmed and emergency admissions from region m in hospital h. I am interested in the estimates of φ_1 and φ_2, which inform about changes in the number of admissions in hospital h originating from region m after the entry of HC teams and NH providers in that region, respectively.[21]

5 Results

Section 5.1 presents the baseline results. Section 5.2 investigates the plausibility of the parallel trend assumption and reports the results of additional robustness checks. Section 5.3 presents the results of the heterogeneity analysis. Section 5.4 examines the impact of the entry of NH

[21] During my study-period, patients awaiting programmed procedures were typically restricted to a specific hospital within their region of residence (they could not shop around for other hospitals that they might perceive as being of higher quality or that have shorter waiting times).

and HC teams on treatment received while at the hospital, hospital readmissions, and other health outcomes. Section 5.5 assesses the impact on hospital costs and Section 5.6 assesses the impact on programmed admissions.

5.1 Baseline Results

The first column of Table 3 shows the estimates of interest from equation (2) and their corresponding 95% confidence intervals. The top estimates correspond to α_1, the vector of indicators for each of the three bed-blocking groups. They convey sizable length of stay differences between each group of bed-blockers and regular patients prior to the entry of HC teams and NH in a region —about 9 additional days for patients living alone, 23 for those with no family to care, and 18 for those with inadequate housing conditions.

The second block of estimates corresponds to α_2 and α_4, the two indicators for periods after the entry of HC teams and NH in a region. These effects are precisely estimated at zero, meaning that the entry of NH and HC teams in a region does not affect the length of stay of regular patients.

The next block of estimates corresponds to α_3, the vector of interaction terms between each group of bed-blockers and the indicator for periods after the entry of HC teams in a region. These estimates convey length of stay reductions of 4 days for individuals living alone and for those with inadequate housing after the entry of HC teams in their region. Note, however, that these 4-day length of stay reductions do not fully eliminate the difference in length of stay between regular patients and bed-blockers —some bed-blocking still persists. For individuals with no family to care, the estimates are imprecise and I cannot rule out sizable increases in the length of stay of these patients after the entry of HC teams in a region.

Finally, the last block of estimates refers to α_5, the vector of interaction terms between each bed-blocking group and the indicator for periods after the entry of NH in a region. These estimates are statistically insignificant, with the point estimates being close to zero.

5.2 Robustness checks

5.2.1 Plausibility of the parallel trend assumption

I report the event-study results from equation (3) in Figures 5 and 6, respectively, for the entry of the first HC team and the first NH facility in a region. Each of the figures has three panels, corresponding to comparisons of the length of stay of each of the three bed-blocking groups and regular patients around the relevant event. Each panel plots the estimates of θ_r for regular patients (full circles) and θ_r^j for each group of bed-blockers j (hollow circles) and the corresponding 95% confidence intervals. The scale on the vertical axis differs across plots.

Table 3: Baseline results from equation (2) and robustness checks

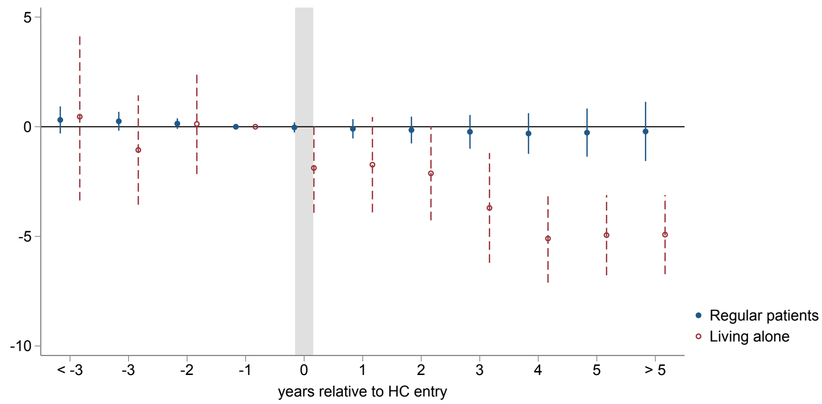
	(1) Baseline	(2) Region-month FE	(3) Region-specific time trends	(4) Hospital FE	(5) 15km radius	(6) 30km radius
Bed-blocking indicators (α_1)						
Living alone	9.226***	9.230***	9.245***	9.227***	8.884***	9.802***
	(1.357)	(1.372)	(1.377)	(1.345)	(1.370)	(1.685)
No family to care	23.282***	23.344***	23.317***	23.284***	21.877***	23.447***
	(4.184)	(4.178)	(4.182)	(4.179)	(3.755)	(4.511)
Housing/econ. issues	17.984***	17.972***	17.952***	17.969***	17.442***	19.178***
	(2.611)	(2.595)	(2.610)	(2.601)	(2.304)	(2.454)
Effects of HC and NH entry						
Post HC (α_2)	0.003		-0.006	-0.001	-0.016	0.028
	(0.105)		(0.094)	(0.106)	(0.070)	(0.076)
Post NH (α_4)	0.095		0.046	0.086	0.023	0.010
	(0.193)		(0.092)	(0.194)	(0.077)	(0.076)
Differential effects of HC entry (α_3)						
Post HC × Living alone	-4.361***	-4.040***	-4.209***	-4.362***	-3.377***	-2.991***
	(1.559)	(1.481)	(1.527)	(1.563)	(1.061)	(1.140)
Post HC × No family to care	-0.384	-0.364	-0.394	-0.403	-1.124	-0.482
	(5.318)	(5.273)	(5.285)	(5.312)	(3.421)	(3.231)
Post HC × Housing/econ. issues	-4.673**	-4.668**	-4.692**	-4.640**	-5.430***	-4.992***
	(2.143)	(2.110)	(2.133)	(2.148)	(1.681)	(1.789)
Differential effects of NH entry (α_5)						
Post NH × Living alone	0.539	0.238	0.354	0.564	-0.001	-1.229
	(1.097)	(1.075)	(1.084)	(1.104)	(1.138)	(1.259)
Post NH × No family to care	0.040	-0.110	-0.060	0.047	2.985	-0.127
	(3.777)	(3.741)	(3.761)	(3.777)	(1.869)	(2.126)
Post NH × Housing/econ. issues	-1.154	-1.128	-1.087	-1.179	0.379	-2.098
	(2.435)	(2.417)	(2.405)	(2.416)	(1.354)	(1.505)
Observations	7,868,350	7,868,350	7,868,350	7,868,350	7,950,636	7,950,636
R^2	0.210	0.212	0.210	0.210	0.210	0.210

NOTES: The table shows the estimates of α_1 to α_5 from robustness checks to equation (2). The dependent variable is the length of stay in days. The baseline model in column 1 includes individual demographics and comorbidities and admission month-by-year, diagnosis-related group, and region (ACES) fixed-effects. Column 2 replaces the region and month fixed effects with region-month fixed-effects. Column 3 includes region-specific time trends. Column 4 includes hospital fixed-effects. Columns 5 and 6 use the 15 and 30km radius around the centroid of the patient's municipality as the relevant region, respectively. The sample excludes admissions in the entry month of the first NH and HC in a region. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

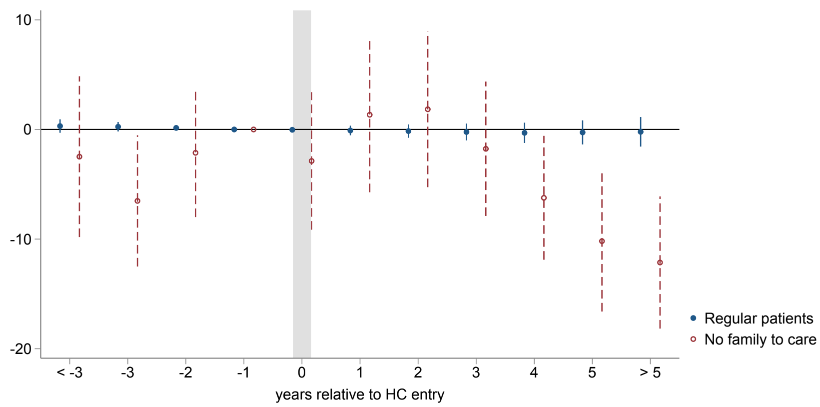
The event-study specification is informative about pre-treatment trends in length of stay for each of the patient groups analyzed. The estimates of θ_r convey that the length of stay of regular patients is constant in relative time. In most of the event-study plots the estimates of θ_r^j for years prior to the entry of the first NH and HC team in a region are not statistically significant, supporting the plausibility of the parallel trend assumption.[22] The exception is panel (b) in Figure 5, which shows a small increasing trend in the length of stay of individuals with no family to care relative to regular patients in the three prior to the entry of the first HC team in a region (significant at 10%). Due to this pre-treatment trend, the corresponding estimate from the baseline analysis is biased towards finding no reductions in the length of stay of individuals with no family to care following the entry of the first HC team in a region. The event-study plot, however, shows that the slight increasing trend in the length of stay of individuals with no family to care relative to regular patients is inverted upon the entry of HC teams in a region.

Overall, the baseline model and the event-study convey similar results. The entry of HC teams leads to reductions in the length of stay of bed-blockers. The event-study plots show that these only occur some periods after the entry of the first HC team and get slightly larger over time. As for the entry of nursing homes, the baseline analysis did not yield significant effects on the length of stay of bed-blockers. However, the event-study plots suggest a slow, gradual decline in the length of stay of bed-blockers following the entry of NH in a region, even if these effects are statistically insignificant.

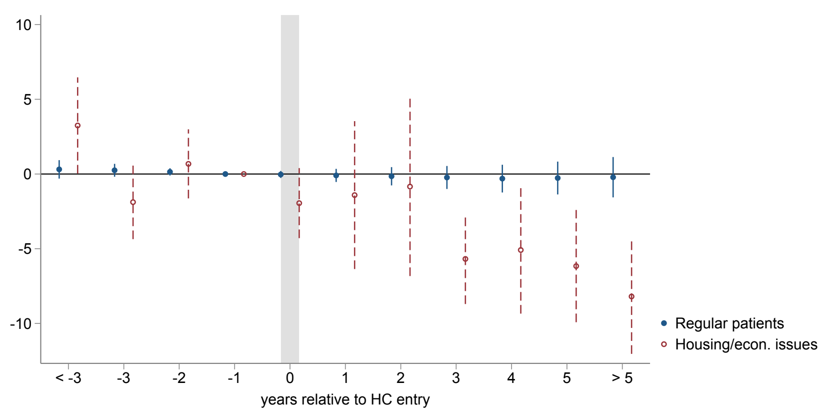
[22] I assess the joint significance of the pre-treatment estimates with an F-test. I do this for the three years prior to each event. For individuals living alone, I cannot reject the hypothesis that these estimates are jointly insignificant (the p-values are 0.5151 and 0.2564, respectively, for the periods prior to the entry of the first HC team and the first NH in a region). For individuals with no family to care, the estimates for the three periods prior to the entry of the first HC team are jointly significant at 10% (p-value=0.0622), but those for periods prior to the entry of the first NH are not (p-value=0.5880). Finally, for individuals with inadequate housing, I cannot reject the hypothesis that the estimates for the three periods prior to the entry of the first HC team and the first NH are jointly insignificant (p-values equal to 0.1621 and 0.8544, respectively).



