Long-term care provision and hospital bed-blocking

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Abstract

Hospital bed-blocking occurs when patients are medically ready to be discharged from a hospital but require some form of post-acute care not readily available, resulting in longer hospital lengths of stay. Although hospital bed-blocking is a shared concern in many countries and may result in severe economic costs, it has received little attention in the economics literature.

This paper assesses whether formal provision of long-term care (LTC) alleviates hospital bed-blocking. Using individual data on the universe of emergency hospital admissions at public hospitals in Portugal for the years 2000-2015, I exploit the staggered introduction of the public LTC network using a difference-in-differences approach.

Preliminary results suggest that teams providing home-care can be successful at alleviating bed-blocking. Reductions in bed-blocking following the entry of nursing home facilities occur only for patients with high levels of dependency. Despite these improvements, some bed-blocking still persists. Going forward, I want to examine specific mechanisms that might be driving this result, such as coordination frictions and capacity constraints.

Keywords: Long-term care; hospital bed-blocking; delayed discharges.

JEL codes: I10; I18; J14.

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1 Introduction

There is a general consensus among economists and policy-makers that healthcare systems are wasteful and inefficient (Garber and Skinner, 2008). However, there is less agreement on both the source of those inefficiencies and ways to eliminate them (Einav et al., 2019). In this paper, I focus on a specific source of inefficiency in the healthcare system commonly referred to as hospital bed-blocking, and assess whether the introduction of highly-subsidized formal long-term care provision can alleviate this inefficiency.

Hospital bed-blocking, often referred to as delayed hospital discharges, occurs when a patient is medically ready to be discharged from an acute-care hospital but requires some form of post-acute care, such as a nursing home or home care, 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. The causes of hospital bed-blocking often relate to the lack of coordination across different settings of healthcare provision, as hospital and long-term care settings are organized and funded separately in many countries (Siciliani, 2014; Fernandez et al., 2018). There are growing concerns about hospital bed-blocking in many developed countries, such as Australia, Austria, Israel, Norway, New Zealand, Sweden, the Netherlands, the United Kingdom, and the United States (Gaughan et al., 2015; Vetter, 2003), and the phenomenon entails potentially large inefficiencies. First, acute care provision acts as a more costly alternative to post-acute care; second, bed-blocking may increase waiting times for acute care; third, longer hospital stays can be detrimental for a patient's health, for example, due to increased risks of contracting new infections or to possible damages to the musculoskeletal system following long periods of bed-confinement. Nevertheless, bed-blocking has received little attention in the economic literature.

This paper assesses whether formal provision of long-term care (LTC) can alleviate hospital bed-blocking. Using individual data on the universe of emergency hospital admissions for all public hospitals in Portugal for the years 2000-2015, I first show that there is a group of patients exhibiting a complex combination of health and socioeconomic needs who have substantially longer length of hospital stay than what can be explained by detailed information on demographics, comorbidities, and medical diagnoses. Throughout the paper, I refer to this group of patients as bed-blockers, as opposed to regular patients. Then, I exploit the staggered introduction of the public LTC network across regions to examine whether it leads to reductions in bed-blocking. In a nutshell, the public LTC Network provides highly subsidized nursing home facilities (NH) and teams providing home care (HCBS), which operate in coordination with hospitals and aim to ease the transition of patients across different settings of care provision. Using both a difference-in-differences and an even-study approach, I assess whether the entry of a NH or HCBS provider in the region where the patient lives leads to length of stay reductions for bed-blockers relative to regular patients.

The results from the difference-in-differences show significant reductions in bed-blocking following the entry of teams providing home-care in their region of residence. Specifically, individuals living alone and those with housing and other economic issues experience length of stay reductions of about 4 days, and individuals waiting for a vacancy in an adequate facility experience reductions of 19 days. Whereas the entry of teams providing home-care in a region alleviates bed-blocking for the average bed-blocker, the entry of nursing home facilities is found to reduce bed-blocking only when restricting the sample to individuals with high levels of dependency, such as those admitted with a stroke diagnosis. For these individuals, the entry of a nursing home in their region leads to a length of stay reduction of 4 and 10 days, respectively, for individuals living alone and those with housing and other economic issues. These results survive a battery of robustness checks, namely with respect to the definition of the relevant region. The event-study analysis conveys that these results are not driven by different pre-trends in lengths of stay across regions treated at different points in time.

While these results suggest that LTC provision can reduce hospital bed-blocking, the resulting reductions in length of stay do not fully close the gap between bed-blockers and regular patients. Some bed-blocking still persists. I then proceed to examine the role of different mechanisms in perpetuating bed-blocking. The first mechanism I study is the existence of coordination frictions between hospitals and the local LTC providers. (analysis in progress).

