Does long-term care provision reduce hospital bed-blocking? Evidence from a policy reform in Portugal

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Job Market Paper

This version: September 18, 2020. Click here for the most recent version

Abstract

Excessive lengths of hospital stay are among the leading sources of inefficiency in healthcare. One reason for excessive lengths of hospital stay is bed-blocking. Bed-blocking occurs when a patient is clinically fit to be discharged but requires some form of support outside the hospital, which is not readily available. The patient remains in the hospital until a safe discharge is possible, resulting in longer lengths of stay. I study whether long-term care (LTC) provision reduces hospital bed-blocking. Using individual data on emergency inpatient admissions at Portuguese hospitals during 2000-2015, I implement a triple-differences design. This design exploits variation in the timing of entry of LTC providers across regions originating from the staggered introduction of the public LTC Network. It also exploits variation in lengths of stay between regular patients and patients exhibiting social factors that put them at risk of bed-blocking, such as living alone, having no family to care, and having inadequate housing. I find that the entry of home-care teams in a region reduces the length of stay of individuals living alone and those with inadequate housing by 4 days relative to regular patients. These reductions in length of stay do not affect the treatment received while at the hospital and, if anything, LTC entry lowers the likelihood of a readmission. Reductions in length of stay upon the entry of nursing homes occur only for patients with high care needs. The beds freed up by bed-blockers are used to admit additional elective patients.
Keywords: Long-term care; hospital bed-blocking; delayed discharges.
JEL codes: H51; I10; I18; J14.

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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 can be challenging (Einav et al., 2019). The World Health Organization considers excessive lengths of hospital stay as one of the leading sources of inefficiency in healthcare (WHO, 2010). One reason for excessive lengths of hospital stay can be bed-blocking.

Bed-blocking occurs when a patient is clinically fit to be discharged but requires some form of support outside the hospital, such as a short stay at a nursing home facility or home-help, which is not readily available. If no safe discharge arrangements can be made, the patient remains in the hospital until a safe transition to the next stage of care provision is possible, resulting in longer lengths of hospital stay. These are not inconsequential. They imply higher hospital costs, have potentially detrimental impacts on patients' health originating from increased risks of mobility loss, nosocomial infections, and loneliness, and can create delays for patients awaiting elective care (Mur-Veeman and Govers, 2011).

Bed-blocking is a growing policy concern in developed countries. This is motivated by several trends. During the last decades, there were significant increases in life expectancy and consequently rising share of the elderly in the population. 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 trends put pressure on existing institutional arrangements within the health system and call for a reorganization of care delivery (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 long-term care arrangements (Lakdawalla and Philipson, 2002).

I examine whether the provision of long-term care (LTC) reduces hospital bed-blocking. I focus on the Portuguese case. In Portugal, on a random day in 2019, 4.7% of beds in public hospitals were occupied with patients who were clinically ready to be discharged but lacked long-term care support, amounting to over 80,000 delayed bed-days.[1,2] I exploit plausibly exogenous variation in the availability of long-term care originating from the introduction of the public LTC Network by the Portuguese government. Before 2006, LTC services were not

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

[2]Figures conveying the magnitude of bed-blocking in different countries are not easily available. In Sweden, the share of bed-blockers was about 7% in 1992 (Styrborn and Thorslund, 1993). In 2006, 6.1% of all hospital-days in the Netherlands were bed-blocking days (Mur-Veeman and Govers, 2011). In England, during December 2019 alone, the number of delayed bed-days reached 148,000, a 15% increase comparing to the same month of the previous year (`https://www.theguardian.com/society/2020/feb/23/bed-blocking-highest-since-2017-hospitals-nhs`).

within the scope of the Portuguese National Health System and individuals relied heavily on informal care provided by family members. The public LTC Network was introduced in 2006, with the aim of filling in this gap in service coverage. It comprises highly subsidized nursing home facilities (NH) and teams providing home-care (HC), which operate in coordination with hospitals, aiming at easing the transition of patients across different settings of care provision. The LTC Network was introduced in a staggered fashion, meaning that different regions experienced the entry of LTC providers at different points in time. Using individual data on the universe of emergency inpatient admissions at public hospitals in Portugal between the years 2000 and 2015, I first show that there is a group of patients exhibiting a complex combination of health and social needs. This group includes individuals who live alone, have no family to care for them, and have inadequate housing conditions or other unfortunate economic circumstances that might hinder a timely discharge. The differences in length of stay between these patients and patients who do not exhibit social needs are sizable. For example, individuals with no family to care have lengths of stay that are, on average, over 20 days longer than regular patients after controlling for demographics, comorbidities, and medical diagnoses. Throughout the paper, I refer to patients who exhibit both health and social needs as bed-blockers, as opposed to regular patients, who exhibit no social needs. In the empirical analysis, I use a triple-differences design to compare the length of stay 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. This identification strategy exploits variation in LTC availability across regions and time originating from the staggered introduction of the LTC Network. It also exploits variation in lengths of stay between regular patients and bed-blockers.

I find evidence of reductions in the length of stay of bed-blockers relative to regular patients following the entry of home-care teams in a region. These reductions amount to 4 days, on average, for individuals living alone and those with inadequate housing and other economic issues. Reductions in the length of stay of bed-blockers relative to regular patients following the entry of nursing homes in a region only when restricting the sample to patients with high care needs, such as those with a stroke diagnosis. This finding is consistent with the hypothesis that admission to a nursing home requires higher levels of disability and dependence. Finally, the entry of nursing homes and home-care teams in a region has a precise zero impact on the length of stay of regular patients, meaning that reductions in the lengths of stay of bed-blockers relative to regular patients originate only from reductions in the length of stay of bed-blockers.

These results are robust to alternative model specifications, outcome variables, relevant regions, and treatment definitions. An event-study design conveys that the results are not typically driven by differences in underlying pre-treatment trends. I also show that the entry of

LTC providers in a region is not associated with changes in the coding frequency of the social factors used to identify bed-blockers. Consistent with the longer length of stay of bed-blockers being unnecessary, I find no reductions in the intensity of care received by bed-blockers during their hospital stay after the entry of LTC providers in a region. Additionally, if anything, the entry of LTC providers decreases the likelihood of a hospital readmission for bed-blockers. Finally, the beds freed up by bed-blockers do not remain unoccupied: I find evidence of increases in programmed activity following the entry of home-care teams in a region.

While these results show that LTC provision can reduce hospital bed-blocking, the resulting reductions in length of stay take some time to materialize and do not fully close the gap between bed-blockers and regular patients. I investigate the role of the accumulation of relationship-specific experience between a hospital-region pair in explaining these results. The findings from this analysis convey that a large number of interactions between a hospital-region pair is needed to generate meaningful reductions in the length of stay of bed-blockers.

Related Literature. This paper relates to several strands of the literature.[3] It speaks most directly to a small but growing literature studying the impacts of LTC availability on hospital bed-blocking (Forder, 2009; Gaughan et al., 2015, 2017a,b). Unlike existing studies, I exploit variation in the availability of LTC induced by a policy reform. In particular, the roll-out of the LTC Network was determined by the central government, and not at the regional level. This helps mitigating potential endogeneity concerns regarding the entry timing and location of LTC providers. Due to the nature of the policy reform, I am able to separate the effects of distinct types of LTC providers, namely nursing homes and home-care teams. Additionally, I propose the use of information on social needs to identify patients at increased risk of bed-blocking and circumvent the fact that the exact length of the delay is typically unobserved (with Holmås et al. (2013) a notable exception). These social needs include the availability of family support and housing conditions, which have been shown to affect both LTC use (Diepstraten et al., 2020; Lopes et al., 2018) and hospital bed-blocking (Costa et al., 2012; Bryan et al., 2006; McDonagh et al., 2000).

A related literature focuses on the substitutability of LTC and acute hospital care. This literature studies, for example, whether LTC can be used in lieu of (the last days of) a hospital stay and whether the use of LTC can delay or avoid the need for hospital care. Overall, this literature finds little to no substitution between LTC and hospital length of stay (McKnight, 2006; Forder, 2009; Gaughan et al., 2015, 2017a; Bakx et al., 2020; Costa-Font et al., 2018;

[3]There is also an extensive literature on bed-blocking outside economics. Scholars in medicine have elaborated on the causes of bed-blocking, characterized the affected population, and quantified the associated monetary losses (see, for example, Bryan et al., 2006; Hendy et al., 2012; Costa et al., 2012). Within 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 and many others).

Kümpel, 2019). My research design allows analyzing substitution of acute care with respect to both home-care and nursing home care, separately for regular patients and bed-blockers. My estimated elasticities of length of stay with respect to both the number and capacity of long-term care providers suggest very little substitution between LTC and acute care.

My finding that reductions in bed-blocking lead to increases in programmed activity relates to a discussion on the internal allocation of resources within a hospital, which goes back to Harris (1977). The specific case of interactions between emergency and elective activities was recently studied by Johar et al. (2013).

This paper also provides new insights on the factors contributing to perpetuate bed-blocking. Fernandez and Forder (2008) study the importance of financial resources allocated to the LTC sector. Holmås et al. (2010) show that monetary incentives to reduce bed-blocking can crowd-out agents' intrinsic motivation and end up being counterproductive. Because the acute and LTC settings are organized and funded separately in many countries (Siciliani, 2014), coordination difficulties across the two settings are likely to occur (Cebul et al., 2008). The role of coordination difficulties in perpetuating bed-blocking has been studied by Fernandez et al. (2018). Drawing on (Kellogg, 2011), I propose an alternative, albeit complementary mechanism based on the accumulation of relationship-specific experience between hospitals and regional teams responsible for finding vacancies in the LTC Network. My findings suggest that only the pairs with the largest number of interactions are able to accumulate a level of experience that allows for meaningful reductions in the length of stay of bed-blockers. This can explain why previous literature has found that larger hospitals, with a high number of admissions, seem to manage discharges more efficiently and thus 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 has focused on interactions between the acute care and LTC settings (i.e. 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 LTC and post-acute sectors as a source of inefficiency in the healthcare system. My paper takes a diametrically opposed stand, suggesting that LTC provision might be a way to reduce inefficiencies associated with bed-blocking in the acute-care setting. In particular, my baseline estimates suggest that LTC provision generates a 28% reduction in annual bed-blocking costs incurred by hospitals.