(a) Living alone



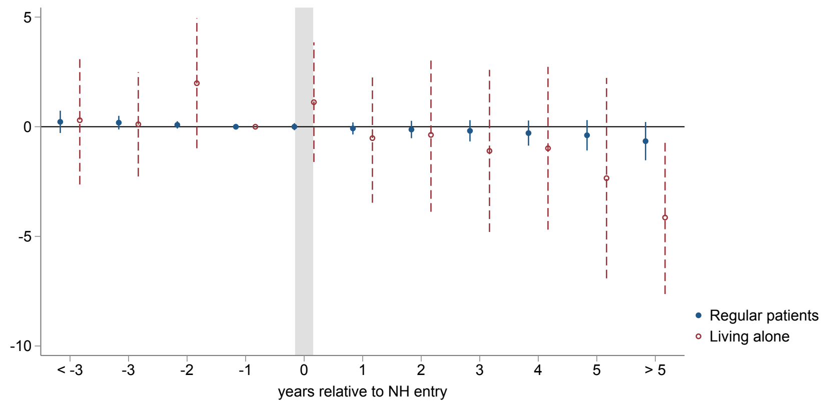
(b) No family to care



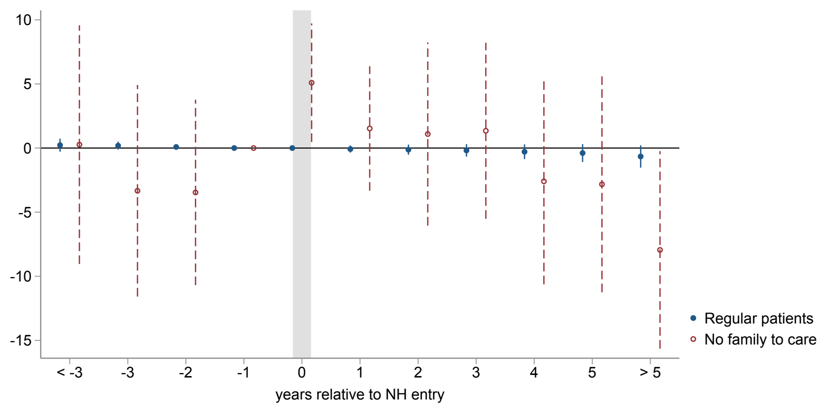
(c) Housing/economic issues

Figure 5: Event-study results for HC entry

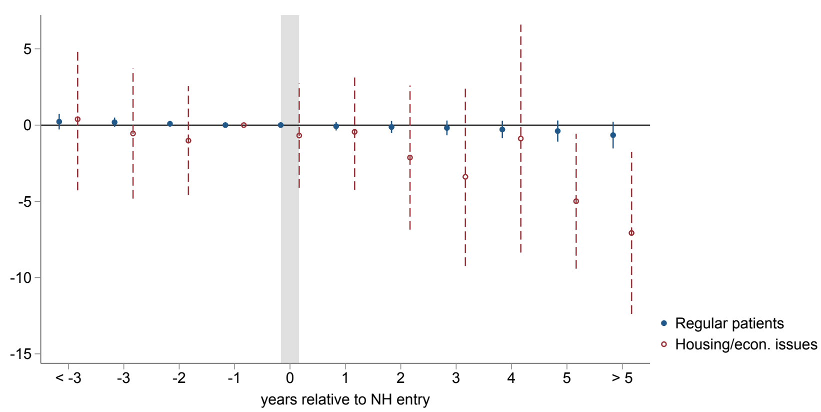
NOTES: Each panel plots the estimates of θ_r and θ_r^j from equation (3) and the corresponding 95% confidence intervals for a specific group of patients in the sample. In each panel, the vertical axis is the length of stay in days and the horizontal axis is time in years relative to the entry of the first home care team in a region. The coefficients on the year just before entry was normalized to zero. The model includes individual demographics and comorbidities, indicators for bed-blocking groups, and admission month-by-year, diagnosis-related group, region (ACES), and relative year fixed-effects, as well as a binary indicator for the presence of a nursing home at the time of admission.



(a) Living alone



(b) No family to care



(c) Housing/economic issues

Figure 6: Event-study results for NH entry

NOTES: Each panel plots the estimates of θ_r and θ_r^j from equation (3) and the corresponding 95% confidence intervals for a specific group of patients in the sample. In each panel, the vertical axis is length of stay in days and the horizontal axis is time in years relative to the entry of the first nursing home in the region. The coefficients on the year just before entry was normalized to zero. The model includes individual demographics and comorbidities, indicators for bed-blocking groups, and admission month-by-year, diagnosis-related group, region (ACES), and relative year fixed-effects, and a binary indicator for the presence of a home care team at the time of admission.

5.2.2 Alternative model specifications, variable definitions, and explanations

The remaining rows of Table 3 show robustness checks to my baseline specification. Column 2 replaces the region and month fixed-effects with region-by-month fixed-effects and column 3 allows for region-specific time trends. Column 4 adds hospital fixed-effects to the baseline specification. The results are unchanged.

ACES regions differ in their territorial area. I alternatively use 15 and 30km radii around the centroid of a patient's municipality of residence as the relevant region.[23] Columns 5 and 6 in Table 3 show that my baseline results are robust to these alternative region definitions.

The results are unchanged when using different sample definitions. Table A.2 in the Appendix shows the results for restricting the sample to a balanced panel of hospitals, excluding patients who were transferred between hospitals and those who have died at the hospital, and including both emergency and programmed admissions in the sample.

As alternative outcome variables in equation (2), I use binary indicators for being above certain percentiles of the pooled distribution of length of stay, and a binary indicator for being above the corresponding DRG trim-point. Columns 2 to 5 of Table A.3 in the Appendix show the results. After the entry of HC teams in their region, individuals living alone and those with inadequate housing are 5 percentage points (pp.) less likely to be above the 50th percentile of the length of stay distribution and 6-7pp. less likely to be above the 90th percentile. They are also 4pp. less likely to have a length of stay beyond their DRG trim-point.

Different regions experienced different intensities of entry of NH facilities and HC teams at distinct speeds. To exploit these additional sources of variation, I define two alternative continuous measures of treatment intensity: the monthly number of HC teams and NH facilities operating in region m and the monthly number of places in HC teams and beds in NH facilities in region m. While the baseline analysis quantifies the effect of having *at least one* HC team or NH in a region on the length of stay of bed-blockers, this analysis quantifies the impact of *one additional* provider or bed in a region on the length of stay of bed-blockers. Table A.4 in the Appendix shows the results. Both the number and capacity of HC and NH providers in a region matter. For example, an additional place in HC (per 10,000) reduces the length of stay of individuals living alone by 0.38 days and an additional NH provider (per 10,000) reduces the length of stay of individuals with no family to care by almost 17 days. These results suggest that the increased number and capacity of NH and HC teams over time might be one explanation for the finding, conveyed by the event-study plots, that reductions in the length of stay of bed-blockers take some periods to materialize and get larger over time.

Table C.1 in the Appendix shows the results from estimating models among each group of bed-blockers, only exploiting variation in treatment timing and thus relaxing the assumption

[23]Municipalities are small territorial units. There are 278 municipalities in mainland Portugal.

that the groups of bed-blockers and regular patients are comparable. Overall, the results suggest evidence of reductions in the length of stay of bed-blockers upon the entry of HC teams, though these reductions seem to be of a smaller magnitude than in the baseline specification and their statistical significance is weaker.

A recent literature in econometrics highlights challenges in difference-in-differences designs that exploit staggered treatments. Goodman-Bacon (2021) shows that the estimate recovered in those cases is a weighted average of all underlying two-by-two difference-in-differences estimates. In particular, early-treated units are also used as control group for units that are treated at a later point in time. This is particularly problematic in the presence of treatment effect heterogeneity.

I deal with concerns about staggered treatment timing in two ways. First, I estimate my baseline model separately for regions treated in different years, therefore limiting the variation in treatment timing. Table C.2 in the Appendix shows the results. While statistical significance is lost in a few cases, the direction and magnitude of the results obtained are in line with my baseline results. Second, I implement the imputation estimator recently proposed in Borusyak et al. (2021). Appendix C.3 provides technical details on the implementation of this estimator, as well as the results obtained. Overall, the results from using the imputation estimator are quite similar to those using OLS. Taken together, the results from these exercises suggest issues related to staggered treatment timing to be limited in my setting.

Finally, I assess the plausibility of alternative explanations for the reductions in the length of stay of bed-blockers. First, the roll-out of NH and HC teams might have been accompanied by reductions in the number of hospital beds, which could explain some of the reductions in length of stay observed for the groups at risk of bed-blocking. Table A.13 in the Appendix shows that the number of inpatients beds at public hospitals did not significantly change with the entry of NH and HC teams. Second, the entry of NH and HC teams might have reduced patient complexity, particularly for those at risk of bed-blocking —if, for example, these patients were already benefiting from NH and HC teams prior to their hospital admission. Table A.14 in the Appendix refutes this hypothesis: Patients at risk of bed-blocking seem to be slightly more complex and have a higher Charlson comorbidity score upon the entry of home care teams in a region.[24] Third, there might have been other policies that influenced the length of stay of bed-blockers, such as the strengthening of local social support networks,

[24]One potential explanation for this finding is that a number of milder cases can now be dealt with at home and thus some patients are able to avoid a hospital admission. The fact that I do not observe changes in the share of hospital admissions of bed-blockers upon the entry of NH and HC teams (Appendix B in the paper) is at odds with this explanation. An alternative explanation is that patients have been referred to home-care by their general practitioner and that receiving home-care delays (but does not avoid) a hospital admission, so that patients are in worse health once they are eventually admitted to the hospital. This might also be one reason why the availability of NH and HC teams does not fully eliminate bed-blocking.

or the entry of other providers not affiliated with the RNCCI. I cannot fully rule out these alternative channels. However, the staggered entry of NH and HC teams helps mitigating this concern as any alternative policy would have to be rolled out in a similar fashion in order to explain my findings.

5.3 Heterogeneity analysis

The baseline results convey no reductions in the length of stay of bed-blockers upon the entry of NH facilities in a region. This result might simply reflect the fact that NH cater to patients with high care needs and the average bed-blocker might not need a NH stay. The most common admission diagnoses among bed-blockers are respiratory illnesses, such as pneumonia and acute bronchitis, whose recovery usually involves resting and avoiding heavy tasks. In contrast, the most common reasons for a NH admission are recovery from surgery and stroke.

To assess this hypothesis, I estimate the baseline model among different patient groups. Specifically, I restrict the sample to individuals admitted to the hospital with a stroke diagnosis, with respiratory conditions, individuals who underwent surgery during their hospital stay, and those whose Charlson comorbidity score is above 1. Table A.5 in the Appendix shows the results. When restricting the sample to patients admitted with a stroke (column 1), I find that individuals living alone and those with inadequate housing experience length of stay reductions of about 3 and 10 days, respectively, after the entry of NH in their region. This supports the hypothesis that NH cater to patients with high care needs. I find a similar pattern when restricting the sample to patients undergoing surgery at the hospital (column 3), but these effects are not statistically significant. The results for patients admitted with respiratory illnesses and for those with Charlson score over 1 are similar to the baseline results.

Table A.6 in the Appendix shows the results of heterogeneity analyses with respect to gender and age. There is little heterogeneity across different demographic groups. Remarkably, bed-blockers under 50 years old also see significant reductions in their length of stay upon the entry of HC teams, highlighting that bed-blocking can affect individuals of any age.

5.4 Impact on intensity of care, readmissions, and other health outcomes

Column 1 of Table 4 shows the results of estimating equation (2) using the number of procedures received while at the hospital as dependent variable. It conveys that, despite reducing the length of stay of bed-blockers, the entry of NH and HC teams does not affect the intensity of care they received at the hospital.

Additionally, the estimates of the bed-blocking indicators convey that, even after controlling for demographics, comorbidities, and detailed medical diagnoses, bed-blockers seem to get more intensive treatment during their hospital stay than regular patients (and that does not change upon the entry of NH and HC teams). A more intensive treatment might require a longer stay. This can be one reason why the gap in length of stay between bed-blockers and regular patients is not fully eliminated upon the entry of NH and HC teams in a region.

The remaining columns of Table 4 show the results of estimating equation (2) using a binary indicator for readmission as dependent variable. Columns 2 and 4 show the results for the probability of readmission within 30 and 60 days, respectively. Columns 3 and 5 focus on readmissions in the same DRG group, which are more likely to signal a recurrent (chronic) condition, or a consequence of the previous admission. In most cases I cannot reject the null hypothesis that the entry of NH and HC teams had no effect on the likelihood of readmission. In some cases, the entry of NH and HC teams is even associated with a reduction in the probability of readmission, potentially reflecting the fact that these types of care can prevent a readmission. These effects are sizable. For example, the entry of NH reduce the likelihood of readmission within 60 days for individuals with inadequate housing by 2pp., a 16% reduction.

Columns 1 and 2 of Table A.7 show the results for the presence of a serious infection as main diagnosis and secondary diagnosis, respectively. The estimates capturing the differential impact of NH and HC teams on bed-blockers are imprecise. Nevertheless, the point estimates in column 2 suggest a reduction in serious infections as secondary diagnosis among bed-blockers, upon the entry of NH and HC teams. This does not occur for serious infections as main diagnosis (column 1), which are more likely to be the reason for hospitalization instead of acquired during the hospital stay.

Column 3 of Table A.7 shows no clear changes in in-hospital mortality upon the entry of NH and HC teams in a region. Using regional mortality data to assess the impact of NH and HC teams on out-of-hospital mortality yields no statistically or economically significant effects (Appendix Table A.12).

Overall, reducing bed-blocking does not harm patients' health. If anything, the findings in this subsection suggest that there might be some benefits to patient's health.

5.5 Cost savings

Computing the cost savings associated with the reductions in bed-blocking helps putting the baseline estimates into perspective. I do this for the year of 2015 and I focus on cost-savings associated with the entry of HC teams only because in the baseline analysis there were no significant effects from NH entry.