This paper relates to several strands of literature. Most narrowly, it directly speaks to the literature on substitution between two types of formal care: acute hospital care and long-term care. Closely related to this paper are Gaughan et al. (2015), who investigate whether greater supply of nursing home beds or lower prices can reduce hospital bed-blocking and Forder (2009), who studies the substitution between hospital and care homes. Both these studies find relatively small substitution effects. Contrary to Gaughan et al. (2015) and Forder (2009), I have individual-level data and an arguably exogenous source of variation in the availability of LTC in a local market because the roll-out of the Portuguese LTC network was done in a centralized way. Costa-Font et al. (2018) study the effect of cash allowances for home care on hospital lengths of stay. In turn, my analysis focuses on in-kind LTC benefits for both home care and nursing home facilities.

A related strand of literature analyzes the contribution of distinct factors to exacerbate or alleviate bed-blocking. A sizable number of studies by scholars in medicine and public health have elaborated on the causes of bed-blocking, characterized the affected individuals, and quantified monetary losses associated with the phenomenon (see, for example, Bryan et al., 2006; Hendy et al., 2012; Costa et al., 2012). Most of these studies focus on a very specific setting such as a single hospital or region. Within the economics literature, there are relatively few contributions. Holmås et al. (2013) find that greater expenditure on long-term care by Norwegian local authorities is associated with reductions in bed-blocking. Another important factor is coordination between different settings of care provision. Using data for the United Kingdom, Fernandez et al. (2018) find that, as the number of downstream institutions that a hospital deals with increases, its patients experience more delays in the discharge process and thus have longer post-operative lengths of stay. Holmås et al. (2010) and Kverndokk and Melberg (2019) exploit a reform in Norway to investigate the effect of introducing fines to the party responsible for each delay in hospital discharges on bed-blocking and reach mixed conclusions. In my paper, I further assess the importance of coordination as a mechanism for explaining my results but also address the role played by other factors such as capacity constraints (rewrite sentence once I am done with that analysis).

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 (ie. Kyle and Williams, 2017 and Doyle Jr et al., 2017). Within this literature, Einav et al. (2019), Einav et al. (2018), and Eliason et al. (2018), are particularly relevant as they specifically study inefficiencies in the interaction between the acute and post-acute care settings in the United States.

The remainder of this paper is organized as follows. Section 2 provides background on the institutional setting, namely on the organization of the hospital and long-term care settings in Portugal. Section 3 describes the data and presents summary statistics. Section 4 describes my empirical approach and section 5 presents the results. Finally, section 6 concludes.

2 Institutional Setting

2.1 Inpatient-care

In Portugal, the majority of inpatient care is provided by public hospitals belonging to the National Health System (SNS). The SNS is predominantly financed through general taxation and characterized by universal coverage 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. DRGs are used to set an annual prospective global budget for inpatient care provided by each hospital, which amounts for 75-85% of total inpatient revenues of SNS hospitals (Mateus, 2011). The remaining revenue corresponds to DRG-based case payments for specific types of patients or surgical procedures.

Overall, hospitals have no financial incentives to keep patients longer in the hospital. Since hospitals are paid according to the number and type of patients they receive, DRG-based funding provides incentives for hospitals to treat more patients and to cut costs, possibly by reducing lengths of stay.

2.2 Long-Term Care

Long-term care is care needed by individuals with some degree of physical or mental dependency. This can include healthcare, personal care (ie, help with activities of daily living), help with other activities (ie, housework, meals, etc.), and accommodation for individuals who cannot live independently (Siciliani, 2014). It can be provided either formally or informally. Formal long-term care provision is done by trained personnel and can occur at the patient's home or at institutions such as nursing homes. Informal care is that provided by relatives, friends, or neighbors.

Until recently, long-term care was not within the scope of the SNS and was mostly provided informally. Formal long-term care was mostly privately funded and provided by non-profit institutions with a religious background (*Misericórdias*). These institutions provide a variety of services including nursing homes and residences for elderly people, meals, laundry services, bathing, etc. (Simões et al., 2017). A 2005 survey conveys generally high satisfaction levels among users of these services, but 30% of those surveyed considered their co-payments excessive. Accordingly, half of the individuals surveyed stated that the cost of the service was its main problem (Santana, 2010).

To fill in this coverage gap, the Portuguese Network for Long-Term Integrated Care (RNCCI, henceforth simply the LTC Network) was created in 2006, as a joint effort of the Ministry of Health and the Ministry of Labor and Social Security (Decree-Law 101/2006).