The remainder of this paper is organized as follows. Section 2 provides institutional background on the Portuguese hospital and LTC settings. Section 3 describes the data used in the analysis. Section 4 describes my 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 System (SNS). The SNS is predominantly financed through general taxation and access to care that is mostly free at the point of use (Simões et al., 2017).
Inpatient care provided by hospitals belonging to the SNS is paid via Diagnosis-Related Groups (DRGs). A DRG groups patients who have similar consumption of resources based on their medical diagnosis, treatment received, and demographic profile. There are over 600 distinct groups in the current DRG system and each has an associated price. DRGs are used to set an annual prospective global budget for inpatient care provided by each hospital, which amounts to 75-85% of total inpatient revenues of SNS hospitals (Mateus, 2011).

Overall, hospitals have no financial incentives 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 lengths 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 the days in excess of the trim point is not. Trim-points and daily amounts were updated by the government at several points during my study-period.

2.2 Long-term care

Long-term care is care needed by individuals with some degree of dependency. It includes healthcare (i.e. rehabilitation after an acute care episode), personal care (i.e. personal hygiene), help with activities of daily living (i.e. housework, meals), and accommodation for individuals who cannot live independently (Siciliani, 2014; Norton, 2000). It can be provided either formally or informally. Formal long-term care is provided by trained personnel at the patient's home or at institutions such as nursing homes. Informal care is provided by relatives, friends, or neighbors.

Before 2006, formal LTC services were not within the scope of the SNS and individuals relied heavily on informal care. While LTC services could be purchased from private providers, namely non-profit religious institutions (*Misericórdias*) (Simões et al., 2017), their costs had to be paid for out of pocket, which took a financial toll on many users (Santana, 2010).

In 2006 the Portuguese government established the National Network for Long-Term Integrated Care (RNCCI, henceforth the Network), as a joint effort of the Ministry of Health

Table 1: Overview of the organization by the LTC Network

	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, hygiene, accommodation, etc.	Preventive care, help with ADLs, food, hygiene, medication, etc.

and the Ministry of Labor and Social Security (Decree-Law 101/2006). This was motivated by concerns regarding demographic, social, and epidemiological trends that put pressure on existing care arrangements, including increasing life expectancy and consequent rising share of elderly in the population, the decline of multi-generational households, and the increasing share of individuals living with multiple comorbidities. The Network was not aimed of reducing bed-blocking, which is a recent topic in the public debate.

The Network comprises two distinct settings of care provision: home and community-based services (HC) and nursing homes (NH). Table 1 provides an overview of these two settings, which are organized very differently. The NH setting operates in a model of public funding and private provision in which the government contracts with private providers, namely the *Misericórdias*, who had been active in care provision for several decades.[4][5] The services contracted include around-the-clock medical care, rehabilitation, accommodation, catering, 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 —these can be thought of as providing post-acute care. Other NH facilities have less intensive medical, nursing, and rehabilitation components, mainly catering to individuals

[4] *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 reduced upon the creation of the SNS in 1979, and most of these small hospitals were closed down.

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

with chronic illnesses and high functional dependency, who might need longer stays. Under the NH contracts the government pays providers an administratively set daily price for the care provided to individuals who are in the Network. The daily price is either fully paid or highly-subsidized by the government.

The HC setting operates in a model of public provision and public funding. The government established specialized teams in primary care centers that visit patients in their homes. HC teams provide services such as preventive care, help with activities of daily living, medication, personal hygiene, etc. They cater to individuals with dependency who need a lower frequency of medical and rehabilitation care and are still able to live in the community. Because HC teams belong to primary care centers, they fall under the SNS and are free of charge to users.

The contracting of NH teams started in 2006, whereas the first HC teams started operating only in 2008. Figure 1 shows the entry year of the first nursing home facility (on the left panel) and the first home-care team (on the right panel) across ACES regions. ACES is the Portuguese acronym for Primary Care Center Groups and these areas are relevant for organizing primary care delivery.[6] 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. It is important to understand the main determinants of the differential entry timing of the Network across regions. In the case of nursing homes, entry during the first 3-4 years 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 prior to the existence of the SNS, and had not yet been repurposed. As for home-care teams, entry timing was largely determined by the availability of human resources in the primary-care center that could be allocated to the new team.

Patients need a referral to access the Network. The referral can be made either by a hospital if they are hospitalized, or by their general practitioner if they live in the community. Because my analysis focuses on patients who are hospitalized I focus on the former channel, which amounts to 65-70% of the referrals to the Network 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 LTC Network. Upon referral, a local coordination team based in the ACES region where the patient lives validates the assessment made by the

[6]There are 55 ACES regions in Portugal. 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.

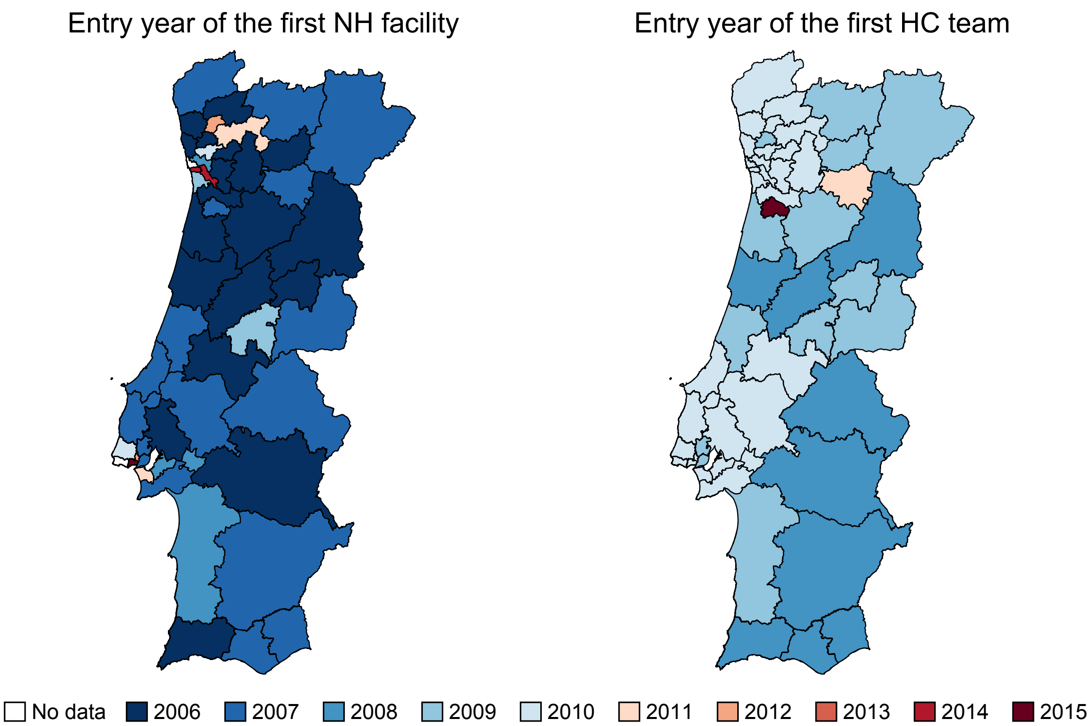


Figure 1: Entry year of the first NH unit and the first HC team across ACES regions

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 Network.

Overall, the implementation of the Network introduced two key changes to the Portuguese long-term care landscape that might reduce hospital bed-blocking. First, it increased the availability and affordability of long-term care by providing highly subsidized alternatives. Before 2006 individuals were easily priced out of the market. Second, it created an integrated platform where different levels of health and social services can coordinate. Before 2006 individuals in need of care after a hospitalization needed to navigate the system themselves and look for a vacancy at an adequate facility, a classic case of care fragmentation (Cebul et al., 2008; Agha et al., 2019). This can be particularly challenging since individuals do not precisely know when they will be discharged or which type of care they might need.

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

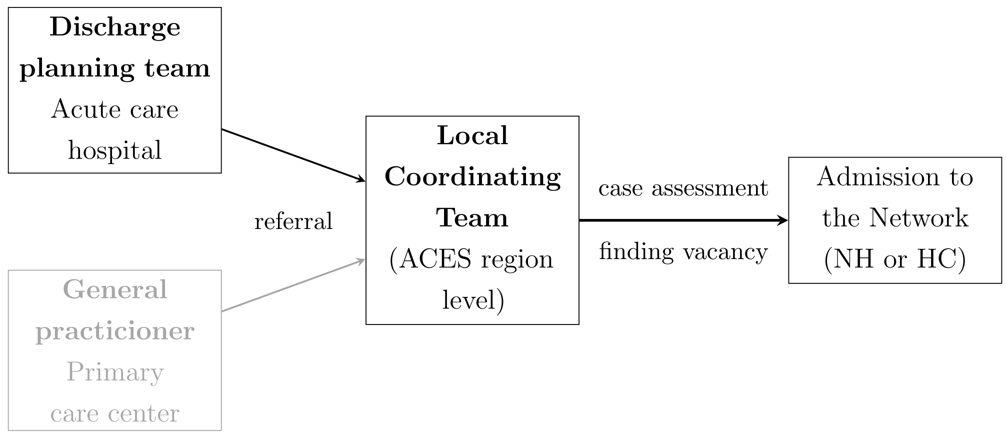


Figure 2: Process of admission to the Network

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 because, as opposed to programmed admissions, they are unpredictable.[7] 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. I exclude admissions into specialized hospitals[8] and admissions of individuals under 18 years old, thus focusing on adult patients admitted to general 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 in days of patient i, who lives in region m and is admitted to the hospital in month t. This measure can be seen as the sum of the length of appropriate stay at the hospital and the bed-blocking period.

I proxy bed-blockers 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 socioeconomic situation because these have been previously associated with long-term care use (Lopes et al., 2019; Diepstraten et al., 2020) and hospital bed-blocking (Costa et al., 2012; Bryan et al., 2006; McDonagh et al., 2000).[9] Information on social needs

[7]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, 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.

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

[9]The codes capturing 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`

is assessed by physicians, nurses, and social workers and added to the patient's file only when expected to affect the discharge process. This information is therefore only available for a subset of patients, who are believed to be at increased risk of experiencing delays in the discharge process. Importantly, the assessment of social needs is done at the hospital and it is independent of the assessment of LTC availability —assessing the availability of long-term care was never a responsibility of hospitals: prior to the LTC Network, patients had ot make their own LTC arrangements. After the introduction of the LTC Network, assessing the availability of an appropriate LTC provider is done by local coordination teams, who are responsible for finding a vacancy for the patient upon referral by the hospital.[10] To see how social factors can put patients at increased risk of bed-blocking, take two clinically identical patients who need help with activities of daily living, such as personal hygiene and meals, for some weeks following a hospital stay. One has a partner at home who can provide support 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.