To assess the cost burden bed-blocking places on the healthcare system, I use the official

Table 4: Impact of the entry of NH and HC teams on treatment intensity and readmissions

	(1) Number of procedures	(2) Readmitted within 30 days	(3) Readmitted within 30 days, same DRG	(4) Readmitted within 60 days	(5) Readmitted within 60 days, same DRG
Bed-blocking indicators (α_1)					
Living alone	0.916***	-0.003	-0.003*	-0.002	-0.003
	(0.123)	(0.003)	(0.002)	(0.004)	(0.002)
No family to care	1.056***	0.015	0.005	0.021*	0.009
	(0.223)	(0.010)	(0.006)	(0.013)	(0.009)
Housing/econ. issues	0.557***	0.024***	0.007**	0.035***	0.010**
	(0.145)	(0.004)	(0.003)	(0.006)	(0.004)
Effects of HC and NH entry					
Post HC (α_2)	0.058	0.002	-0.000	0.002	-0.000
	(0.168)	(0.001)	(0.000)	(0.002)	(0.001)
Post NH (α_4)	-0.386**	-0.000	0.000	-0.001	-0.000
	(0.185)	(0.002)	(0.001)	(0.002)	(0.001)
Differential effects of HC entry (α_3)					
Post HC × Living alone	0.207	-0.011**	0.001	-0.005	0.002
	(0.253)	(0.005)	(0.003)	(0.005)	(0.003)
Post HC × No family to care	0.052	-0.031**	-0.016**	-0.043**	-0.022**
	(0.365)	(0.013)	(0.008)	(0.018)	(0.010)
Post HC × Housing/econ. issues	-0.177	0.005	0.003	0.005	0.004
	(0.214)	(0.006)	(0.003)	(0.009)	(0.004)
Differential effects of NH entry (α_5)					
Post NH × Living alone	-0.060	0.008	0.002	0.002	0.001
	(0.163)	(0.006)	(0.002)	(0.009)	(0.004)
Post NH × No family to care	0.178	0.012	0.009	0.020	0.011
	(0.201)	(0.014)	(0.007)	(0.018)	(0.008)
Post NH × Housing/econ. issues	0.317	-0.012*	-0.007**	-0.020**	-0.010**
	(0.254)	(0.006)	(0.003)	(0.008)	(0.004)
Mean of the dep. variable	5.956	0.088	0.020	0.125	0.028
Observations	7,856,898	7,216,328	7,216,328	5,919,920	5,919,920
R^2	0.356	0.079	0.052	0.102	0.060

NOTES: The table shows the OLS estimates of α_1 to α_5 from equation (2). In column 1 the dependent variable is the number of procedures received by patient i during his hospital stay. In columns 2 and 4, the dependent variable is an indicator for readmission to the same hospital within 30 and 60 days, respectively. In columns 3 and 5, the dependent variable is an indicator for readmission to the same hospital and the same DRG within 30 and 60 days, respectively. The sample excludes admissions in the entry month of the first NH and HC in a region. Additionally, the sample in columns 2 and 3 excludes admissions in December and the sample in columns 4 and 5 excludes admissions in the period October-December. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

valuation of the cost of one day in inpatient care, which is €230.[25] This figure might be an overestimate because a bed-blocking day likely involves lower costs than an average day for a patient who is still receiving acute medical care. Therefore, I also use a more conservative estimate of €87 for the value of a day in the hospital for patients who no longer need inpatient care. This is the amount by which the government compensates hospitals for the additional costs imposed by patients with length of stay beyond their DRG trim-point, thus it can be seen as capturing the "hotel costs" associated with an inpatient day (i.e. food, bedding, etc.).

Table A.11 in the Appendix provides an overview of the calculations for estimating the cost burden associated with bed-blocking and its reduction upon the entry of HC teams in a region. In 2015 there were 7,135 patients at increased risk of bed-blocking: 4,021 living alone; 1,192 with no family to care; and 1,992 with inadequate housing conditions. Absent the entry of NH and HC teams, my baseline estimates of α_1 from equation (2) imply a total of 99,415 bed-blocking days in 2015 and an associated cost burden of €230×99,415 = €M22.9 in 2015.

My baseline estimates of α_3 imply that the entry of HC teams in a region reduces the number of bed-blocking days in 2015 to 72,440 days. Consequently, the cost burden associated with bed-blocking goes down by €$203\times(99,415 - 72,440) =$ €M6, or 27%.

Using a conservative valuation of the costs of a bed-blocking day, I estimate the burden of bed-blocking in 2015 at €M8.7 in the absence of the entry of NH and HC teams. After the entry of HC teams, this amount is reduced to €M6.3.

From the perspective of the healthcare system, the cost of care provided in HC teams must be taken into account. I value one day of home care provision using the amount that the government pays to RNCCI providers for ambulatory services, which is €9.6 per session.[26] If reductions in bed-blocking days are replaced one-to-one with home care use, then my baseline estimates imply that the cost of home care provision is $(99,415 - 72,440) \times 9.6 =$ €M0.26 in 2015. This barely affects my savings estimate.[27]

Overall, the cost savings from reducing bed-blocking are small, consistent with bed-blocking being a relatively rare event in the period I analyze. While about €849(=€M6 $\div$ 7,135) can be saved annually per patient at risk of bed-blocking, these patients represent a small share of total inpatient admissions. This suggests that resources in the Portuguese healthcare system were allocated rather efficiently during my study-period.

My cost savings estimates are conservative in that they do not account for potential health

[25]The official figure from ACSS (2007) is €219 and corresponds to 2007, the last year for which cost estimates are available. I update this figure to 2015 euros using the consumer price index for the healthcare sector.

[26]A "session of home care" consists of a visit by the HC team on a given day. These visits take only a couple of hours and HC teams visit several patients in one day.

[27]More generally, the average duration of home care use was 64.2 days in 2015 (Lopes et al., 2019). Assuming one session of home care per day, I estimate the costs of home care provision in 2015 at €M4.4.

benefits of reducing length of stay for bed-blockers (i.e. prevented mobility losses, avoided re-admissions, improved mental health).

5.6 Impact on programmed admissions

Columns 1 and 2 of Table 5 show the estimates from equation (4) assuming the distribution of the error term is normal and logistic, respectively. The results convey an increase of 1.7 percentage points in the share of programmed admissions originating from region m, following the entry of HC teams in the region.[28]

Columns 3 and 4 of Table 5 show the results of estimating equation (5) using as dependent variable the monthly number of programmed admissions and the monthly number of emergency admissions, respectively. Column 3 conveys an increase of 10 programmed admissions per month in hospital h originating from region m upon the entry of the first HC team in that region. Consistent with NH entry not reducing the length of stay of the average bed-blocker, it also is not associated with increases in programmed admissions. Column 4 conveys no change in the number of emergency admissions following the entry of NH and HC teams. So increases in the share of programmed admissions originate solely from increases in the number of programmed admissions and not from reductions in the number of emergency admissions.

Overall, these findings suggest that hospitals devote the resources freed up by bed-blockers to elective care. The results are driven by the hospitals with the highest occupancy rates as of 2005, for whom reductions in bed-blocking might have been crucial in freeing up capacity to admit additional elective patients. No increases in elective admissions occur for hospitals with below median occupancy rates in 2005 (Tables A.8 and A.9 in the Appendix).

6 Mechanisms: Accumulation of experience

My main results convey reductions in bed-blocking following the entry of NH and HC teams. The event-study plots show that these effects get larger over time, although bed-blocking is never fully eliminated.

In this section, I study whether a larger number of interactions between a hospital and a coordination team located in an ACES region allows for greater reductions in bed-blocking. This should not be interpreted as causal, and rather be seen as a descriptive exercise.

The underlying idea is that interactions between a given hospital-region pair hm allow the accumulation of experience from dealing with patients at risk of bed-blocking that are residents of m and are admitted to h. This pair-specific experience is acquired from interactions between

[28] During my study-period, 55% of hospital admissions are programmed and the remaining are emergencies.

Table 5: Results from estimating equations (4) and (5)

	(1) Programmed admission (OLS)	(2) Programmed admission (Logit)	(3) Monthly programmed admissions	(4) Monthly emergency admissions
Post HC	0.017**	0.018**	10.572**	-0.832
	(0.008)	(0.009)	(3.876)	(0.898)
Post NH	0.004	0.006	-1.374	-0.826
	(0.013)	(0.012)	(5.787)	(1.179)
Observations	17,633,499	17,633,499	154,054	154,054
(Pseudo-)R^2	0.081	0.091	0.043	0.021

NOTES: Columns 1 shows the estimates of ϕ_1 and ϕ_2 from equation (4) using OLS and column 2 shows the corresponding marginal effects after logit evaluated at the mean of the independent variables. The estimation sample consists in all individual inpatient admissions to public hospitals (programmed and emergency) between 2000 and 2015. Columns 3 and 4 show the estimates of φ_1 and φ_2 from equation (5). In column 3 the dependent variable is the monthly number of programmed admissions from region m in hospital h. In column 4 the dependent variable is the monthly number of emergency admissions from region m in hospital h. The sample in columns 3 and 4 is a panel of region-hospital-month admissions. All models include hospital, region, and month fixed-effects. In all columns 1 to 4, the estimation sample excludes the entry month of the first NH and HC. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the discharge planning team at the hospital and the local coordination team in the ACES region, which can foster teamwork and coordination across settings of care provision.

I distinguish pair-specific experience from experience accumulated independently by hospitals and regions. Recall that, in an emergency situation, patients are not restricted to the hospital in their area of residence and can visit any hospital. As a result, hospitals admit emergency patients originating from various regions. Therefore, hospital h also accumulates experience from admitting and referring patients at risk of bed-blocking originating from regions other than m. This experience might benefit bed-blockers from region m if, for example, it contributes to a more timely identification of potential bed-blockers, regardless of their region of residence, by the discharge planning team.

Additionally, region m also accumulates experience from dealing with patients at risk of bed-blocking who are referred from hospitals other than h. This experience might benefit patients at risk of bed-blocking who visited hospital h if, for example, it makes the local coordination team in the ACES region more efficient at finding vacancies in NH and HC teams within its area of influence, regardless of the hospital they visited.

To understand the role of the different types of experience in reducing the length of stay of bed-blockers, I draw on Kellogg (2011) and estimate the following equation:

$$y_{it} = \mu_1 BB_i + \mu_2 g(Exp_{hm\tau}) + \mu_3 g(Exp_{hm\tau}) BB_i + \delta X_i + \gamma_d + \gamma_t + \gamma_{mh} + \varepsilon_{it}, \qquad (6)$$

where γ_{mh} are fixed-effects for a hospital-region pair and $g(Exp_{hm\tau})$ is a function of the experience accumulated by hospital h and region m during period τ. All remaining notation is as previously defined. I specify g as follows:

$$g(Exp_{hm\tau}) = \eta_1 Exp_{h\text{-}m\tau} + \eta_2 Exp_{\text{-}hm\tau} + \eta_3 Exp_{hm\tau}, \qquad (7)$$

where $Exp_{hm\tau}$ is the experience accumulated by pair hm during period τ, $Exp_{h\text{-}m\tau}$ is the experience accumulated by hospital h during period τ from interacting with hospitals other than m, and $Exp_{\text{-}hm\tau}$ is the experience accumulated by region m during period τ from interacting with hospitals other than h. The specification in equation (6) allows the effects of each of the three types of experience on the length of hospital stay to differ for regular patients and for each type of patient at risk of bed-blocking.

For this analysis, I restrict the sample to patients admitted to the hospital in periods after the entry of the first NH or HC team (whichever enters first) in their region of residence. A relationship between a hospital-region pair hm starts at the moment when there is a patient at risk of bed-blocking originating from region m in hospital h.

I measure the experience accumulated by a hospital-region pair using the cumulative number of bed-blockers originating from region m that are admitted to hospital h during a certain period τ. This is a proxy for the *actual* number of interactions between h and m, which I do no observe. I measure the experience accumulated by a hospital (region) from dealing with bed-blockers coming from other regions (hospitals) during period τ in a similar fashion. I alternatively define τ as the period since the entry of the first NH or HC provider in region m until month t, the year preceding month t, and the 2-year period preceding month t.

Table 6 shows the estimates from equation (6) corresponding to the impact of pair-specific experience on the length of stay of bed-blockers and regular patients. First, pair-specific experience does not affect the length of stay of regular patients. Second, there is a negative association between pair-specific experience and the length of stay of bed-blockers. According to these estimates, the pair-specific experience accumulated by the average hm pair is associated with a 1.2 days reduction in the length of stay of individuals with no family to care relative to regular patients. For individuals living alone and with inadequate housing, this reduction amounts to about 0.3 days.