The LTC Network comprises two main settings of care provision: home and community-based services (HCBS) and nursing homes (NH). HCBS encompass nursing, medical, and rehabilitation care provided to individuals with functional dependence and difficulties in performing activities of daily living in their home by teams belonging to primary care centers.

Within the NH setting, there are distinct types of institutions that cater to populations with different care needs and degrees of dependency: Convalescence Units, which provide medical, nursing and rehabilitation care to individuals with an expected length of stay up to 30 consecutive days; Medium Term and Rehabilitation Units, which offer less intensive nursing and rehabilitation care for individuals with an expected length of stay between 31 and 90 consecutive days; and Long-term and Maintenance Units, which target individuals with difficulties of community inclusion and caregivers' respite care with an expected length of stay over 90 consecutive days.[1]

To set up the NH component of the LTC Network, the Government contracted with existing institutions throughout the country, namely the religious *Misericórdias*. Such institutions were already active in LTC provision across the country for several decades. Overall, the model for the NH setting is one of private provision and public financing. That is, the care provided by contracted institutions is heavily subsidized by the Ministry of Health and the Ministry of Labor and Social Security but public ownership of NH occurs only for 2% of the providers. In contrast, the HCBS setting of the LTC Network is composed of teams which are based in primary care centers, meaning that home-care is both publicly provided and publicly financed.

LTC prices prices depend on the specific LTC setting and are determined by law on an annual basis. Daily prices in 2015 were set at €105 for Convalescence Units (fully paid by the Ministry of Health); €87 for Medium Term and Rehabilitation Units (€67 of which is paid by the Ministry of Health); and €60 for Long-term and Maintenance Units (half of which is paid by the Ministry of Health). The differential between the price and the amount covered by the Ministry of Health is paid by the Ministry of Labor and Social Security, with means-tested co-payments by users.

To access the LTC Network, patients must be referred either by a hospital if they are hospitalized, or by their primary care center if they live in the community. The majority

[1] Until 2015 the LTC network also included a few Palliative Care Units offering end-of-life care to patients with terminal illnesses. These are disregarded in my analysis.

of referrals to the Network are made by discharge management teams located at acute-care hospitals (citation here). Because my analysis focuses on patients who are hospitalized, I describe in more detail the referral process when it is made by hospitals. Every hospital has a discharge management team. This is a multidisciplinary team whose main job is to prepare and manage hospital discharges. It specifically targets patients in need of some form of post-acute care 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 management team ensures continuity of care across the acute and post-acute settings by connecting the patient with adequate long-term care providers belonging to the LTC Network. After the discharge management team refers a patient, local coordination teams based in primary care centers will validate the assessment made by the discharge management team and try to find an adequate vacancy for the patient. Primary care centers usually operate within a municipality, but not all primary care centers have a local coordination team. Instead, local coordination teams are created at the level of the broader ACES regions. ACES is the Portuguese acronym for Primary Care Center Groups (*Agrupamento de Centros de Saúde*) and these areas are relevant for organizing primary care delivery. There are slightly over 50 ACES in Portugal. In urban areas, ACES borders often coincide with municipal ones, but in rural areas ACES typically group a few neighboring municipalities. Figure 1 summarizes the process of admission to the LTC Network.

Overall, the implementation of the LTC Network introduced two key changes to the Portuguese long-term care landscape that might reduce hospital length of stay for bed-blockers. First, it increased the availability and affordability of long-term care by providing highly subsidized LTC alternatives. This is important because before 2006 individuals in need of long term care were easily priced out of the market. Second, it provided an integrated platform where different levels of health and social services can coordinate transitions between acute and post-acute care. Before 2006, individuals in need of LTC after a hospitalization needed to navigate the system themselves and look for a vacancy at an adequate facility. This