I complement the inpatient dataset with monthly data on the roll-out of the long-term care network. For most of my analysis, I measure the availability of long-term care providers in the patient's region of residence using two binary indicators for months after the entry of the first nursing home and the first home-care team in the region. In robustness checks I use alternative treatment definitions, such as the monthly number of NH facilities and HC teams in the region and their capacity.

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

Throughout the empirical analysis, I control for patient demographics, comorbidities, DRG group, admission month, 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 in place at a certain point

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 socioeconomic 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 LTC needs (i.e. legal matters), or associated with services and populations outside of the scope of the Network (i.e. mental health, children).

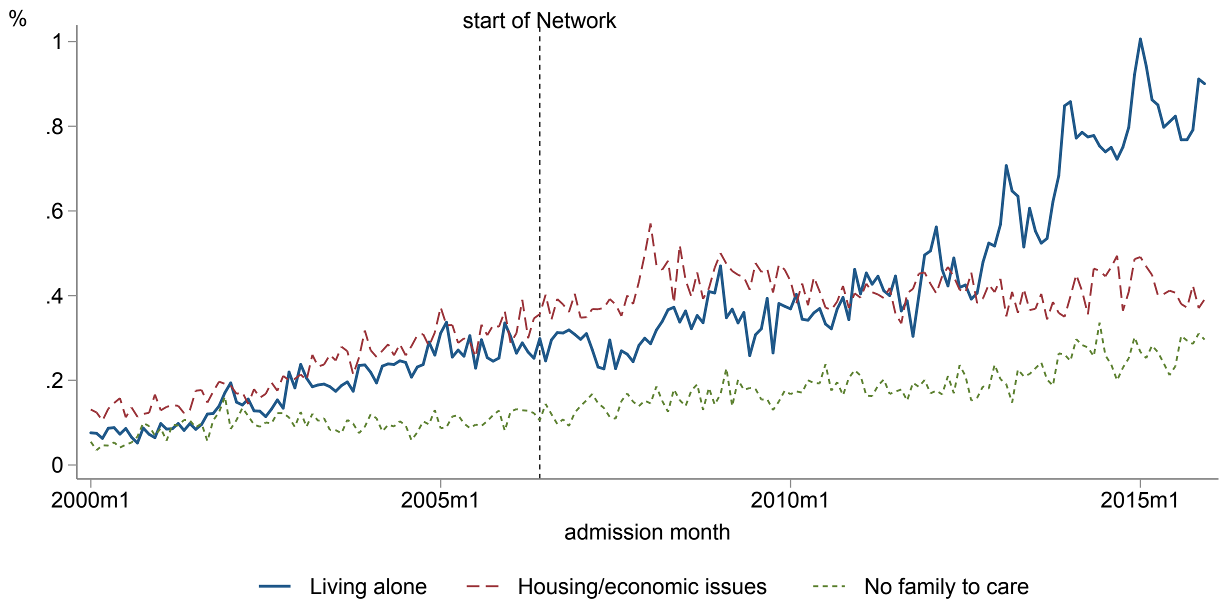
[10] In robustness checks I show that the coding of the social factors used to identify bed-blockers is, indeed, not affected by the entry of LTC providers.

in time. I collected this data from the laws passed by the Government.[11]

3.2 Summary Statistics

Figure 3 shows the frequency of monthly emergency admissions in each of the three categories of patients at increased risk of bed-blocking over my study-period. Despite the upward trend over time, each of these categories 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.

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 Network. Entry of nursing homes and home-care teams occurred in a staggered way after the start of the Network.

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

[11]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.

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
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
Charlson score	1.2	1.9	1.9	2.1	2.2	2.5	2.0	2.4
Charlson Comorbidities (%):								
AMI	3.9	19.5	5.0	21.7	3.0	17.1	2.9	16.6
Heart failure	11.1	31.4	22.2	41.5	13.2	33.8	12.4	32.9
Stroke	11.5	31.9	21.5	41.1	29.6	45.6	21.1	40.8
Dementia	2.5	15.7	6.5	24.7	10.4	30.5	6.8	25.2
COPD	7.8	26.8	14.6	35.4	8.9	28.5	11.1	31.4
Diabetes	13.1	33.8	19.4	39.6	18.0	38.4	15.1	35.8
Renal Disease	6.2	24.1	10.6	30.8	8.8	28.3	6.4	24.5
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; AMI: acute myocardial infarction; COPD: chronic obstructive pulmonary disease.

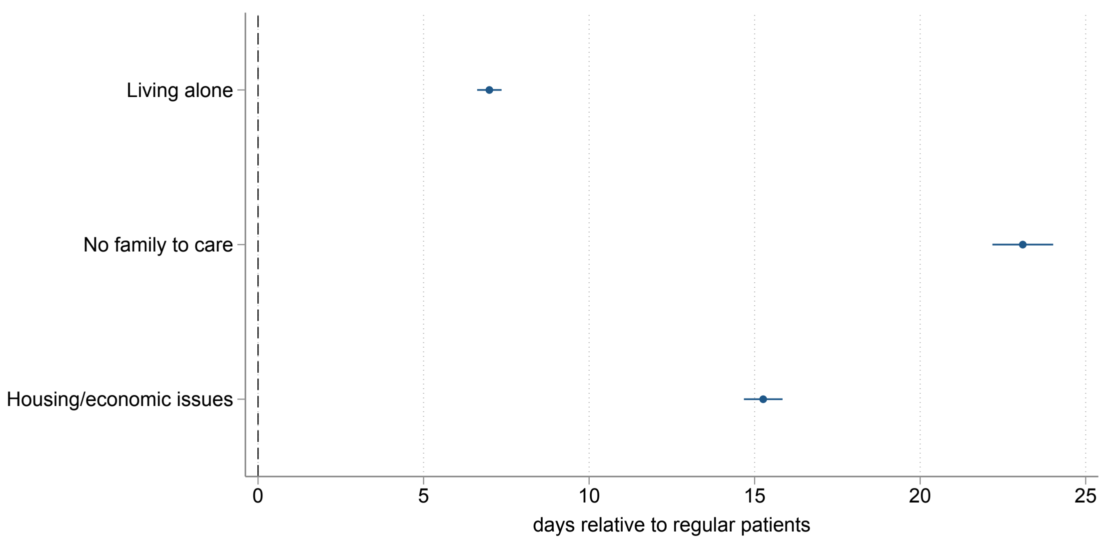
To understand whether risk factors such as living alone, having no family to care, and having inadequate housing and other economic difficulties are associated with longer lengths of stay after controlling for differences in demographics, medical diagnoses, and comorbidities, I estimate the following equation:

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

where i, d, h, and t index the patient, their DRG group, the hospital they are admitted to, and the admission month, respectively. The dependent variable y_{it} is the length of stay of the episode in days. BB_i is a vector containing three binary indicators for each potential bed-blocking category: 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, and admission month fixed effects,[12] and ε_{it} is an error term. Vector β contains the parameters of interest, which measure the additional length of stay of each potential bed-blocking category relative to regular patients throughout my study-period.

Figure 4 shows the estimates of β from equation (1) and their 95% confidence intervals. Bed-blockers have lengths of stay considerably longer than regular patients, even after controlling for demographics, comorbidities, DRG group, admission month, and hospital of admission. For example, individuals living alone have hospital stays that are, on average, a week longer than regular patients. Individuals with inadequate housing and other economic issues stay at the hospital, on average, two weeks longer than regular patients. Individuals with no family to care have stays that are, on average, 23 days longer than regular patients. Overall, I conclude that these factors are associated with longer lengths of stay and appropriately identify 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 LTC providers in a region.

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, diagnosis-related group, and hospital fixed-effects. The sample consists on 7,950,636 emergency inpatient episodes between the years 2000 and 2015.

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

4 Empirical Strategy

4.1 Baseline Model

My main empirical specification is a triple-differences model comparing the length of stay of each of the bed-blocking categories and the length of stay of regular patients, before and after the entry of nursing homes and home-care teams in a region. I estimate:

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

where i, d, and t index the patient, their DRG group, and the month of hospital admission, and m indexes the region where the patient lives. The dependent variable is the length of stay (in days) of patient i admitted in calendar month t. $PostNH_{mt}$ 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.[13]

The estimates of interest are contained in α_1 to α_5. More precisely, the estimates of α_1 are informative about the differences in length of stay between bed-blockers and regular patients, prior to the entry of LTC providers 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. Because regular patients are not at risk of bed-blocking, their length of stay should not change upon the entry of long-term care providers in a region. I therefore expect these estimates to be zero. 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 home-care teams and nursing home facilities, the estimates of α_2 to α_5 are informative about the effect of having *at least one* home-care team and one nursing home in the region of residence on lengths of stay. Additionally, because I do not observe individual take-up of the services provided by the LTC Network, the estimates have an intent-to-treat flair.

One feature of my specification is that it includes both bed-blockers and regular patients. Regular patients help 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 lengths of stay for all patients due to some unobserved factor. Then, estimating the model among bed-blockers only

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

(thus only exploiting variation in treatment timing) would result in overestimating the effect of the HC team. Additionally, because there are relatively few bed-blockers in the sample, the inclusion of regular patients increases the precision of the estimates of the covariates included in the model.[14,15]

The inclusion of DRG fixed-effects, λ_d, is also worth of discussion. Note that 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 lengths of appropriate stay. Including DRG fixed-effects in the estimation therefore captures 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 any 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.

4.2 Model assumptions

The core identifying assumption of my triple-differences design is that, in the absence of the entry of long-term care providers, any trends in lengths of stay of both the groups of bed-blockers and regular patients would, in expectation, have been similar across regions. This is the so-called parallel trend assumption. Formally:

$$\mathbb{E}[Y^0_{i,Post(m)} - Y^0_{i,Pre(m)} \mid BB_i = 1, Z_{it} = z] = \mathbb{E}[Y^0_{i,Post(m)} - Y^0_{i,Pre(m)} \mid BB_i = 0, Z_{it} = z], \quad (3)$$

where Z_{it} denotes a vector of all the covariates included in equation (2) and z denotes its realization. $Y^0_{i,Pre(m)}$ denotes the potential outcome of patient i in the absence of the entry of long-term care providers in his region of residence, in the periods prior to the entry of LTC providers —this is observed. In turn, $Y^0_{i,Post(m)}$ denotes the potential outcome of patient i in the absence of the entry of long-term care providers in his region of residence, in periods after the entry of LTC providers in the region. The parallel trend assumption is untestable because I do not know what lengths of stay would have evolved, had long-term care providers

[14]My main empirical specification is similar to the triple-difference models in Berger et al. (2018); Bitler and Carpenter (2016), and Chari et al. (2019), among others. It differs in that I have two distinct treatments.