A significant number of interactions between a hospital and a region is needed in order to generate meaningful reductions in the length of stay of bed-blockers. For example, the

Table 6: Results from estimating equation (6)

	(1) Total experience	(2) Last year	(3) Last 2 years
Pair-specific experience			
$Exp_{hm\tau}$	0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
$Exp_{hm\tau}$×Living alone	-0.001***	-0.003***	-0.002***
	(0.000)	(0.001)	(0.000)
$Exp_{hm\tau}$×No family to care	-0.004***	-0.004	-0.004**
	(0.001)	(0.004)	(0.002)
$Exp_{hm\tau}$×Housing/econ. issues	-0.001***	-0.001	-0.001
	(0.000)	(0.002)	(0.001)
Mean $Exp_{hm\tau}$	313.64	85.53	154.63
P90 $Exp_{hm\tau}$	730	197	354
P95 $Exp_{hm\tau}$	1,063	265	477
Observations	3,859,751	3,655,882	3,640,309
R^2	0.230	0.229	0.229

NOTES: The table shows the estimates from equation (6) corresponding to the accumulation of pair-specific experience. Column 1 considers experience accumulated since the entry of the first NH or HC provider in a region. Columns 2 and 3 consider experience accumulated during the 1 and 2 years preceding each episode, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

pair-specific experience accumulated by the 10% pairs with the largest number of interactions is associated with reductions of 2.8 days in the length of stay of individuals with no family to care, and of 0.7 days in the length of stay of individuals living alone and those with inadequate housing. Comparing across columns, recent experience seems as relevant as total experience.

The full set of estimates from equation (6) is available in Table A.10 in the Appendix. Overall, the results confirm the importance of pair-specific experience for reducing bed-blocking. Experience accumulated by hospital h from dealing with bed-blockers who live in regions other than m and experience accumulated by m from dealing with bed-blockers who visited hospitals other than h show no clear association with reductions in bed-blocking. In some cases, they even seem counterproductive and are associated with increases in the length of stay of bed-blockers relative to regular patients.

7 Conclusion

I study whether and to what extent the availability of nursing homes and teams providing home care reduces bed-blocking in Portuguese public hospitals. My baseline results show that HC teams are relatively successful at reducing bed-blocking. For example, individuals living alone and those with inadequate housing experience, on average, a reduction of 4 days in hospital length of stay after the entry of HC teams in their region of residence. This can have sizable impacts on patients health, as each day of bed confinement is associated with a 1-3% loss of muscle strength (Rousseau, 1993). NH facilities only reduce the length of stay of bed-blockers with high care needs, such as a those admitted with a stroke.

The reductions in the length of stay of bed-blockers do not come at a cost for patients' health. Moreover, the reductions in the length of stay of bed-blockers allow for increases in programmed admissions, suggesting that increased waiting times to elective care are a relevant economic cost of bed-blocking. I find that hospital-region pairs which interact more experience greater reductions in bed-blocking, possibly due to improved coordination across different settings of care provision.

My results can be interpreted in the context of the health production function. Inpatient care, nursing care, and home care are all inputs in the health production function. The reductions in bed-blocking following the entry of NH and HC teams in a region, combined with the absence of a deterioration in health, suggest that both nursing care and home care can be substitutes for inpatient care received by bed-blockers. One important caveat to this interpretation is that I only observe the presence of the inputs and not the quantity of inputs used, which would allow computing elasticities of substitution between the inputs. Longitudinal data following patients across different settings of care provision and monitoring their health outcomes is essential to better inform this question.

From a policy perspective, my results convey that NH and HC teams target different patients and should therefore be used in combination. Overall, HC teams seem a better policy tool to reduce bed-blocking because the majority of patients at risk of bed-blocking does not have sufficiently high care needs in order to benefit from NH care. This is not a peculiarity of my setting. The medical literature has emphasized that not all cases of delayed discharge are necessarily clinically complex (Pellico-López et al., 2019). Additionally, HC teams are more flexible than NH as their capacity can be easily adjusted with respect to demand fluctuations.

Although the entry of nursing homes in a region did not generate clear, immediate reductions in bed-blocking, the results from using continuous measures of treatment indicate that the intensive margin matters. Increasing the number of nursing homes in a region (or the number of beds) is associated with reductions in bed-blocking, suggesting that the initial capacity of nursing homes was insufficient. Further expanding the supply of nursing home services might be a promising solution for policy-makers to reduce bed-blocking.

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A Supplementary tables and figures

Table A.1: Results from estimating equation (2) with different sets of covariates

	(1) Region and time FE	(2) Add DRG FE	(3) Baseline
Bed-blocking indicators (α_1)			
Living alone	12.184***	9.430***	9.226***
	(1.457)	(1.361)	(1.357)
No family to care	27.703***	18.022***	17.984***
	(4.225)	(4.187)	(4.184)
Housing/econ. issues	21.434***	18.022***	17.984***
	(2.754)	(2.631)	(2.611)
Effects of HC and NH entry			
Post HC (α_2)	-0.047	0.008	0.003
	(0.125)	(0.106)	(0.105)
Post NH (α_4)	0.009	0.048	0.095
	(0.206)	(0.187)	(0.193)
Differential effects of HC entry (α_3)			
Post HC × Living alone	-5.284***	-4.303***	-4.361***
	(1.689)	(1.550)	(1.559)
Post HC × No family to care	-0.892	-0.242	-0.384
	(5.572)	(5.320)	(5.318)
Post HC × Housing/econ. issues	-5.318**	-4.664**	-4.673**
	(2.252)	(2.145)	(2.143)
Differential effects of NH entry (α_5)			
Post NH × Living alone	0.535	0.516	0.539
	(1.259)	(1.099)	(1.097)
Post NH × No family to care	0.438	0.078	0.040
	(4.082)	(3.756)	(3.777)
Post NH × Housing/econ. issues	-1.263	-1.084	-1.154
	(2.584)	(2.455)	(2.435)
Observations	7,868,350	7,868,350	7,868,350
R^2	0.019	0.203	0.210

NOTES: The table shows the estimates of α_1 to α_5 from equation (2) using different sets of covariates. Column 1 only includes region and admission month-by-year fixed-effects. Columns 2 adds the DRG fixed-effects. Finally, in column 3 adds the individual demographics and comorbidities. The specification in column 3 is my baseline specification. The sample excludes admissions in the entry month of the first NH and HC in a region. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Results from estimating equation (2) with alternative sample definitions

	(1) Baseline	(2) Balanced panel of hospitals	(3) Excluding patients who died	(4) Excluding transferred patients	(5) Including programmed admissions
Bed-blocking indicators (α_1)					
Living alone	9.226***	9.224***	8.939***	9.202***	9.470***
	(1.357)	(1.361)	(1.333)	(1.418)	(1.233)
No family to care	23.282***	23.444***	20.998***	23.061***	25.802***
	(4.184)	(4.219)	(3.941)	(4.113)	(4.036)
Housing/econ. issues	17.984***	18.026***	16.530***	18.037***	18.304***
	(2.611)	(2.614)	(2.412)	(2.721)	(2.581)
Effects of HC and NH entry					
Post HC (α_2)	0.003	-0.000	0.014	0.003	-0.054
	(0.105)	(0.106)	(0.104)	(0.106)	(0.060)
Post NH (α_4)	0.095	0.093	0.059	0.204	0.036
	(0.193)	(0.194)	(0.191)	(0.157)	(0.079)
Differential effects of HC entry (α_3)					
Post HC × Living alone	-4.361***	-4.397***	-4.369***	-4.470***	-4.310***
	(1.559)	(1.569)	(1.577)	(1.620)	(1.521)
Post HC × No family to care	-0.384	-0.555	1.290	-0.184	-0.034
	(5.318)	(5.380)	(4.976)	(5.449)	(5.255)
Post HC × Housing/econ. issues	-4.673**	-4.917**	-4.150**	-4.573**	-5.555**
	(2.143)	(2.135)	(2.057)	(2.179)	(2.197)
Differential effects of NH entry (α_5)					
Post NH × Living alone	0.539	0.545	0.556	0.629	0.699
	(1.097)	(1.097)	(1.107)	(1.185)	(1.043)
Post NH × No family to care	0.040	-0.076	0.204	0.077	-2.653
	(3.777)	(3.765)	(3.819)	(3.900)	(3.539)
Post NH × Housing/econ. issues	-1.154	-1.306	-0.676	-1.389	-0.244
	(2.435)	(2.435)	(2.219)	(2.456)	(2.713)
Observations	7,868,350	7,806,365	7,239,610	7,484,930	17,632,688
R^2	0.210	0.210	0.230	0.216	0.284

NOTES: The table shows the estimates of α_1 to α_5 in equation (2) using alternative. Column 1 reproduces the baseline results. Columns 2 restricts the sample to a balanced panel of hospitals. Columns 3 and 4 exclude patients who died in the hospital and those who were transferred to other hospitals, respectively. Finally, column 5 includes both emergency and programmed inpatient admissions. All samples exclude admissions in the entry month of the first NH and HC in a region. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Results from estimating equation (2) with alternative outcome variables

	(1) Baseline	(2) LOS>p50	(3) LOS>p75	(4) LOS>p90	(5) LOS>Trim-point
Bed-blocking indicators (α_1)					
Living alone	9.226***	0.124***	0.177***	0.146***	0.077***
	(1.357)	(0.011)	(0.016)	(0.015)	(0.012)
No family to care	23.282***	0.166***	0.294***	0.303***	0.195***
	(4.184)	(0.016)	(0.028)	(0.037)	(0.033)
Housing/economic issues	17.984***	0.167***	0.268***	0.253***	0.149***
	(2.611)	(0.014)	(0.020)	(0.025)	(0.021)
Effects of HC and NH entry					
Post HC (α_2)	0.003	0.000	0.001	-0.000	-0.001
	(0.105)	(0.005)	(0.004)	(0.002)	(0.001)
Post NH (α_4)	0.095	-0.008	0.005	0.004	0.002
	(0.193)	(0.010)	(0.006)	(0.003)	(0.001)
Differential effects of HC entry (α_3)					
Post HC × Living alone	-4.361***	-0.054***	-0.095***	-0.076***	-0.040***
	(1.559)	(0.018)	(0.025)	(0.022)	(0.012)
Post HC × No family to care	-0.384	-0.010	-0.004	0.011	-0.013
	(5.318)	(0.023)	(0.040)	(0.049)	(0.038)
Post HC × Housing/econ. issues	-4.673**	-0.053***	-0.076***	-0.062**	-0.046**
	(2.143)	(0.013)	(0.020)	(0.024)	(0.017)
Differential effects of NH entry (α_5)					
Post NH × Living alone	0.539	0.025	0.040	0.032*	0.001
	(1.097)	(0.020)	(0.025)	(0.017)	(0.010)
Post NH × No family to care	0.040	0.017	0.047	0.043	0.000
	(3.777)	(0.020)	(0.033)	(0.037)	(0.029)
Post NH × Housing/econ. issues	-1.154	0.011	0.026	0.026	-0.003
	(2.435)	(0.015)	(0.023)	(0.026)	(0.020)
Observations	7,868,350	7,868,350	7,868,350	7,868,350	7,031,266
R^2	0.210	0.306	0.213	0.165	0.087

NOTES: The table shows the estimates of α_1 to α_5 from equation (2) using alternative outcome variables. In the baseline model the dependent variable is length of stay in days. In columns 2 to 4 the dependent variable is a binary indicator taking value 1 for individuals above percentiles 50, 75, and 90 of pooled the distribution of length of stay, respectively. Finally, in column 5 it is a binary indicator for episodes with length of stay above their DRG trim-point. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. The sample excludes admissions in the entry month of the first NH and HC in a region. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Results from estimating equation (2) using continuous treatment variables

	(1) No. of places	(2) No. of places, per 10,000 inhab.	(3) No. of providers	(4) No. of providers, per 10,000 inhab.
Bed-blocking indicators (α_1)				
Living alone	8.470***	8.206***	8.501***	7.821***
	(1.030)	(0.814)	(0.869)	(0.517)
No family to care	23.723***	24.631***	25.521***	25.614***
	(3.724)	(3.566)	(3.575)	(3.235)
Housing/econ. issues	16.572***	16.522***	17.253***	16.914***
	(2.400)	(2.110)	(2.214)	(1.862)
Intensity measures(α_2 and α_4)				
HC intensity	0.001	0.021	0.022	0.291
	(0.001)	(0.014)	(0.019)	(0.287)
NH intensity	0.000	-0.000	-0.012	-0.256
	(0.001)	(0.013)	(0.015)	(0.286)
HC interactions (α_3)				
Living alone × HC intensity	-0.013**	-0.383*	-0.544**	-7.135*
	(0.006)	(0.221)	(0.234)	(3.646)
No family to care × HC intensity	0.023	0.219	-0.043	-4.283
	(0.014)	(0.393)	(0.380)	(6.687)
Housing/econ. issues × HC intensity	-0.001	-0.015	-0.514	-6.945
	(0.014)	(0.355)	(0.362)	(6.149)
NH interactions (α_5)				
Living alone × NH intensity	-0.006	-0.033	-0.007	-0.198
	(0.005)	(0.096)	(0.116)	(2.585)
No family to care × NH intensity	-0.038**	-0.739***	-0.990**	-16.940**
	(0.016)	(0.259)	(0.378)	(6.731)
Housing/econ. issues × NH intensity	-0.022***	-0.445***	-0.420*	-9.277**
	(0.008)	(0.140)	(0.212)	(4.339)
Mean HC intensity in 2015	102.09	5.92	5.03	0.32
Mean NH intensity in 2015	139.46	9.16	5.58	0.37
Observations	7,868,350	7,868,350	7,868,350	7,868,350
R^2	0.210	0.210	0.210	0.210