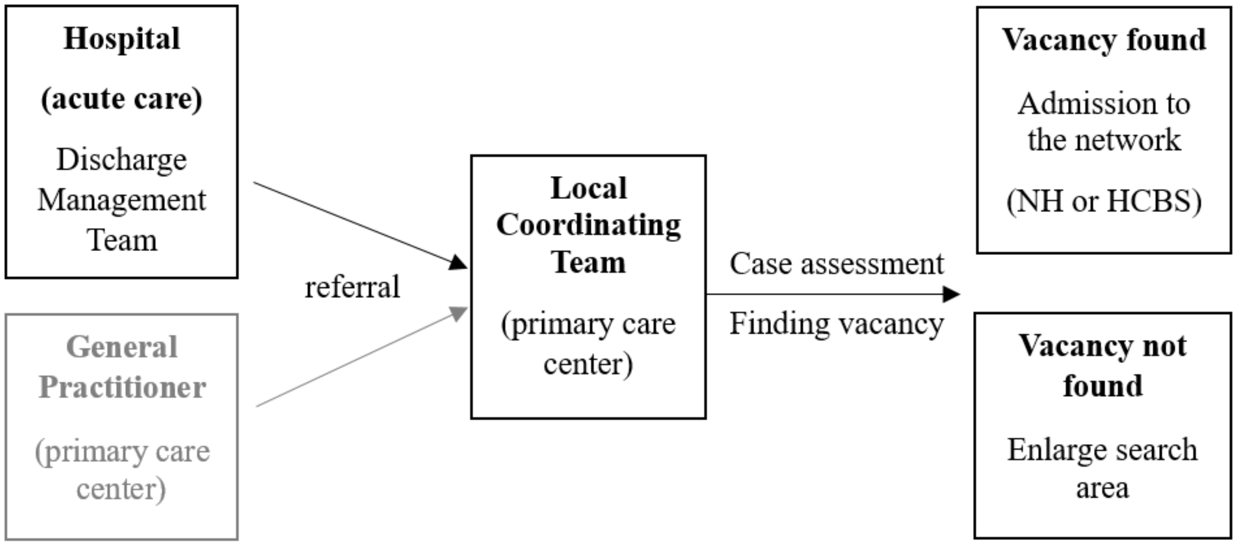


Figure 1: Process of admission to the long-term care network (adapted from Santana, 2010)

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 and Summary Statistics

3.1 Data

The main data source used for the analysis contains information on the universe of inpatient stays at Portuguese public hospitals between the years 2000 and 2015.[2] For each inpatient stay, these data contain admission and discharge dates, basic information on patient demographics and place of residence, and detailed information on medical diagnoses, procedures, and comorbidities.

I complement the inpatient dataset with data on the roll-out of the long-term care network. Specifically, I observe the start date of each contract with a long-term care provider, the exact location of the long-term provider, the type of service (nursing home, home care) and

[2]The data is maintained by Administração Central do Sistema de Saúde, I.P. (ACSS). Access to the data is possible under the data-sharing agreement between ACSS and the Health Economics & Management Knowledge Center at Nova School of Economics, with which I am affiliated.

capacity contracted, and the ownership type of the provider (private, public, non-profit).

3.2 Sample definition

Throughout the analysis I focus on emergency hospital admissions because, as opposed to programmed admissions, they are unpredictable. This minimizes the concern that individuals might make their own LTC arrangements in advance when they know they will be hospitalized on a certain date, introducing potential biases in the estimates of interest. Additionally, I exclude admissions into specialized hospitals, such as cancer and psychiatric hospitals, and admissions of individuals below 18 years old.

3.3 Local markets

My analysis focuses on the impact of NH and HCBS entry into a local market on the hospital length of stay of bed-blockers compared to regular patients. At baseline, local markets are defined using ACES regions. These are relevant because the local coordination teams that find vacancies in LTC providers for referred patients are are established at the ACES level. Because ACES can be very different in terms of their geographic area, in robustness checks I define local markets using radius around patients' municipality of residence.

3.4 Identifying bed-blockers

I use the rich inpatient data to identify bed-blockers. Specifically, I use the set of ICD-9-CM diagnosis codes capturing underlying factors influencing health status and contact with health services, namely those referring to administrative and social admissions by the Clinical Classification Software. These codes identify episodes which feature an additional relevant non-clinical component that prevents safe discharge arrangements to be made.[3] These codes

[3]See `https://www.hcup-us.ahrq.gov/toolssoftware/ccs/AppendixASingleDX.txt` under the header "Administrative/social admissions" for the full list of codes used.

identify slightly over 200,000 episodes in the sample, amounting to 2.54%. The episodes can be grouped in the following six categories:

1. Living alone: 28,685 observations (14.2%)
2. Housing/economic issues: 26,875 (13.30%)
3. No family to care: 12,156 (6.01%)
4. Awaiting admission to adequate facility elsewhere: 10,986 (5.44%)
5. Living in a residential institution: 97,127 (48.10%)
6. Other (legal matters): 26,151 (12.94%)