[15]Table B.1 in the Appendix, shows results from a specification that only exploits variation in treatment timing, therefore excluding regular patients from the analysis.

not entered a region: $Y^0_{i,Post(m)}$ is unobserved. Instead, I observe the *actual* lengths of stay after the entry of LTC providers in a region, $Y^1_{i,Post(m)}$. In the notation of equation (2), $\mathbb{E}[Y^1_{i,Post(m)} - Y^0_{i,Pre(m)} \mid BB_i = 1, Z = z] = \alpha_2 + \alpha_3$ and $\mathbb{E}[Y^1_{i,Post(m)} - Y^0_{i,Pre(m)} \mid BB_i = 0, Z = z] = \alpha_2$ when the treatment is the entry of home-care teams in a region. Similarly, $\mathbb{E}[Y^1_{i,Post(m)} - Y^0_{i,Pre(m)} \mid BB_i = 1, Z = z] = \alpha_4 + \alpha_5$ and $\mathbb{E}[Y^1_{i,Post(m)} - Y^0_{i,Pre(m)} \mid BB_i = 0, Z = z] = \alpha_4$ when the treatment is the entry of nursing homes in a region. To inform about the plausibility of the parallel trends 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 first HC team in a region. The event-study framework allows the effect of the entry of nursing homes and home-care teams on the length of stay of bed-blockers and regular patients to vary over time. I estimate the following event-study equation separately for each event:

$$y_{it} = \theta_r^{bb} BB_i f(r) + \theta_r f(r) + \theta BB_i + \delta X_i + \lambda_d + \lambda_m + \lambda_t + \varepsilon_{it}, \tag{4}$$

$$f(r) = \begin{cases} 1 & \text{if } r < -5 \\ I_r & \text{if } -5 \geq r \leq 5 \\ 1 & \text{if } r > 5 \end{cases}$$

, where 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 a five-year event-window ($I_{-5}, I_{-4}, ..., I_5$), a binary indicator for relative years prior to the event-window ($r < -5$), and a binary indicator for relative years after the event-window ($r > 5$). That is, I assume that outside of the five-year 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 just 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^{bb}. The estimates of θ_r capture the evolution of the length of stay of regular patients in the years around the event. I expect these estimates to be zero because the length of stay of regular patient should be unaffected by the entry of long-term care providers.

The estimates contained in θ_r^{bb}, in turn, convey the evolution of the length of stay differential between bed-blockers and regular patients around the event. Since I normalize $f(-1) = 0$, the common trend assumption requires the estimates of θ_r^{bb} 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 long-term care providers in a region, confirming the plausibility of the common trend assumption in my setting.

Equation (4) is estimated 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 equation for the entry of the first NH, I add to the regressors an indicator variable controlling for the presence of HC teams in the region. When estimating the event-study equation for the entry of the first HC, I control for the presence of NH units in the region in a similar way.

There is also a concern about compositional changes to the groups of bed-blockers and regular patients. These could originate from changes in the way hospitals code the social factors I use to identify bed-blockers if, for example, the coding of these factors became more salient due to the roll-out of the Network. I test for such compositional changes by examining whether there were any changes in the coding frequency of each of the three bed-blocking categories following the entry of HC teams and NH providers in a region. Specifically, I estimate the following equation:

$$BB_i^j = \rho_1 PostHC_{mt} + \rho_2 PostNH_{mt} + \lambda_m + \lambda_t + \epsilon_i, \tag{5}$$

where BB_i^j is a binary indicator for individual i being coded in bed-blocking category j (that is, BB_i^j is one of the three components of BB_i) and all remaining notation has been previously defined. The estimates of interest are those of ρ_1 and ρ_2, which capture the change in the frequency of patients coded in category j upon the entry of home-care teams and nursing homes in a region, respectively. Obtaining both statistically and economically insignificant estimates for these two parameters would reassure that coding behavior is not affected by the presence of HC teams and NH providers in a region. I estimate equation (5) separately for each of the three groups of bed-blockers. I alternatively assume that the error term follows a normal distribution and a logistic distribution.

5 Results

I now present the results. Section 5.1 presents the baseline results. Section 5.2 investigates the plausibility of the modeling assumptions and reports the results of additional robustness checks. Section 5.3 presents the results of the heterogeneity analysis, Section 5.4 examines the impact on treatment received while at the hospital and Section 5.5 examines the impact of LTC entry on hospital readmissions. Section 5.6 assesses the impact on hospital costs and Section 5.7 assesses the impact on programmed hospital activity.

5.1 Baseline Results

Figure 5 shows the estimates of interest from equation (2) and their corresponding 95% confidence intervals. The top estimates correspond to α_1, the three indicators for each bed-blocking category. They convey sizable length of stay differences between each type of bed-blocker and regular patients prior to the entry of home-care teams and nursing homes in a region. The second block of estimates corresponds to α_2 and α_4, the two indicators for periods after the entry of home-care teams and nursing homes in a region. These effects are precisely estimated at zero, meaning that the entry of NH and HC providers 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 bed-blocking category and the indicator for periods after the entry of home-care 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 this 4-day length of stay reductions do not fully eliminate the difference in lengths 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 category and the indicator for periods after the entry of nursing homes in a region. These estimates are statistically insignificant.

5.2 Robustness checks

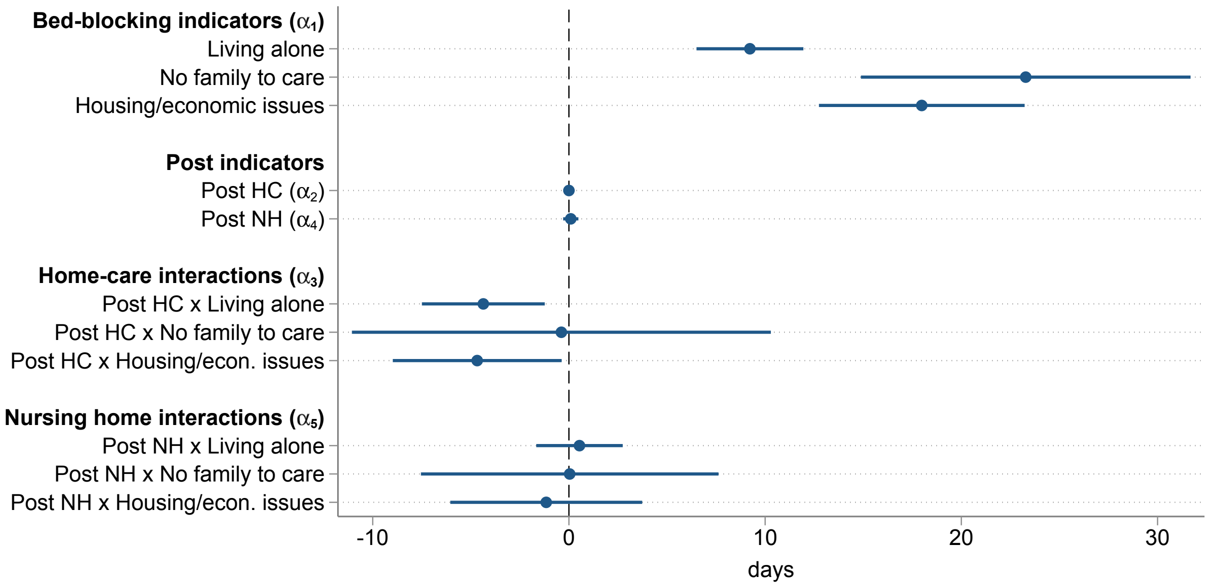
Section 5.2.1 elaborates on the plausibility of the model assumptions. It shows that (i) my baseline results are not typically driven by pre-treatment trends; (ii) the entry timing of the first NH and HC team in a region is unrelated with the share of bed-blockers originating from that region; and (iii) hospitals did not change the coding frequency of the factors used to identify bed-blockers upon the entry of LTC providers.

Section 5.2.2 shows that my baseline results do not depend on the choice of relevant region, outcome variable, and model specification.

5.2.1 Model assumptions

To examine pre-treatment trends, I estimate the event-study specification in equation (4). I report the event-study results in Figures 6 and 7, 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 categories and regular

Figure 5: Estimates of α_1 to α_5 from equation (2)



NOTES: The figure shows the estimates of α_1 to α_5 from equation (2) and their corresponding 95% confidence intervals. The dependent variable is the length of stay in days. The model includes individual demographics and comorbidities, and admission month, DRG, and region (ACES) fixed-effects. The sample excludes admissions in the entry month of the first NH and HC team in a region, amounting to 7,868,350 observations. Standard errors are heteroskedasticy-robust and clustered at the region level.

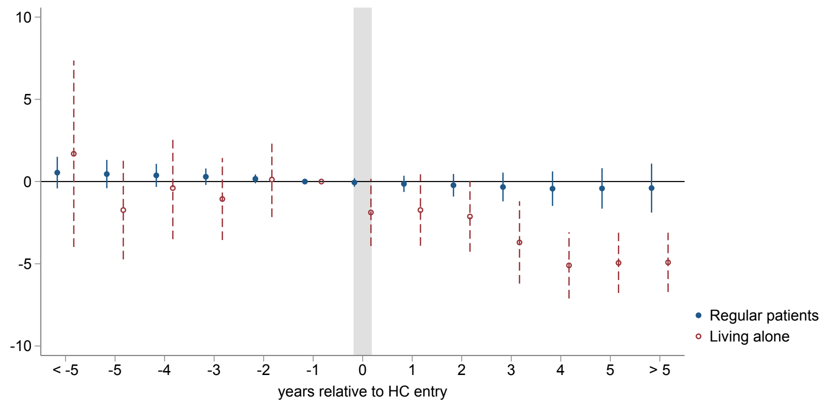
patients around the relevant event. Each panel plots the estimates of θ_r for regular patients (full circles) and θ_r^{bb} for each type of bed-blocking (hollow circles) from equation (4) and the corresponding 95% confidence intervals. The scale on the vertical axis differs across plots.