NOTES: The table shows the estimates of α_1 to α_5 in equation (2) using continuous treatment measures. The dependent variable is the length of stay in days. In column 1 the treatment is the monthly number of places in home care teams and beds in nursing home units in region m. In column 2, this measure is scaled by the population living in region m. In column 3 the treatment is the monthly number of home care teams and nursing home units in region m. In column 4, this measure is scaled by the population living in region m. The middle panel shows the 2015 mean of the treatment variables. The sample excludes admissions in the entry month of the first NH and HC in a region. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Results from estimating equation (2) among specific patient groups

	(1) Baseline	(2) Stroke	(3) Respiratory conditions	(4) Underwent surgery	(5) Charlson>1
Bed-blocking indicators (α_1)					
Living alone	9.226***	13.883***	6.872***	15.853***	9.460***
	(1.357)	(3.304)	(1.402)	(3.567)	(1.290)
No family to care	23.282***	28.687***	17.905***	43.942***	26.445***
	(4.184)	(5.755)	(4.037)	(7.618)	(4.944)
Housing/econ. issues	17.984***	27.084***	14.044***	37.104***	20.563***
	(2.611)	(4.655)	(2.559)	(6.237)	(3.257)
Effects of HC and NH entry					
Post HC (α_2)	0.003	-0.294	0.162	0.078	-0.008
	(0.105)	(0.258)	(0.171)	(0.148)	(0.160)
Post NH (α_4)	0.095	0.337	0.403	-0.016	0.298
	(0.193)	(0.557)	(0.257)	(0.176)	(0.281)
Differential effects of HC entry (α_3)					
Post HC × Living alone	-4.361***	-5.393*	-4.009**	-0.739	-4.860***
	(1.559)	(2.742)	(1.826)	(3.482)	(1.660)
Post HC × No family to care	-0.384	1.801	2.083	-15.132	-4.086
	(5.318)	(8.170)	(4.594)	(10.685)	(5.168)
Post HC × Housing/econ. issues	-4.673**	-0.385	-4.315	-11.159**	-5.251**
	(2.143)	(3.524)	(2.586)	(4.944)	(2.279)
Differential effects of NH entry (α_5)					
Post NH × Living alone	0.539	-2.862*	1.231	-4.262	1.039
	(1.097)	(1.604)	(1.169)	(3.787)	(1.396)
Post NH× No family to care	0.040	-1.856	1.670	3.635	2.387
	(3.777)	(6.668)	(3.938)	(9.661)	(4.242)
Post NH × Housing/econ. issues	-1.154	-9.634**	1.191	-3.511	-1.319
	(2.435)	(3.905)	(2.849)	(5.328)	(3.000)
Observations	7,868,350	278,198	913,309	1,847,227	2,232,164
R^2	0.210	0.070	0.111	0.296	0.162

NOTES: The table shows the estimates of α_1 to α_5 from equation (2) for alternative patient groups. Column 1 reproduces the baseline results. Columns 2 and 3 restrict the sample to individuals admitted for stroke and respiratory conditions (pneumonia, bronchitis, etc.), respectively. Finally, columns 4 and 5 restrict the sample to individuals who underwent surgery during their stay at the hospital and to patients whose Charlson score is above 1, respectively. The sample excludes admissions in the entry month of the first NH and HC in a region. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Results form estimating equation (2) among specific demographic groups

	(1) Baseline	(2) Under 50	(3) Over 50	(4) Over 65	(5) Men	(6) Women
Bed-blocking indicators (α_1)						
Living alone	9.226***	10.715***	9.049***	8.768***	8.831***	9.550***
	(1.357)	(1.848)	(1.431)	(1.457)	(1.041)	(1.786)
No family to care	23.282***	28.872***	22.041***	21.334***	23.978***	22.606***
	(4.184)	(6.588)	(3.934)	(4.285)	(4.243)	(4.233)
Housing/econ. issues	17.984***	13.112***	19.612***	19.427***	17.017***	19.087***
	(2.611)	(1.905)	(3.013)	(3.050)	(2.073)	(3.508)
Effects of HC and NH entry						
Post HC (α_2)	0.003	-0.022	-0.016	-0.022	-0.074	0.060
	(0.105)	(0.042)	(0.147)	(0.152)	(0.134)	(0.096)
Post NH (α_4)	0.095	-0.081	0.208	0.249	0.123	0.076
	(0.193)	(0.097)	(0.259)	(0.267)	(0.236)	(0.167)
Differential effects of HC entry (α_3)						
Post HC $\times$ Living alone	-4.361***	-8.100***	-3.959**	-3.885**	-2.939**	-5.413***
	(1.559)	(2.247)	(1.637)	(1.705)	(1.273)	(1.901)
Post HC $\times$ No family to care	-0.384	1.408	-0.422	-1.178	0.712	-1.246
	(5.318)	(7.604)	(5.299)	(5.570)	(5.222)	(5.770)
Post HC $\times$ Housing/econ. issues	-4.673**	-5.507**	-4.296*	-3.618	-5.645***	-3.472
	(2.143)	(2.240)	(2.293)	(2.221)	(1.948)	(2.591)
Differential effects of NH entry (α_5)						
Post NH $\times$ Living alone	0.539	1.195	0.455	0.246	0.373	0.639
	(1.097)	(2.478)	(1.104)	(1.017)	(1.384)	(1.062)
Post NH $\times$ No family to care	0.040	-8.617	1.492	2.326	-1.673	1.522
	(3.777)	(6.696)	(3.683)	(3.525)	(4.027)	(4.048)
Post NH $\times$ Housing/econ. issues	-1.154	-0.595	-1.610	-1.647	0.716	-3.357
	(2.435)	(2.150)	(2.554)	(2.350)	(2.377)	(2.657)
Observations	7,868,350	2,877,662	4,990,661	3,834,418	3,294,812	4,573,522
R^2	0.210	0.248	0.169	0.164	0.178	0.234

NOTES: The table shows the estimates of α_1 to α_5 in equation (2) for patients with different demographics. Column 1 reproduces the baseline results. Columns 2 to 4 restrict the sample to individuals under 50, over 50, and over 65 years old, respectively. Columns 5 and 6 restrict the sample to men and women, respectively. The sample excludes admissions in the entry month of the first NH and HC in a region. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Results for other health outcomes: infections and in-hospital mortality

	(1) Infection as Main Diagnosis	(2) Infection as Secondary Diagnosis	(3) In-hospital Mortality
Bed-blocking indicators (α_1)			
Living alone	-0.003	0.008***	-0.024***
	(0.002)	(0.003)	(0.009)
No family to care	-0.004***	0.019***	-0.020*
	(0.001)	(0.006)	(0.010)
Housing/econ. issues	-0.004**	0.020***	-0.022**
	(0.002)	(0.004)	(0.010)
Effects of HC and NH entry			
Post HC	-0.004**	-0.003***	0.000
	(0.002)	(0.001)	(0.002)
Post NH	-0.001	0.000	0.004*
	(0.002)	(0.001)	(0.002)
Differential effects of HC entry (α_3)			
Post HC × Living alone	0.002	0.002	-0.023**
	(0.003)	(0.005)	(0.009)
Post HC× No family to care	-0.003	-0.007	0.003
	(0.003)	(0.007)	(0.009)
Post HC × Housing/econ. issues	0.003	-0.005	0.004
	(0.003)	(0.004)	(0.007)
Differential effects of NH entry (α_5)			
Post NH × Living alone	0.005*	-0.008	0.012
	(0.002)	(0.005)	(0.009)
Post NH × No family to care	0.003	-0.003	0.001
	(0.003)	(0.006)	(0.011)
Post NH × Housing/econ. issues	0.001	-0.009**	0.002
	(0.003)	(0.004)	(0.007)
Mean of the dep. variable	0.030	0.027	0.080
Observations	7,868,350	7,868,350	7,868,350
R^2	0.469	0.146	0.199

NOTES: The table shows the estimates of α_1 to α_5 in equation (2) using patient health outcomes as dependent variable. In column 1 the outcome variable is a binary indicator for having a serious infection as main diagnosis. In column 2, it is a binary indicator for having a serious infection as secondary diagnosis. Finally, in column 3 the outcome variable is a binary indicator for whether the patient died during his hospital stay. The sample excludes admissions in the entry month of the first NH and HC in a region. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Heterogeneous effects on the share of elective admissions

	(1) All hospitals	(2) Hospitals above median occcupancy rate in 2005	(3) Hospitals below median occcupancy rate in 2005
Post HC	0.017**	0.022	0.009
	(0.008)	(0.013)	(0.009)
Post NH	0.006	0.013	-0.018
	(0.011)	(0.015)	(0.011)
Observations	17,633,408	8,793,849	8,553,122
R^2	0.117	0.092	0.137

NOTES: Columns 1 shows the estimates of ϕ_1 and ϕ_2 from equation (4) using OLS. The estimation sample consists in all individual inpatient admissions to public hospitals (programmed and emergency) between 2000 and 2015. In columns 2 and 3 the estimation sample is restricted to individuals admitted to hospitals which had occupancy rates in 2005 that were above and below the median occupancy rate in that year, respectively. All models include hospital, region, and month fixed-effects. The estimation sample excludes the entry month of the first NH and HC. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Heterogeneous effects on the number of elective and emergency admissions

	(1)	(2)	(3)	(4)	(5)	(6)
	Programmed admissions			Emergency admissions		
	All hospitals	Hospitals above median occcupancy rate in 2005	Hospitals below median occcupancy rate in 2005	All hospitals	Hospitals above median occcupancy rate in 2005	Hospitals below median occcupancy rate in 2005
Post HC	10.572***	15.880**	8.145	-0.832	1.711	-0.978
	(3.876)	(6.644)	(8.719)	(0.898)	(1.640)	(1.658)
Post NH	-1.374	-4.543	3.875	-0.826	1.140	-2.505
	(5.787)	(6.580)	(8.947)	(1.170)	(2.223)	(2.047)
Observations	154,053	75,526	72,095	154,053	75,526	72,095
R^2	0.043	0.074	0.100	0.021	0.069	0.092

NOTES: Columns 1 and 4 show the estimates of φ_1 and φ_2 from equation (5). In column 3 the dependent variable is the monthly number of programmed admissions from region m in hospital h. In column 4 the dependent variable is the monthly number of emergency admissions from region m in hospital h. In columns 2 and 5 the estimation sample is restricted to individuals admitted to hospitals which had occupancy rates in 2005 that were above the median occupancy rate in that year. In columns 3 and 6 the estimation sample is restricted to individuals admitted to hospitals which had occupancy rates in 2005 that were below the median occupancy rate in that year. All models include hospital, region, and month fixed-effects. The estimation sample excludes the entry month of the first NH and HC. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Full set of results from estimating equation (6)

	(1) Total experience	(2) Last year	(3) Last 2 years
Hospital h, regions other than m			
$Exp_{h\text{-}m\tau}$	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Living alone × $Exp_{h\text{-}m\tau}$	-0.000**	-0.002***	-0.001***
	(0.000)	(0.001)	(0.000)
No family to care × $Exp_{h\text{-}m\tau}$	0.005***	0.027***	0.015***
	(0.001)	(0.008)	(0.004)
Housing/econ. issues× $Exp_{h\text{-}m\tau}$	0.001**	0.006***	0.003***
	(0.001)	(0.002)	(0.001)
Region m, hospitals other than h			
$Exp_{\text{-}hm\tau}$	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Living alone × $Exp_{\text{-}hm\tau}$	-0.000	0.002	0.001
	(0.000)	(0.001)	(0.001)
No family to care × $Exp_{\text{-}hm\tau}$	0.000	0.011***	0.005**
	(0.002)	(0.004)	(0.002)
Housing/econ. issues × $Exp_{\text{-}hm\tau}$	0.000	0.005*	0.001
	(0.001)	(0.003)	(0.001)
Hospital h, region m			
$Exp_{hm\tau}$	0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Living alone × $Exp_{hm\tau}$	-0.001***	-0.003***	-0.002***
	(0.000)	(0.001)	(0.000)
No family to care × $Exp_{hm\tau}$	-0.004***	-0.004	-0.004**
	(0.001)	(0.004)	(0.002)
Housing/economic issues × $Exp_{hm\tau}$	-0.001***	-0.001	-0.001
	(0.000)	(0.002)	(0.001)
Mean $Exp_{hm\tau}$	313.64	85.53	154.63
P50 $Exp_{hm\tau}$	156	49	87
P90 $Exp_{hm\tau}$	730	197	354
P95 $Exp_{hm\tau}$	1,063	265	477
Observations	3,859,751	3,655,882	3,640,309
R^2	0.230	0.229	0.229

NOTES: The table shows the full set of experience estimates from equation (6). Column 1 considers experience accumulated since the entry of the first provider in a region. Columns 2 and 3 consider experience accumulated during the last 1 and 2 years, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Estimating annual cost-savings from reducing bed-blocking, 2015

		Absent NH and HC entry		After HC entry	
Bed-blocking type	Patients	Bed-blocking period ($\hat{\alpha_1}$)	Bed-blocking days (Patients$\times\hat{\alpha_1}$)	Bed-blocking period ($\hat{\alpha_1} - \hat{\alpha_3}$)	Bed-blocking days (Patients$\times(\hat{\alpha_1} - \hat{\alpha_3})$)
Living alone	4,021	9.226	37,097	4.865	19,562
No family to care	1,192	23.282	27,752	22.989	27,294
Housing/econ. issues	1,922	17.984	34,565	13.311	25,584
Total	7,135		99,415		72,440
Valuation, €M			22.9		16.7
Conservative valuation, €M			8.7		6.3

NOTES: Column 1 shows the number of bed-blocking patients in 2015, per type of bed-blocking. Column 2 shows the estimates of α_1 from equation (2), corresponding to the bed-blocking period prior to the entry of NH and HC teams. Column 3 multiplies columns 1 and 2 to compute the number of bed-blocking days in 2015, absent the entry of NH and HC teams. Column 4 shows the estimates of $(\alpha_1 - \alpha_3)$ from equation (2), corresponding to the bed-blocking period after to the entry of HC teams in a region. Finally, multiplies columns 1 and 4 to compute the number of bed-blocking days after the entry of HC teams. For the valuation estimate, the cost of a day in the hospital is €230 and for the conservative valuation estimate it is €87.

Table A.12: Effects on regional mortality rates

	Mortality Rate
Post HC	0.025
	(0.016)
Post NH	0.002
	(0.010)
Observations	733
R^2	0.982

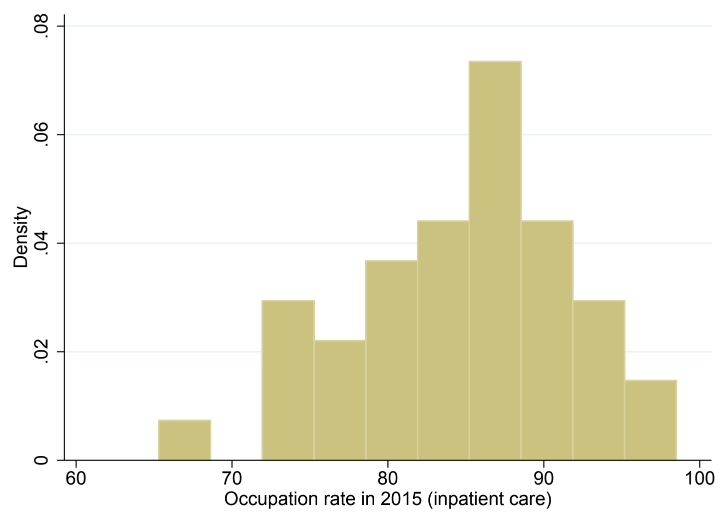
NOTES: The table shows the results of a regression of mortality rates in an ACES region on binary indicators for periods after the entry of NH and HC teams. The model includes region and year fixed-effects. The sample excludes the entry year of the first NH and CH team in a region. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: Effects on the number of inpatient beds

	(1) Within 10km	(2) Within 15km	(3) Within 20km	(4) Within 30km	(5) Modal hospital
Post HC	32.539	6.463	14.303	12.620	31.432
	(35.145)	(17.670)	(18.831)	(26.288)	(20.686)
Post NH	-23.875	-11.479	-17.815	2.704	-13.294
	(17.284)	(13.112)	(12.784)	(2.937)	(14.152)
Observations	629	629	629	629	832
R^2	0.970	0.970	0.970	0.970	0.974

NOTES: Columns 1 to 4 of the table show the results of regressions of the annual number of inpatient beds in a hospital on indicators for periods after the entry of NH and HC teams within a given distance from the hospital (10, 15, 20, and 30 kilometers, respectively for columns 1 to 4). The unit of observation is the hospital-year and the models include both hospital and year fixed-effects. Standard errors are heteroskedasticy-robust and clustered at the hospital level. Column 5 shows the results of a regression of the annual number of inpatient beds in the modal hospital of each region on binary indicators for periods after the entry of NH and HC teams. The unit of observation in this model is the region-year and the model includes region and year fixed-effects. Standard errors are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A.1: Histogram of inpatient bed occupancy rates, 2015



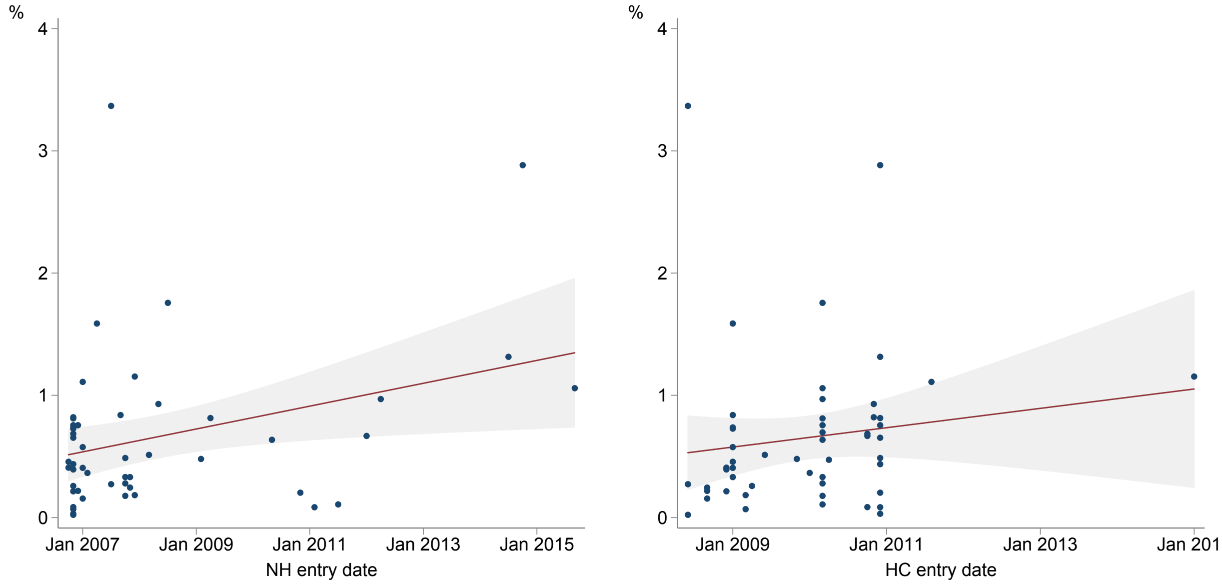
NOTES: The histogram shows the distribution of inpatient bed occupancy rates across the hospitals in my sample, over the year of 2015. The average occupancy rate is 85%, but there is a non-negligible share of hospitals with occupancy rates over 90%.

Table A.14: Assessing changes in patient characteristics

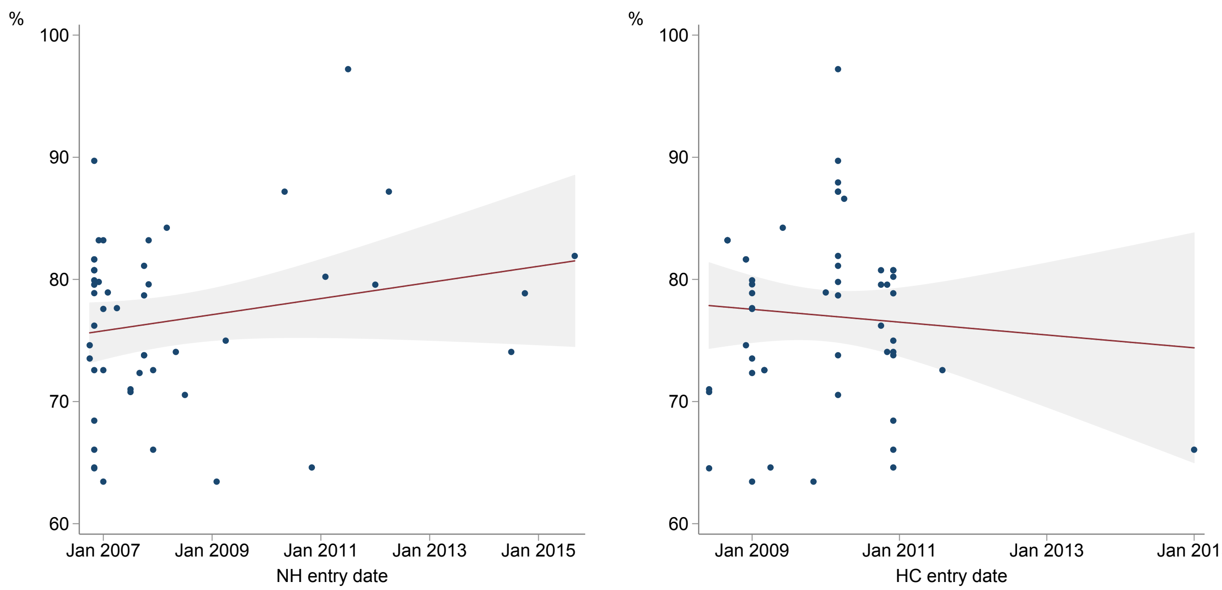
	(1) DRG weight	(2) Charlson score
Bed-blocking indicators (α_1)		
Living alone	0.008	-0.010
	(0.024)	(0.021)
No family to care	0.190***	0.136***
	(0.059)	(0.044)
Housing/econ. issues	0.216***	0.023
	(0.033)	(0.025)
Post indicators (α_2 and α_4)		
Post HC	0.011*	-0.001
	(0.007)	(0.013)
Post NH	-0.014	-0.055***
	(0.010)	(0.019)
HC interactions (α_3)		
Post HC × Living alone	-0.038	0.123***
	(0.044)	(0.027)
Post HC × No family to care	0.232*	0.284***
	(0.131)	(0.055)
Post HC × Housing/econ. issues	-0.109**	0.072**
	(0.041)	(0.036)
NH interactions (α_5)		
Post NH × Living alone	0.075***	-0.028
	(0.028)	(0.030)
Post NH × No family to care	0.117	-0.004
	(0.137)	(0.063)
Post NH × Housing/econ. issues	0.069	-0.009
	(0.055)	(0.030)
Mean of dep. var.	1.164	1.189
Observations	7,849,378	7,868,350
R^2	0.083	0.484

NOTES: In column 1 the dependent variable is DRG weight, a measure of the complexity of the patient's DRG group. In column 2 the dependent variable is the patient's Charlson comorbidity score. Both models include region and month fixed-effects and the model in column 2 also includes DRG fixed-effects. The estimation sample excludes the entry month of the first NH and HC. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A.2: Exogeneity of treatment timing I