The event-study specification is informative about pre-treatment trends in lengths 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, as expected. In most of the event-study plots the estimates of θ_r^{bb} for years prior to the entry of the first long-term care provider in a region are not statistically significant, supporting the plausibility of the parallel trend assumption.[16] The exception is panel (b) in Figure 6, which shows an increasing trend in the length of stay of individuals with no family to care relative to regular patients prior to the entry of the first

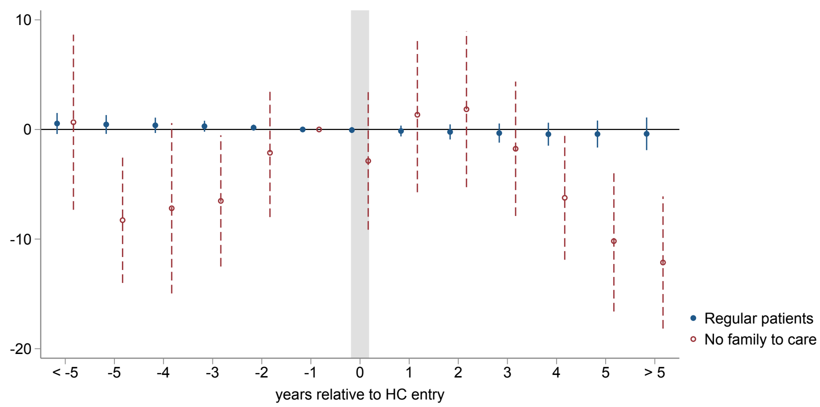
[16]More precisely, the joint significance of the pre-treatment estimates can be assessed with an F-test. For individuals living alone, one cannot reject the hypothesis that these estimates are jointly insignificant (the corresponding p-values are 0.6677 and 0.5827, respectively, for periods prior to the entry of the first HC team and the first NH in a region). For individuals with no family to care, the estimates for periods prior to the entry of the first HC team are jointly significant (p-value=0.000), but those for periods prior to the entry of the first NH are not (p-value=0.2536). Finally, for individuals with inadequate housing, the F-test on the joint significance of the estimates for periods prior to the entry of the first HC team and the first NH has p-values equal to 0.0249 and 0.0584, respectively. These relatively low p-values are driven by the earliest pre-treatment periods (relative year -5 and earlier). Excluding those early periods yields p-values of 0.1620 and 0.8455, respectively for periods prior to the entry of the first HC team and the first NH.

HC team in a region. 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, in turn, shows that the increasing trend in the length of stay of individuals with no family to care relative to regular patients is inverted upon the entry of home-care teams in a region.

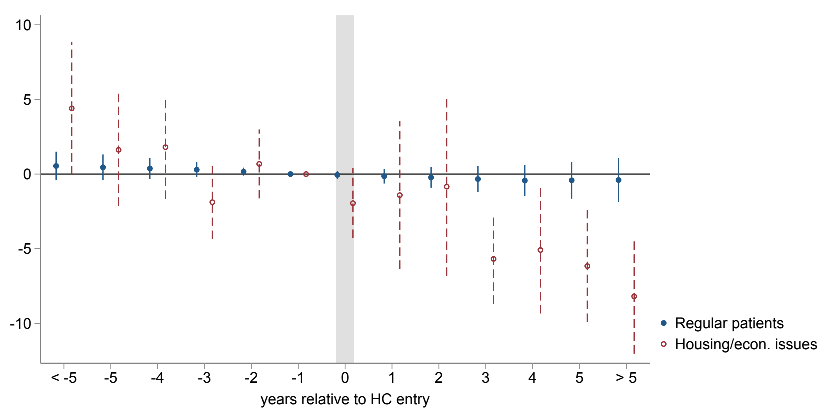
Overall, the baseline model and the event-study convey similar results. While the entry of HC teams leads to reductions of about 5 days in the length of stay for individuals living alone and those with housing issues, the entry of nursing homes does not lead to reductions in length of stay for the average bed-blocker. The event-study plots show, however, that the length of stay reductions experienced by bed-blockers take some time to materialize and do not occur immediately after the entry of the first HC team. I will return to this issue in Section 6.



(a) Living alone



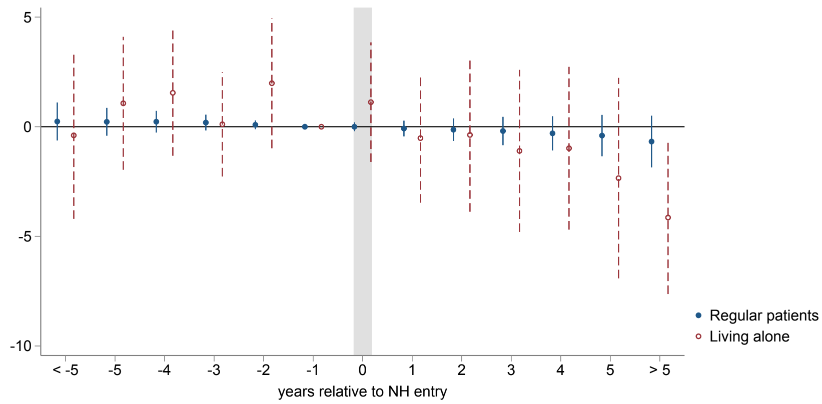
(b) No family to care



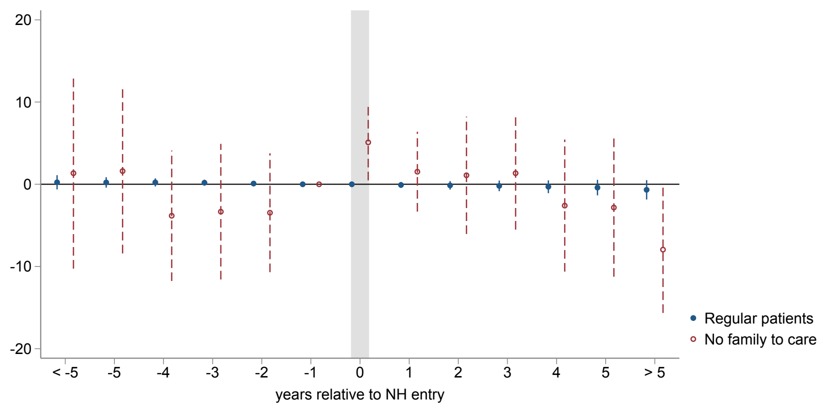
(c) Housing/economic issues

Figure 6: Event-study results for HC entry

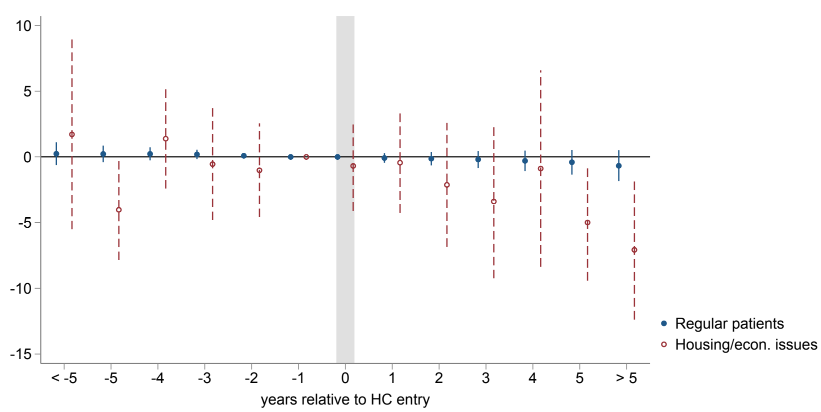
NOTES: Each panel plots the estimates of θ_r and θ_r^{bb} from equation (4) and the corresponding 95% confidence intervals for a specific group of patients in the sample. In each panel, the vertical axis is the length of stay in days and the horizontal axis is time in years relative to the entry of the first home-care team in a region. The coefficient on the year just before entry was normalized to zero. The model includes individual demographics and comorbidities, indicators for type of bed-blocking, and admission month, 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 7: Event-study results for NH entry

NOTES: Each panel plots the estimates of θ_r and θ_r^{bb} from equation (4) 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 coefficient on the year just before entry was normalized to zero. The model includes individual demographics and comorbidities, admission month, diagnosis-related group, and region (ACES) fixed-effects, indicators for each type of bed-blocking, relative year fixed-effects, and a binary indicator for the presence of a home-care team at the time of admission.

While applied researchers often take the presence of pre-trends as evidence against the exogeneity of a treatment, absence of pre-trends does not ensure exogeneity holds because there might simply not be enough power to detect statistically significant pre-trends (Freyaldenhoven et al., 2019). To rule out concerns about endogeneity of treatment timing, panel (a) of Figure 8 plots the percentage of bed-blockers out of the total number of emergency inpatient admissions originating from each ACES region in 2005 (the year prior to the introduction of the Network) against the entry month of the first NH and HC team in that region. Panel (b) of Figure 8 plots the average 2005 occupancy rate of the modal hospital visited by patients living in a region against the entry month of the first NH and HC team in that region. The plots convey no relationship between treatment timing and the percentage of bed-blockers or the capacity constraints of the hospital, supporting the plausible exogeneity of treatment timing.