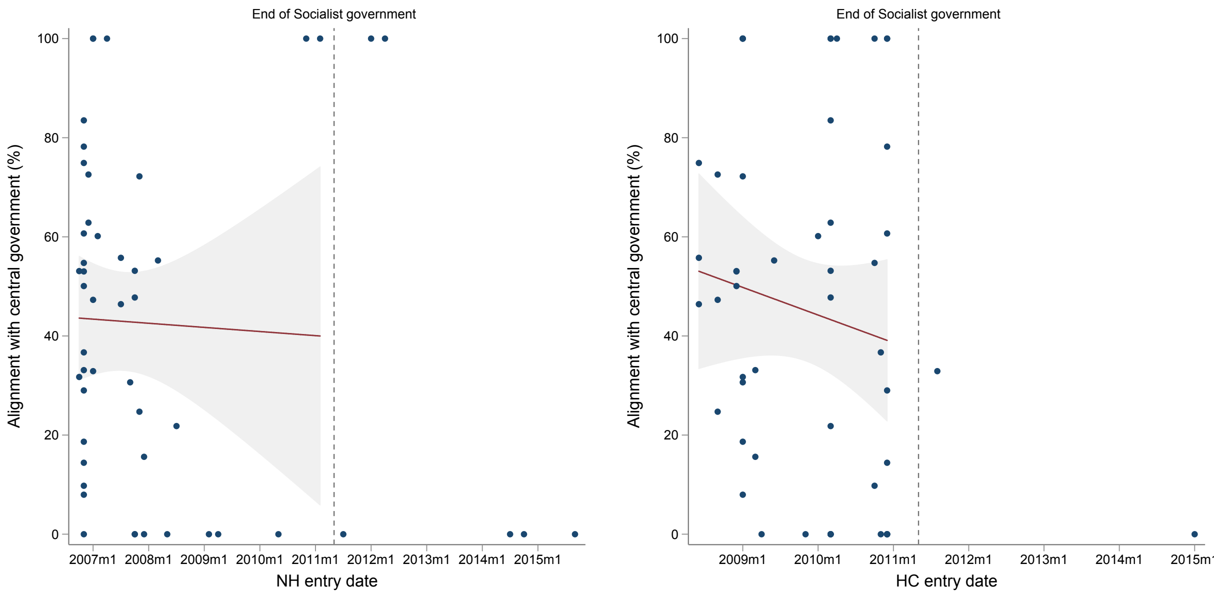
(a) With respect to share of bed-blockers in the region



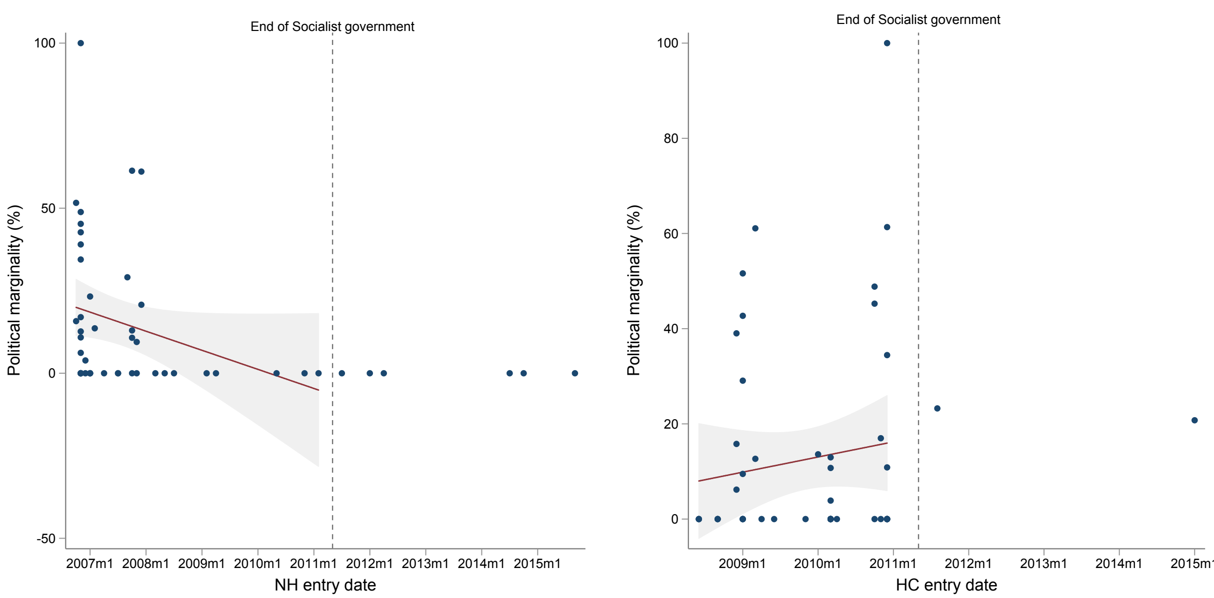
(b) With respect to the occupancy rate of the modal hospital visited by patients in the region

NOTES: The figures in the top panel plot the percentage of bed-blockers in a region in year 2005 against the timing of entry of the first nursing home (left) and home care team (right) in the region. The figures in the bottom panel plot the average occupancy rate of the modal hospital visited by patients living in each region as of year 2005 against the timing of entry of the first nursing home (left panel) and home care team (right panel) in the region. Each of the 52 dots corresponds to an ACES region. The line corresponds to the predictions from a linear regression using these 52 data points and the shaded area corresponds to the 95% confidence interval.

Figure A.3: Exogeneity of treatment timing II



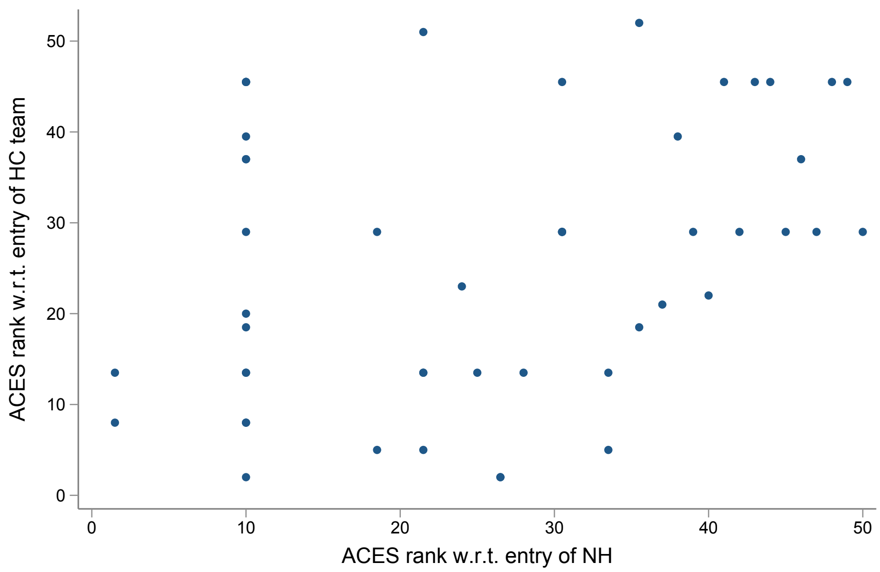
(a) With respect to alignment with the central government



(b) With respect to the political marginality of the region

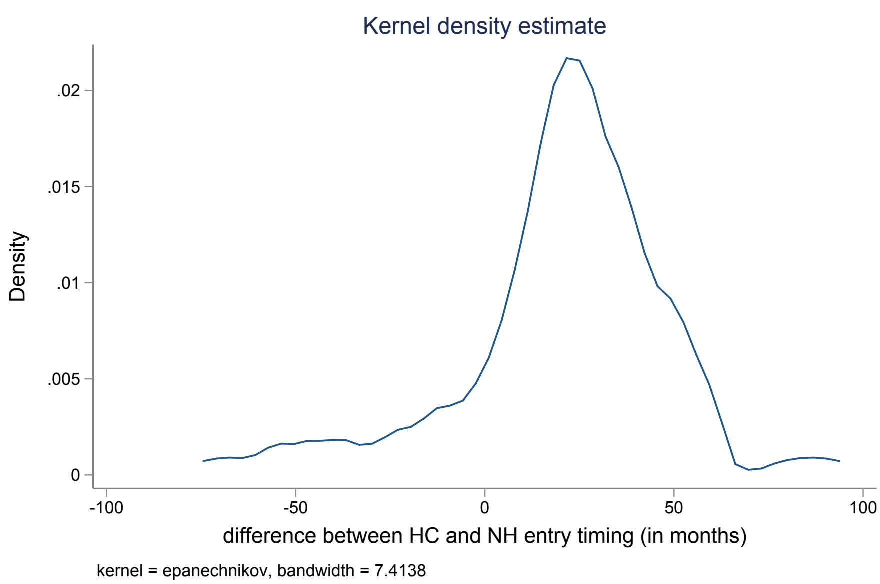
NOTES: The figures in the top panel plot the degree of political alignment with the central government against the timing of entry of the first nursing home (left) and home care team (right) in a region. The degree of political alignment is measured as the share of municipalities in a region whose mayor is affiliated with the political party in power (the Socialist Party), weighted by population size. National and local elections took place in February and October 2005, respectively, and I measure political alignment at the end of 2005. The figures in the bottom panel plot the degree of political marginality of a region in 2005 against the timing of entry of the first nursing home (left) and home care team (right) in the region. The degree of political marginality is measured as the share of municipalities in a region where the Socialist Party won by a small margin or lagged behind by a small margin (below 5 percentage points) in the 2005 election, weighted by population size. Each of the 52 dots is an ACES region. The line corresponds to the predictions from a linear regression using these 52 data points and the shaded area is the 95% confidence interval. The vertical dashed line marks the end of the socialist government in May 2011.

Figure A.4: Relationship between region rankings with respect to entry of first NH and HC team



NOTES: The scatterplot conveys the relationship between the ranking of regions with respect to the entry of their first NH and the entry of their first HC team. I allow for ties in the rankings. Each point corresponds to an ACES region. Some of the points overlap in the plot. The correlation between the two rankings in 0.29.

Figure A.5: Density of months between entry of the first NH and the first HC team in a region



NOTES: Kernel density estimate of the difference between HC and NH treatment timing, in months. The unit of observation is the region.

B Compositional changes

Compositional changes to the groups of bed-blockers and regular patients could originate from changes in the way hospitals code the social factors I use to identify bed-blockers. For example, the coding of these factors can become more salient with the roll-out of the Network.

I assess this possibility in two ways. First, I examine whether hospitals change the coding frequency of the social factors I use to identify individuals at increased risk of bed-blocking upon the entry of NH and HC teams nearby. I estimate:

$$BB_{it}^{j} = \omega_1 PostHC_{ht} + \omega_2 PostNH_{ht} + \lambda_h + \lambda_t + \varepsilon_{it}, \tag{8}$$

where BB_{it}^{j} is a binary indicator for individual i, who is admitted to the hospital in period t, being coded in bed-blocking group j; $PostNH_{ht}$ and $PostHC_{ht}$ are indicator variables taking value 1 for periods after the entry of the first NH and the first HC team in a neighborhood around hospital h, respectively; λ_h and λ_t are hospital and month fixed effects; and ε_{it} is an error term. The estimates of interest are those of ω_1 and ω_2, which capture changes in the frequency of patients coded in group j upon the entry of HC teams and NH in nearby the hospital they visit, respectively.

Second, I examine whether there are changes in the coding frequency of the social factors I use to identify individuals at increased risk of bed-blocking following the entry of HC teams and NH providers in the region where patient i lives. I estimate:

$$BB_{it}^{j} = \rho_1 PostHC_{mt} + \rho_2 PostNH_{mt} + \lambda_m + \lambda_t + \varepsilon_{it}, \tag{9}$$

where BB_{it}^{j} is a binary indicator for individual i being coded in bed-blocking group j; $PostNH_{mt}$ and $PostHC_{mt}$ are indicator variables taking value 1 for periods after the entry of the first NH and the first HC team in a region, respectively; λ_m and λ_t are region and month fixed effects; and ε_{it} is an error term. The estimates of interest are those of ρ_1 and ρ_2, which capture changes in the frequency of patients coded in group j upon the entry of HC teams and NH in their region of residence, respectively.

Table B.1 reports the estimates of interest from equation (8). I show the results for entry of NH and HC teams within 5 and 15km around hospital h on the left and right panels, respectively.[29] Table B.2 reports the estimates of interest from equation (9). The left panel shows OLS estimates. The right panel shows marginal effects after logit, evaluated at the mean of the independent variables.

None of the estimates in Tables B.1 and B.2 are statistically or economically significant,

[29] Results for other distances yield similar conclusions and are available upon request from the author.

indicating no clear association between the entry of NH and HC teams and the coding of the social factors used to identify bed-blockers. These results are reassuring that the increase in the frequency of bed-blockers in recent years is not endogenous to the availability of NH and HC teams, but rather reflects social and demographic changes.

Table B.1: Results from estimating equation (8)

	5km around hospital			15km around hospital		
	Living alone	No family to care	Housing/econ. issues	Living alone	No family to care	Housing/econ. issues
Post HC (ω_1)	0.0013	0.0006	-0.0005	-0.0007	0.0005	0.0008
	(0.0012)	(0.0004)	(0.0006)	(0.0008)	(0.0004)	(0.0005)
Post NH (ω_2)	0.0005	0.0002	0.0013	0.0006	0.0006	-0.0008
	(0.0011)	(0.0004)	(0.0008)	(0.0008)	(0.0004)	(0.0007)
Observations	7,853,502	7,837,101	7,851,623	7,831,512	7,815,214	7,829,698
R^2	0.004	0.001	0.002	0.003	0.001	0.002

NOTES: The table shows the estimates of ω_1 and ω_2 from equation (8). The left and right panels reports the estimates for HC and NH entry within 5 and 15km from hospital h, respectively. For each column, the sample of individuals consists on those classified in the group stated in the column title and the regular patients. The samples exclude admissions in the entry month of the first NH and HC within 5 and 15km around the hospital where the patient is admitted, respectively for the first and last three columns. All models include admission month-by-year and hospital fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Results from estimating equation (9)

	OLS			Logit		
	Living alone	No family to care	Housing/econ. issues	Living alone	No family to care	Housing/econ. issues
Post HC (ρ_1)	0.0010	0.0000	0.0003	0.0006	-0.0001	0.0001
	(0.0006)	(0.0003)	(0.0005)	(0.0004)	(0.0002)	(0.0003)
Post NH (ρ_2)	-0.0000	0.0001	-0.0005	0.0005	0.0001	-0.0001
	(0.0009)	(0.0003)	(0.0006)	(0.0005)	(0.0002)	(0.0003)
Observations	7,830,074	7,813,746	7,828,255	7,830,074	7,813,746	7,828,255
(Pseudo-)R^2	0.004	0.001	0.002	0.071	0.043	0.044

NOTES: The table shows the estimates of ρ_1 and ρ_2 from equation (9). The left panel reports OLS estimates. The right panel reports marginal effects after logit evaluated at the mean of the independent variables. For each column, the sample of individuals consists on those classified in the group stated in the column title and the regular patients. The sample excludes admissions in the entry month of the first NH and HC in a region. All models include admission month-by-year and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Alternative empirical approaches

C.1 Exploiting only variation in treatment timing

One crucial assumption in the main specification presented in equation (2) is that regular patients and bed-blockers are comparable. To relax that assumption, I estimate an alternative model specification, which does not use regular patients as control group ad thus only exploits variation in the length of stay of bed-blockers originating from differential treatment timing. I estimate:

$$y_{it} = \zeta_1 PostHC_{mt} + \zeta_2 PostNH_{mt} + \delta X_i + \gamma_d + \gamma_m + \gamma_t + \varepsilon_{it} \tag{10}$$

Notation is as before. The coefficients of interest are ζ_1 and ζ_2, capturing the change in the length of stay of bed-blockers after the entry of home-care teams and nursing homes in a region, respectively. Equation (10) is estimated three times, for each of the three groups of bed-blockers. Table C.1 shows the results. The number of observations used in each estimation is substantially smaller. The results show that the entry of the home-care teams in a region reduces the length of stay of individuals living alone by 3.4 days, similar to the baseline results. The estimates for the remaining bed-blocking groups are not statistically significant, but their sign goes in the direction of reducing length of stay upon the entry of home-care teams.

Table C.1: Results from exploiting differential treatment timing

	(1) Living alone	(2) No family to care	(3) Housing/ econ. issues
Post HC	-3.569**	-1.207	-1.678
	(1.589)	(3.107)	(1.836)
Post NH	3.190	0.143	1.408
	(4.816)	(3.889)	(3.101)
Observations	28,068	11,706	26,249
R^2	0.179	0.243	0.220

NOTES: The table shows the estimates of ζ_1 and ζ_2 from equation (10). In column 1 the sample consists of individuals living alone. In columns 2 and 3 it consists of individuals with no family to care and with housing issues or other economic circumstances, respectively. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. The sample excludes admissions in the entry month of the first NH and HC in a region. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C.2 Exploiting only differences between bed-blockers and regular patients

These specifications are similar to equation (2), but restrict the comparison between bed-blockers and regular patients living in regions that were treated in a given year, thereby greatly limiting the variation in treatment timing. I focus on the years were the largest number of regions was treated. For the entry of the first nursing home I focus on the years of 2006 and 2007 (38% and 34% of the regions experienced the entry of the first NH in these years, respectively). For the entry of the first home care team, I focus on the years of 2008, 2009, and 2010 (17%, 25%, and 54% of the regions experienced the entry of the first HC team in these years, respectively).

Table C.2 shows the results. For ease of comparison, column 1 shows the baseline results using all the treatment cohorts. In general, the patterns are similar across regions treated in different years, even though statistical significance is sometimes lost. This suggests that concerns about variation in treatment timing are limited in my settings.

C.3 Implementing an alternative estimator

Staggered treatments create a few challenges to the estimation of traditional difference-in-differences designs. Recent papers have shown that the OLS estimate is a weighted average of all possible 2 by 2 difference-in-difference estimates (2 groups, 2 time periods). In particular, treated units are also used as control group for units which are treated at a later point in time. This is particularly problematic in the presence of treatment effect heterogeneity. There are various new estimators proposed in the recent literature, which mainly differ in the computation of potential untreated outcomes.

As an alternative to OLS, I implement the imputation estimator recently proposed in Borusyak et al. (2021). The estimation proceeds in three steps. The first step estimates a model for non-treated potential outcomes using the non-treated (i.e. never-treated or not-yet-treated) observations only. The second step extrapolates the model from step 1 to treated observations, imputing non-treated potential outcomes $Y_{it}(0)$, and obtains an estimate of the treatment effect $\tau_{it} = Y_{it} - Y_{it}(0)$ for each treated observation. Finally, the third step takes averages of estimated treatment effects. The authors provide a Stata command `did_imputation` to implement the imputation estimator.

There are two main characteristics of this estimator that make it attractive for my setting. First, it can be applied to repeated cross-sections (in each period, I observe a different sample of patients from a region). Second, it allows for having a specific group of patients in a treated region who are affected by the treatment (in my case, the patients at risk of bed-blocking), as

opposed to all individuals in a region being affected by the treatment.
However, accommodating multiple treatments (in my case, the entry of NH and HC teams) is not possible without imposing additional assumptions. Therefore, to implement this estimator, I focus on one treatment at a time and control for the presence of the other treatment in the first step of the procedure. Additionally, I restrict the controls used in the estimation and include only region and year-by-month fixed effects. While the command accommodates additional covariates, Stata crashed every time I added all the diagnoses information in the estimation.
In a first specification, I restrict the sample to patients at risk of bed-blocking, thus excluding regular patients. Table C.3 shows the results. For convenience, the table also shows the equivalent OLS results. Overall, the conclusion from using the imputation estimator are in line with the OLS ones: the entry of HC teams reduces the length of stay of patients at risk of bed-blocking, whereas the entry of NH does not show significant effects. The point estimates have stronger magnitude and significance when using the estimator by Borusyak et al. (2021). One potential reason for this is that OLS places more weight on comparisons in the middle of the sample period and less weight on comparisons towards the end of the sample period. However, as conveyed by the even-study plots, the effects from NH and HC teams get larger over time.
In a second specification, I include regular patients as a control group in the estimation. Table C.4 shows the results. For convenience, the top panel shows the OLS results. The results from using the imputation estimator proposed by Borusyak et al. (2021) are very similar to those obtained using OLS.
Taken together, these findings give additional confidence to the OLS results.

Table C.2: Results from estimating equation (2) for specific treatment years

	(1) Baseline	(2) NH in 2006	(3) NH in 2007	(4) HC in 2008	(5) HC in 2009	(6) HC in 2010
Bed-blocking indicators						
Living alone	9.266***	7.150***	10.885***	7.883***	12.730***	8.514***
	(1.357)	(1.265)	(2.638)	(1.614)	(2.370)	(1.649)
No family to care	23.282***	11.781***	32.638***	17.537***	35.693***	18.912***
	(4.184)	(2.505)	(7.784)	(5.062)	(8.994)	(2.779)
Housing/econ.issues	17.984***	14.329***	24.014***	16.236***	23.141***	15.971***
	(2.611)	(2.487)	(3.078)	(3.526)	(3.900)	(2.779)
Effects of HC and NH entry						
Post HC (α_2)	0.003	-0.038	-0.005	-0.158	-0.254	0.288*
	(0.105)	(0.132)	(0.236)	(0.217)	(0.266)	(0.146)
Post NH (α_4)	0.095	0.344	0.056	0.033	-0.102	0.209
	(0.193)	(0.267)	(0.205)	(0.257)	(0.148)	(0.239)
Differential effects of HC entry (α_3)						
Post HC × Living alone	-4.361***	-1.050	-5.850***	-0.596	-5.280***	-3.923*
	(1.559)	(1.672)	(1.167)	(1.614)	(0.965)	(2.221)
Post HC × No family to care	-0.384	0.902	-13.539**	2.868	-11.355*	4.488
	(5.318)	(2.217)	(4.898)	(3.232)	(5.745)	(5.621)
Post HC × Housing/econ. issues	-4.673**	-3.658	-7.000***	-5.790	-6.049**	-3.068
	(2.143)	(2.209)	(2.199)	(5.376)	(2.485)	(2.617)
Differential effects of NH entry (α_5)						
Post NH × Living alone	0.539	0.118	-0.674	-0.748	-2.845	1.772
	(1.097)	(1.562)	(2.291)	(1.373)	(1.691)	(1.372)
Post NH × No family to care	0.040	0.249	3.752	-6.249**	-2.975	4.034
	(3.777)	(2.555)	(4.528)	(1.983)	(3.701)	(5.238)
Post NH × Housing/econ. issues	-1.154	-1.436	-3.082	0.976	-5.456***	0.383
	(2.435)	(2.223)	(1.882)	(4.439)	(1.171)	(3.417)
Observations	7,868,350	2,766,703	2,824,736	1,282,011	2,412,916	4,033,208
R^2	0.210	0.214	0.200	0.205	0.200	0.223

NOTES: The table shows the estimates of α_1 to α_5 from equation (2). Column 1 shows the baseline results. Columns 2 and 3 restrict the sample to regions where the first nursing home entered in 2006 and 2007, respectively. Columns 4 to 6 restrict the sample to regions where the first home care team entered in 2008, 2009, and 2010, respectively. All models include individual demographics and comorbidities and admission month-by-year, DRG, and region (ACES) fixed-effects. The sample excludes admissions in the entry month of the first NH and HC in a region. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Alternative estimator to deal with differential treatment timing (excluding regular patients)

	Living alone (1)	No family to care (2)	Housing/econ. issues (3)
Panel A: OLS			
Post HC	-4.467**	-3.180	-2.338
	(1.955)	(3.843)	(1.918)
Post NH	3.912	1.830	2.077
	(5.869)	(4.135)	(3.372)
Observations	28,219	11,891	26,400
Panel B: Borusyak et al. (2021)			
Post HC	-6.717***	-22.165***	-2.371*
	(1.153)	(1.751)	(1.302)
Observations	18,038	8,339	21,202
Panel C: Borusyak et al. (2021)			
Post NH	5.050	-2.960	3.097
	(3.881)	(3.416)	(2.077)
Observations	28,219	11,891	26,400

NOTES: Panel A shows the results of an OLS regression of length of stay on the two post indicators for periods after the entry of a NH and a HC team in a region. Panel B implements the imputation estimator in Borusyak et al. (2021) for the HC treatment, while controlling for the availability of NH in a region. Finally, panel C implements the same estimator for the NH treatment, while controlling for the availability of HC teams in a region. All models include admission month-by-year and region (ACES) fixed-effects. In columns 1, 2, and 3 the sample is restricted to patients living alone, with no family to care, and with inadequate housing conditions, respectively. The samples exclude admissions in the entry month of the first NH and HC in a region. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Alternative estimator to deal with differential treatment timing (including regular patients)

	Living alone (1)	No family to care (2)	Housing/econ. issues (3)
Panel A: OLS			
Post HC	-5.285***	-0.895	-5.326**
	(1.690)	(5.574)	(2.252)
Post NH	0.577	0.458	-1.249
	(1.159)	(4.088)	(2.587)
Observations	7,830,074	7,813,746	7,828,255
Panel B: Borusyak et al. (2021)			
Post HC	-4.913***	-0.596	-6.150**
	(1.488)	(4.035)	(2.373)
Observations	7,830,074	7,813,746	7,828,255
Panel C: Borusyak et al. (2021)			
Post NH	-3.016	-0.148	-4.727
	(1.321)	(3.929)	(2.704)
Observations	7,830,074	7,813,746	7,828,255

NOTES: Panel A shows the results of an OLS regression of length of stay on the two post indicators for periods after the entry of a NH and a HC team in a region. Panel B implements the imputation estimator in Borusyak et al. (2021) for the HC treatment, while controlling for the availability of NH in a region. Finally, panel C implements the same estimator for the NH treatment, while controlling for the availability of HC teams in a region. All models include admission month-by-year and region (ACES) fixed-effects. In columns 1 the sample consists in regular patients and patients living alone. In columns 2 and 3 patients living alone are replace by those with no family to care and with inadequate housing, respectively. The samples exclude admissions in the entry month of the first NH and HC in a region. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$