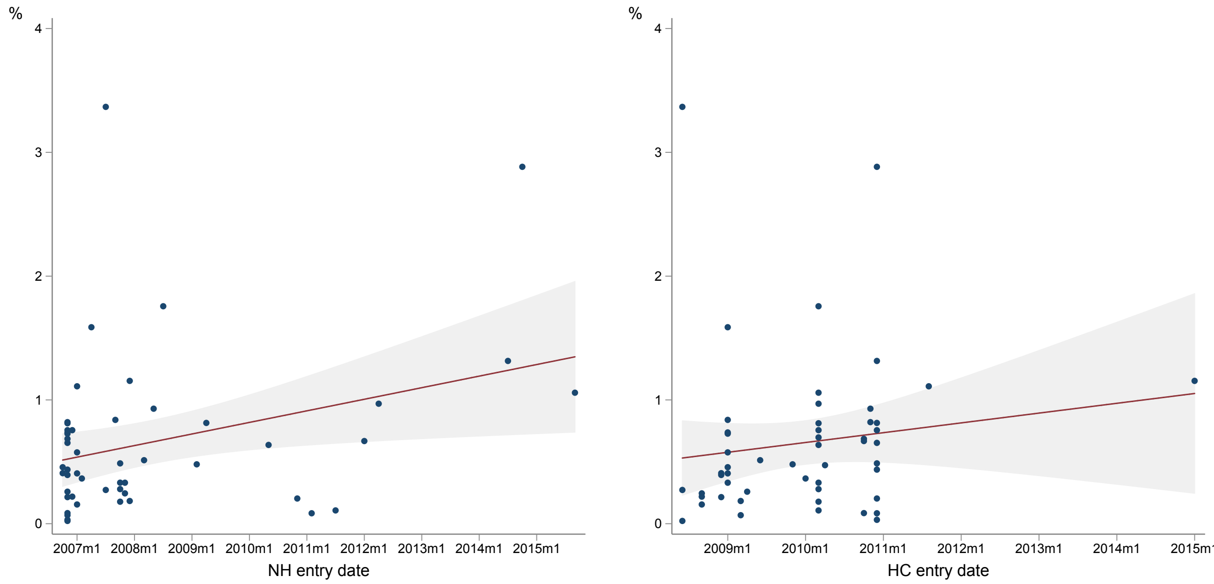
Table 3 reports the results from equation (5), assessing changes in the coding of the risk-factors used to identify bed-blockers after the entry of HC teams and NH providers in a region. The left panel shows OLS estimates. The right panel shows marginal effects after logit, evaluated at the mean of the independent variables. None of the estimates are statistically or economically significant, indicating no clear association between the entry of LTC providers 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 LTC providers, but rather reflects social and demographic changes.

Table 3: Results from estimating equation (5)

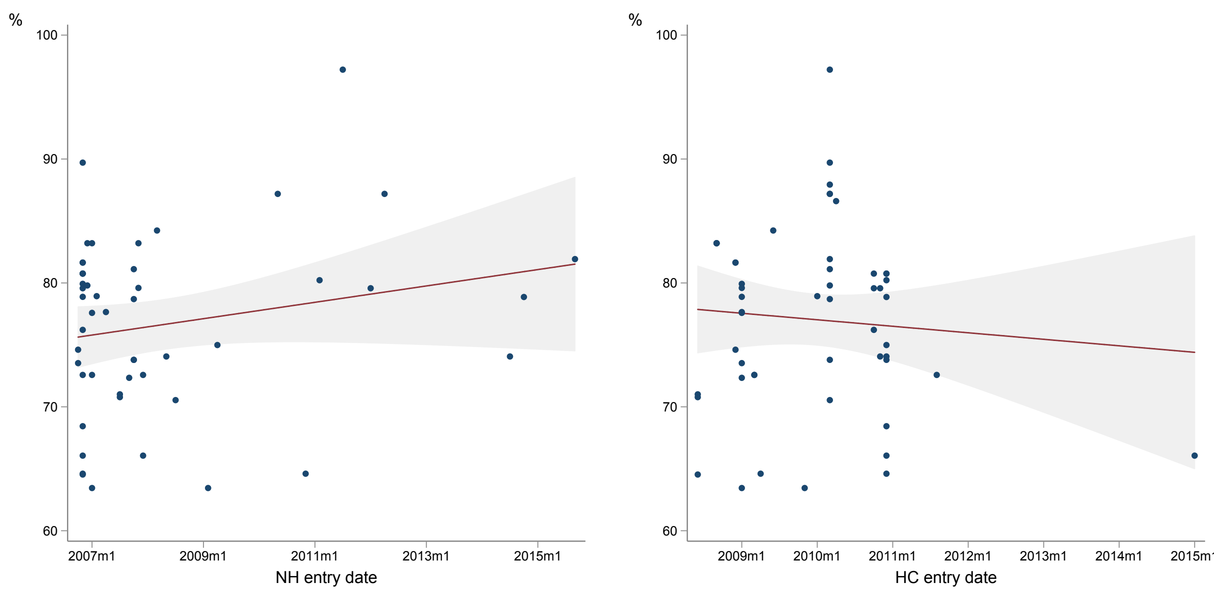
	OLS			Logit		
	(1) Living alone	(2) No family to care	(3) Housing/econ. issues	(4) Living alone	(5) No family to care	(6) Housing/econ. issues
Post HC (ρ_1)	0.0010	0.0000	0.0003	0.0006	-0.0001	0.0001
	(0.0006)	(0.0003)	(0.0005)	(0.0004)	(0.0002)	(0.0003)
Post NH (ρ_2)	-0.0000	0.0001	-0.0005	0.0005	0.0001	-0.0001
	(0.0009)	(0.0003)	(0.0006)	(0.0005)	(0.0002)	(0.0003)
Observations	7,830,074	7,813,746	7,828,255	7,697,852	7,681,524	7,696,033
(Pseudo-)R^2	0.004	0.001	0.002	0.073	0.045	0.045

NOTES: The table shows the estimates of ρ_1 and ρ_2 from equation (5). 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 category stated in the column title and those not classified in any category (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 and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 8: Exogeneity of treatment timing



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



(b) With respect to the occupation 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 panel) and home-care team (right panel) in the region. The figures in the bottom panel plot the average occupation 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. The sample consists in all 516,003 hospital admissions in year 2005.

5.2.2 Alternative model specifications and variable definitions

For convenience, column 1 of Table 4 reproduces the baseline results. As robustness checks to the baseline model specification, I alternatively replace the region and month fixed-effects with region-month fixed-effects in column 2 and region-specific time trends in column 3. Column 4 adds hospital fixed-effects to the baseline specification. The results are unchanged.

Because 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.[17] Columns 4 and 5 in Table 4 show that these alternative region definitions yield similar results to the baseline specification.

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. Table A.2 in the Appendix shows 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 lengths of stay beyond their DRG trim-point.

Finally, a recent literature in econometrics highlights challenges in difference-in-differences designs that exploit staggered treatments. Goodman-Bacon (2018) shows that the estimate recovered in those cases is a weighted average of all underlying two-by-two difference-in-differences estimates. Because weights can be negative, even if all underlying two-by-two effects are positive, they might be aggregated in a negative effect. To the best of my knowledge, no extension of these concepts to triple-differences designs exists yet. Table B.2 in the Appendix shows the results from estimating my baseline model separately among regions treated in different years, therefore limiting the variation in treatment timing. While statistical significance is lost in a few cases, the direction and magnitude of the results obtained are very much in line with my baseline results, suggesting issues related to staggered treatment timing to be limited in my setting.

5.2.3 Elasticities

Different regions experienced different intensities of entry of nursing homes and home-care teams at distinct speeds. To exploit these additional sources of variation, I define two alternative continuous measures of treatment intensity: the monthly number of home-care teams and nursing home units operating in region m and the monthly number of places in home-care teams and beds in nursing home facilities in region m. This is a fundamentally

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

Table 4: Robustness checks to the baseline estimation of equation (2)

	(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)
Post indicators (α_2 **and** α_4)						
Post HC	0.003		-0.006	-0.001	-0.016	0.028
	(0.105)		(0.094)	(0.106)	(0.070)	(0.076)
Post NH	0.095		0.046	0.086	0.023	0.010
	(0.193)		(0.092)	(0.194)	(0.077)	(0.076)
HC interactions (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)
NH interactions (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, 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

distinct exercise from the baseline analysis: while the baseline analysis quantifies the effect of having *at least one* HC team or NH provider 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. To interpret the results as (an approximation of) elasticities, I take the natural logarithm (+1) of length of stay as well as the of treatment intensity variables.

Table A.3 in the Appendix shows the results. In general, the estimated elasticities are very small. A 10% increase in the number of available spots in home-care teams (about 10 spots) would reduce the length of stay of individuals living alone by only 0.3%. A 20% increase in the number of HC teams in a region (1 additional team) would reduce the length of stay of individuals living alone and those with inadequate housing by 1.6% and 1.5%, respectively. These results suggest that the increased number of LTC providers over time is unlikely to be the main driver of the finding (conveyed by the event-study plots in Figure 6) that reductions in the length of stay of bed-blockers do not occur immediately after the entry of the first home-care team, but rather take time to materialize.

5.3 Heterogeneity analysis

While the baseline results convey no reductions in the length of stay of bed-blockers following the entry of nursing homes in a region, that might simply be reflecting the fact that nursing homes cater to patients with high care needs and the average bed-blocker might not need a nursing home —the most common admission diagnoses among bed-blockers are respiratory illnesses, such as pneumonia and acute bronchitis, whose post-acute recovery usually involves resting and avoiding heavy tasks. To study this hypothesis, I estimate the baseline model among different patient groups. Specifically, I restrict the sample to individuals admitted 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 5 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 nursing homes in their region. This supports the hypothesis that nursing homes cater to patients with high care needs.[18] The results for the remaining patient groups are in line with the baseline results.

[18]Patients undergoing hip surgery also often need nursing home care after their hospital stay. However, most of these procedures are scheduled and thus do not show up in my emergency inpatient admissions.

Table 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)
Post indicators (α_2 and α_4)					
Post HC	0.003	-0.294	0.162	0.078	-0.008
	(0.105)	(0.258)	(0.171)	(0.148)	(0.160)
Post NH	0.095	0.337	0.403	-0.016	0.298
	(0.193)	(0.557)	(0.257)	(0.176)	(0.281)
HC interactions (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)
NH interactions (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, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

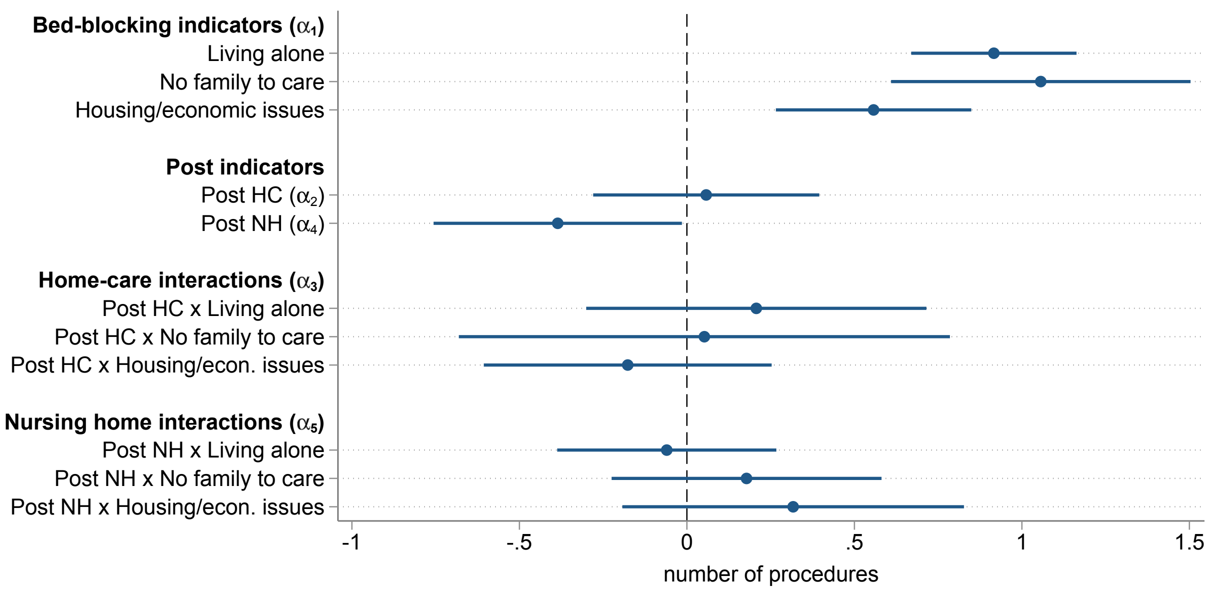
5.4 Impact on treatment received

One concern is that the reductions in the length of stay of bed-blockers might be accompanied by changes 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 (see for example Kleiner (2019)).

Figure 9 shows the results. Its two bottom panels convey that, despite reducing the length of stay of bed-blockers, the entry of LTC providers does not affect the intensity of care they received at the hospital. This finding is consistent with the idea that the longer lengths of stay of bed-blockers are unnecessary and do not entail any meaningful care provision.

Additionally, the first panel of Figure 9 conveys that even after controlling for demographics, comorbidities, and detailed information on 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 LTC providers). A more intensive treatment might require a longer stay. This can be one reason why the difference in lengths of stay between bed-blockers and regular patients is reduced albeit not fully eliminated upon the entry of LTC providers in a region.

Figure 9: Impact of LTC entry on intensity of care received



NOTES: The figure shows the estimates of α_1 to α_5 from equation (2) and their corresponding 95% confidence intervals using the number of procedures received by patient i during his hospital stay as dependent variable. The model includes individual demographics and comorbidities, and admission month, DRG, and region (ACES) fixed-effects. The sample excludes admissions in the entry month of the first NH and HC in a region, amounting to 7,865,898 observations. Standard errors are heteroskedasticy-robust and clustered at the region level.

5.5 Impact on hospital readmissions

The reductions in the length of stay of bed-blockers following the entry of LTC providers in a region might also impact their consumption of acute care in the future. On the one hand, if these individuals have now a form of support outside of the hospital, they might be able to better manage their condition without needing inpatient care thus avoiding a readmission. On the other hand, if their longer stay at the hospital was beneficial in some way that is not captured by the number of procedures, then reducing lengths 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 for perfectly following patients across years and across hospitals. In this analysis I therefore focus on readmissions to the same hospital, within 30 and 60 days of the discharge date. To make sure I capture admissions within the same calendar year, I remove admissions in December of each year when looking at the likelihood of readmission within 30 days. Similarly, I remove admissions between October and December when looking at the likelihood of readmission within 60 days. I estimate the model using OLS.

Table 6 shows the results. Columns 1 and 3 shows the results for changes in the probability of readmission upon the entry of nursing homes and home-care teams in a region. Columns 2 and 4 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. Overall, all columns convey a the same finding. If anything, the entry of LTC providers is associated with a reduction in the probability of readmission. The statistically significant effects have a rather large magnitude, given the mean values of the dependent variable. For example, the entry of home-care teams reduce the likelihood of readmission within 30 days for individuals with no family to care by 3pp., which amounts to a 35% reduction. But in most cases I cannot reject the null hypothesis that the entry of LTC providers had no effect on the likelihood of readmission.

Table 6: Results from estimating equation (2) among specific patient groups

	(1) Within 30 days	(2) Within 30 days, same DRG	(3) Within 60 days	(4) Within 60 days, same DRG
Bed-blocking indicators (α_1)				
Living alone	-0.003	-0.003*	-0.002	-0.003
	(0.003)	(0.002)	(0.004)	(0.002)
No family to care	0.015	0.005	0.021*	0.009
	(0.010)	(0.006)	(0.013)	(0.009)
Housing/econ. issues	0.024***	0.007**	0.035***	0.010**
	(0.004)	(0.003)	(0.006)	(0.004)
Post indicators (α_2 and α_4)				
Post HC	0.002	-0.000	0.002	-0.000
	(0.001)	(0.000)	(0.002)	(0.001)
Post NH	-0.000	0.000	-0.001	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)
HC interactions (α_3)				
Post HC × Living alone	-0.011**	0.001	-0.005	0.002
	(0.005)	(0.003)	(0.005)	(0.003)
Post HC × No family to care	-0.031**	-0.016**	-0.043**	-0.022**
	(0.013)	(0.008)	(0.018)	(0.010)
Post HC × Housing/econ. issues	0.005	0.003	0.005	0.004
	(0.006)	(0.003)	(0.009)	(0.004)
NH interactions (α_5)				
Post NH × Living alone	0.008	0.002	0.002	0.001
	(0.006)	(0.002)	(0.009)	(0.004)
Post NH × No family to care	0.012	0.009	0.020	0.011
	(0.014)	(0.007)	(0.018)	(0.008)
Post NH × Housing/econ. issues	-0.012*	-0.007**	-0.020**	-0.010**
	(0.006)	(0.003)	(0.008)	(0.004)
Mean of the dep. variable	0.088	0.020	0.125	0.028
Observations	7,216,328	7,216,328	5,919,920	5,919,920
R^2	0.079	0.052	0.102	0.060

NOTES: The table shows the estimates of α_1 to α_5 from equation (2) using binary indicators for readmission as dependent variable. In columns 1 and 3, the dependent variable is an indicator for readmission in the same hospital with 30 and 60 days, respectively. In columns 2 and 4, the dependent variable is an indicator for readmission in the same hospital and the same DRG with 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 1 and 2 excludes admissions in December and the sample in columns 3 and 4 excludes admissions in October-December. All models include individual demographics and comorbidities and admission month, DRG, and region (ACES) fixed-effects. Standard errors in parenthesis are heteroskedasticy-robust and clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.6 Cost savings

Computing the cost savings associated with the reductions in the length of stay of bed-blockers helps putting the baseline estimates into perspective. I do this analysis for the year 2015.

To assess the cost burden bed-blocking places on hospitals, I use the official estimate of the cost of one day in inpatient care, which is €230.[19] Absent the entry of long-term care providers, I estimate that the cost burden associated with the longer lengths of stay of bed-blockers relative to regular patients would have been €M22.9 in 2015. My baseline estimates imply that the entry of HC teams in a region reduces these costs by €M6.

The government transfers funds to compensate hospitals for the additional costs imposed by patients with lengths of stay beyond their DRG trim-point. The government thus bears part of the above cost burden. In 2015, the daily amount paid for lengths of stay beyond the corresponding DRG trim-point was €87.56. Absent the entry of long-term care providers, I estimate that the additional payments made to hospitals for the exceptionally long hospital stays of bed-blockers would have amounted to €M3.5 in 2015. The entry of HC teams in a region generates reductions in these payments to the extent that it reduces the length of stay of bed-blockers. These reductions are small, lowering the total amount transferred by the government by about €M1.

Overall, my baseline results imply that the entry of HC teams in a region reduced hospital costs (net of government transfers) associated with bed-blocking by €M5 (28%) in 2015, from €M19.5 (=22.9-3.5) to €M14.3 (=22.9-2.5-6).

From the perspective of the health system, the cost of providing long-term care services must be taken into account. No information on the cost of one day of home-care is available. Therefore, I value one day of home-care provision using the daily amount paid by the government to providers in the LTC Network for ambulatory services, which is €9.6 per day. If reductions in hospital lengths of stay are replaced one-to-one with home-care use, then my baseline estimates imply that the cost of home-care provision is €M0.26 in 2015. This barely affects my savings estimate. More generally, the €M6 savings estimate can be seen as an upper bound for the costs associated with home-care provision to be desirable from a budgetary viewpoint: as long as the costs of home-care provision are below €M6, some savings are generated.

[19]The official figure taken from ACSS (2007) is €219 and corresponds to 2007, the last year for which cost estimates are available. I use the consumer price index for the healthcare sector to update the cost of one day in inpatient care to 2015 euros. I acknowledge that this figure might be overestimating to some extent the costs bed-blocking imposes on hospitals because a bed-blocking day likely involves lower costs than a day of an average patient who is still receiving acute medical care. But this is the best cost estimate available.

5.7 Impact on programmed activity

The 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 programmed admissions 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 resources freed up by bed-blockers can be devoted to programmed admissions. To examine whether such reallocation of hospital activity occurs I make use of the full inpatient dataset, which includes both inpatient emergency and programmed admissions at public hospitals in Portugal. First, I estimate the following equation:

$$Programmed_{it} = \phi_1 PostHC_{mt} + \phi_2 PostNH_{mt} + \lambda_m + \lambda_t + \lambda_h + \varepsilon_{it} \tag{6}$$

, 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, and hospital fixed-effects. The estimates of ϕ_1 and ϕ_1 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 a region, respectively. Columns 1 and 2 of Table 7 show the estimates from equation (6) 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 following the entry of HC teams in a region.

To ensure that the increase in the share of programmed admissions is being driven by increases in the number of programmed admissions, I collapse my data at the the region-hospital-month level and estimate the following equation:

$$NumberAdm_{hmt} = \varphi_1 PostHC_{mt} + \varphi_2 PostNH_{mt} + \lambda_m + \lambda_t + \lambda_h + \varepsilon_{hmt} \tag{7}$$

, 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 the region, respectively.[20] Columns 3 and 4 of Table 7 show the results. 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

[20]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).

Table 7: Results from estimating equations (6) and (7)

	(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 (6) 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 (7). 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

that region. Consistent with the entry of nursing homes 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 LTC providers. Overall, these results suggest that hospitals devote the resources freed up by bed-blockers to programmed admissions.

6 Mechanisms: Relationship-specific experience

While my main results convey reductions in bed-blocking following the entry of long-term care providers, the event-study plots show that these take some time to materialize and bed-blocking is never fully eliminated. Fernandez et al. (2018) examine the role of coordination frictions between hospitals and local teams in perpetuating bed-blocking. They find that patients in hospitals that deal with a larger number of local teams experience more discharge delays and that hospital size helps mitigating this effect. Larger hospitals might, for example, be more efficient at managing the discharge process (De Volder et al., 2020). In this section, I study the accumulation of relationship-specific experience between a hospital and an ACES region, in the spirit of Kellogg (2011). This mechanism can potentially explain why the reductions in the length of stay of bed-blockers from my baseline analysis do not seem to take place immediately after the entry of the first LTC provider in the region.

The underlying idea is that a given hospital-region pair hm accumulates experience from dealing with bed-blockers that are residents of m and are admitted to hospital h. This pair-specific experience is built from frequent interactions between the discharge planning team at the hospital and the local coordinating team in the ACES region, which can foster teamwork and coordination.

Because a hospital admits patients originating from different regions, and the residents of a region can visit different hospitals, I can separate pair-specific experience from experience accumulated by hospital h dealing with bed-blockers from regions other than m; and experience accumulated by region m dealing with bed-blockers that visited hospitals other than h.

The experience accumulated by a hospital from interacting with regions other than m might, for example, contribute to a more timely identification of potential bed-blockers by the discharge planning team. In turn, the experience accumulated by a region from interacting with hospitals other than h might improve the coordination between the local coordinating team and LTC providers in the region, thus lowering times to find a vacancy for a patient. Accumulation of these types of experience might therefore also benefit patients living in region m who visit hospital h.

To understand the role of these three different types of experience in reducing the length of stay of bed-blockers, I estimate the following equation:

$$y_{it} = \mu_1 BB_i + \mu_2 g(Exp_{hm\tau}) + \mu_3 g(Exp_{hm\tau}) BB_i + \delta X_i + \gamma_d + \gamma_t + \gamma_{mh} + \varepsilon_{it} \tag{8}$$

, 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:

$$g(Exp_{hm\tau}) = \eta_1 Exp_{h\text{-}m\tau} + \eta_2 Exp_{\text{-}hm\tau} + \eta_3 Exp_{hm\tau} \tag{9}$$

, 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 dealing with hospitals other than m, and $Exp_{\text{-}hm\tau}$ is the experience accumulated by region m during period τ from dealing with hospitals other than h.

For this analysis, I restrict the sample to region-periods after the entry of the first provider affiliated with the LTC Network in a region (either a home-care team or a nursing home, whichever enters first). A relationship between a hospital-region pair hm starts at the moment when there is a bed-blocker originating from region m in hospital h. I measure the accumulated experience of 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 entire period between the episode of patient i and the entry of the first LTC provider in region m, the year preceding episode i, and the two-year period preceding episode i.

Table 8 shows the estimates from equation (8) corresponding to the impact of the accumulation of relationship-specific experience by hospital h and region m on the length of stay of bed-blockers relative to regular patients. First, relationship-specific experience does not affect the length of stay of regular patients. Second, there is a negative relationship between the accumulated, pair-specific experience and the length of stay of bed-blockers relative to regular patients. According to these estimates, relationship-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 flow of bed-blockers 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 relationship-specific experience accumulated by pairs at the top 10% of the experience distribution 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, recently accumulated experience seems no more relevant than total accumulated experience.

The full set of estimates from equation (8) is available in Table A.4 in the Appendix. Overall, these confirm the importance of relationship-specific experience relatively to other types of experience. Neither experience accumulated by hospital h from dealing with bed-blockers from regions other than m or experience accumulated by region m from dealing with bed-blockers from hospitals other than h show a clear association with reductions in the length of stay of bed-blockers. In some cases, they are even counterproductive and associated with increases in the length of stay of bed-blockers relative to regular patients.

Table 8: Results from estimating equation (8)

	(1) Total experience	(2) Last year	(3) Last 2 years
Relationship-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 (8) corresponding to the accumulation of relationship-specific experience. Column 1 considers experience accumulated since the entry of the first LTC provider in a region. Columns 2 and 3 consider experience accumulated during the 1 and 2 years preceding each episode, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

I analyze whether the entry of long-term care providers alleviates bed-blocking in Portuguese public hospitals. The bed-blockers in my sample are patients with a complex combination of health and social needs, who stay considerably longer at the hospital than regular patients. My empirical analysis relies on a triple-differences design comparing the length of stay of bed-blockers and the length of stay of regular patients, before and after the entry of the first nursing home and the first home-care team in a region.

My baseline results show that home-care teams are 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 home-care teams in their region of residence. The entry of nursing homes only reduces the length of stay of bed-blockers with high care needs, such as a those admitted with a stroke.

These results are robust to alternative model specifications and definitions of the outcome variables, the relevant region, and treatment variables. An event-study approach shows that these results are typically not driven by underlying pre-trends. I find no evidence of changes in the coding frequency of the factors used to identify bed-blockers after the entry of LTC providers in a region. The reductions in the length of stay of bed-blockers do not affect the intensity of care received while at the hospital and, if anything, LTC entry reduces the likelihood of a hospital readmission for bed-blockers. Finally, the reductions in the length of stay of bed-blockers seem to allow for increases in programmed activity, suggesting that the beds freed by bed-blockers are put to an alternative use.

My results also have important policy implications. If policy-makers aim at reducing bed-blocking, then the provision of home-care services is more effective than the opening of nursing home facilities. Indeed, the average bed-blocker does not seem to have sufficiently high care needs in order to benefit from nursing home care. Additionally, home-care teams are more flexible than nursing homes in that their capacity can be easily adjusted with respect to demand fluctuations. This is relevant for other countries where bed-blocking threatens the regular functioning of the health system.

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A Supplementary tables

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

	(1) Region and time FE	(2) Add DRG FE	(3) Baseline
Post indicators (α_2 and α_4)			
Post HC	-0.047	0.008	0.003
	(0.125)	(0.106)	(0.105)
Post NH	0.009	0.048	0.095
	(0.206)	(0.187)	(0.193)
HC interactions (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)
NH interactions (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 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 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)
Post indicators (α_2 and α_4)					
Post HC	0.003	0.000	0.001	-0.000	-0.001
	(0.105)	(0.005)	(0.004)	(0.002)	(0.001)
Post NH	0.095	-0.008	0.005	0.004	0.002
	(0.193)	(0.010)	(0.006)	(0.003)	(0.001)
HC interactions (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)
NH interactions (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, 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.3: Elasticities estimates

	(1) Ln No. of places	(2) Ln No. of places, per 10,000 inhab.	(3) No. of providers	(4) Ln No. of providers, per 10,000 inhab.
Bed-blocking indicators (α_1)				
Living alone	0.415***	0.419***	0.417***	0.385***
	(0.041)	(0.039)	(0.040)	(0.025)
No family to care	0.786***	0.827***	0.837***	0.870***
	(0.100)	(0.096)	(0.095)	(0.080)
Housing/econ. issues	0.661***	0.668***	0.669***	0.660***
	(0.070)	(0.070)	(0.069)	(0.058)
Intensity measures(α_2 and α_4)				
ln(HC intensity)	0.006*	0.014*	0.014*	0.068*
	(0.003)	(0.007)	(0.008)	(0.036)
ln(NH intensity)	-0.006	-0.020*	-0.026**	-0.151***
	(0.005)	(0.012)	(0.012)	(0.049)
HC interactions (α_3)				
Living alone × ln(HC intensity)	-0.030**	-0.065**	-0.082***	-0.427*
	(0.012)	(0.029)	(0.030)	(0.219)
No family to care × ln(HC intensity)	0.019	0.070	0.019	-0.077
	(0.028)	(0.063)	(0.065)	(0.308)
Housing/econ. issues × ln(HC intensity)	-0.022	-0.031	-0.076**	-0.454*
	(0.013)	(0.035)	(0.034)	(0.250)
NH interactions (α_5)				
Living alone × ln(NH intensity)	0.005	-0.013	0.007	0.010
	(0.014)	(0.028)	(0.035)	(0.174)
No family to care × ln(HNH intensity)	-0.010	-0.097	-0.055	-0.554*
	(0.027)	(0.059)	(0.070)	(0.298)
Housing/econ. issues × ln(NH intensity)	-0.008	-0.060	-0.021	-0.285
	(0.018)	(0.039)	(0.045)	(0.216)
Mean Ln HC intensity in 2015	4.35	1.75	1.64	0.26
Mean Ln NH intensity in 2015				
Observations	7,868,350	7,868,350	7,868,350	7,868,350
R^2	0.314	0.315	0.315	0.315

NOTES: The table shows the estimates of α_1 to α_5 in equation (2) using continuous treatment measures. The dependent variable is the natural logarithm of length of stay (+1). In column 1 the treatment is the natural log of the monthly number of places in home-care teams and beds in nursing home units in region m (+1). In column 2, this measure is scaled by the population living in region m. In column 3 the treatment is the natural log monthly number of home-care teams and nursing home units in region m (+1). 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, 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.4: Full set of results from estimating equation (8)

	(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 (8). Column 1 considers experience accumulated since the entry of the first LTC provider in a region. Columns 2 and 3 consider experience accumulated during the last 1 and 2 years, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Alternative empirical approaches

B.1 Exploiting only variation in treatment timing

This specification does not use regular patients as control group, thus only exploiting variation in the length of stay of bed-blockers originating from differential treatment timing. I estimate:

$$y_{it} = \omega_1 PostHC_{mt} + \omega_2 PostNH_{mt} + \delta X_i + \gamma_d + \gamma_m + \gamma_t + \varepsilon_{it} \tag{10}$$

Notation is as before. The coefficients of interest are ω_1 and ω_2, capturing the change in the length of stay of bed-blockers after the entry of the first home-care team and the first nursing home in a region, respectively. Equation (10) is estimated three times, for each of the three types of bed-blocker. Table B.1 shows the results. The number of observations used in each estimation is substantially smaller. The impact of the entry of the first home-care team in a region reduces the length of stay of individuals living alone by 3.4 days, similar to the baseline results. The other estimates are not statistically significant.

Table B.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 ω_1 and ω_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, 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.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 B.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.

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

	(1) Baseline	(2) NH in 2006	(3) NH in 2007	(4) HCBS in 2008	(5) HCBS in 2009	(6) HCBS in 2010
Post indicators (α_2 and α_4)						
Post HC	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	0.095	0.344	0.056	0.033	-0.102	0.209
	(0.193)	(0.267)	(0.205)	(0.257)	(0.148)	(0.239)
HC interactions (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)
NH interactions (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, 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$