All the categories above identify patients with complex social and health needs. However, not all of them are expected to prevent a timely discharge. In particular, individuals living in a residential institution are expected to have a safe place to be discharged from the hospital.[4] Their length of stay should in principle be similar to that of regular patients and this should not change upon the introduction of the LTC Network. Additionally, the category "others" mostly includes individuals who stay longer at the hospital due to legal matters (ie. family breakdowns due to domestic violence, substance abuse, etc.), which are unrelated to long-term care needs. Because I expect no impact of the introduction and expansion of the LTC Network on the length of stay of individuals living in a residential institution or of those being kept at the hospital for legal reasons, these two groups are used as a falsification test in the analysis. Table 1 compares basic demographic and health variables for individuals in the sample. Bed-blockers are different from regular patients. They have longer lengths of stay but they are also older, have poorer health (as measured by the Charlson score), and are more likely to suffer from comorbidities such as diabetes or renal disease. Figure 2 illustrates the frequency of different types of potential bed-blocking admissions over my study-period. While most

[4]Residential institutions might include nursing homes, but more generally they include other types of social structures where the elderly and people with dependencies can live, which do not provide post-acute medical care (ie, board and care homes).

Table 1: Descriptive statistics

	Regular patients		Bed-blockers	
	Mean	St. Dev.	Mean	St. Dev.
Female (%)	0.581	0.493	0.580	0.494
Age (years)	58.311	22.418	73.029	18.660
Length of stay (days)	8.711	12.362	18.109	34.894
Died (%)	0.078	0.269	0.150	0.357
Charlson score	1.174	1.852	1.824	2.087
AMI	0.040	0.195	0.036	0.186
Heart failure	0.110	0.313	0.188	0.391
Stroke	0.113	0.317	0.228	0.419
Dementia	0.024	0.152	0.104	0.306
COPD	0.078	0.268	0.109	0.311
Diabetes	0.130	0.337	0.193	0.395
Renal Disease	0.061	0.239	0.118	0.323
N	7,760,739		201,978	

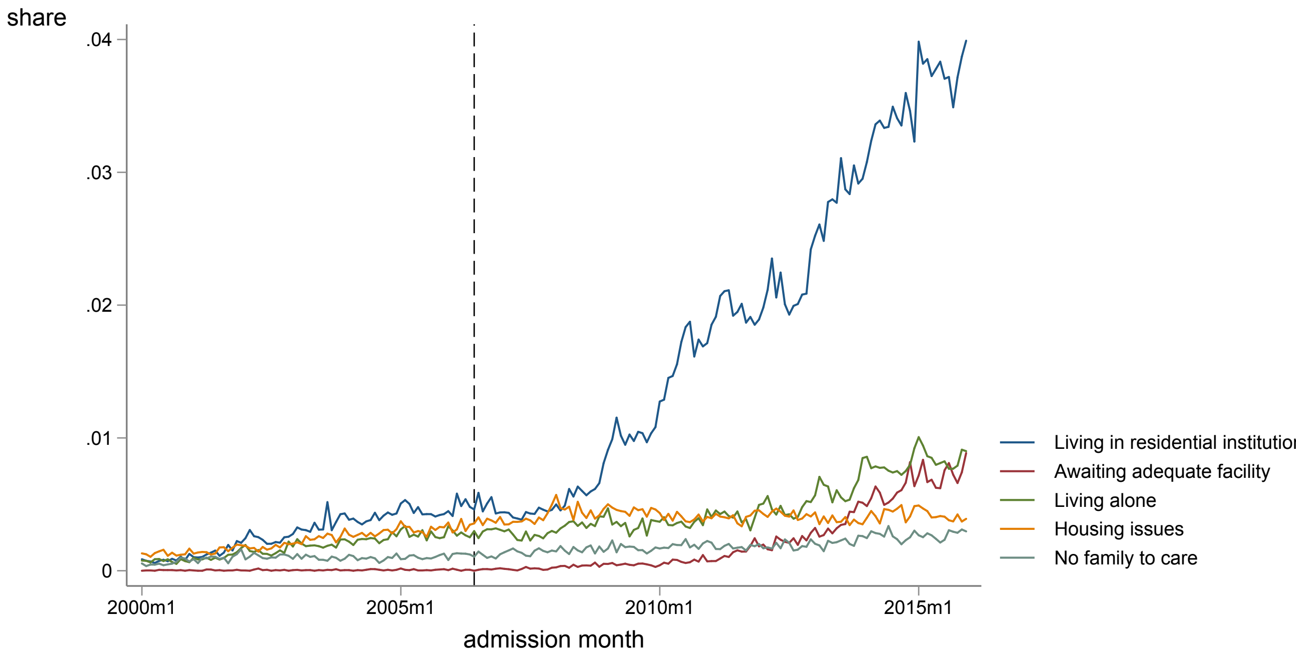
categories are relatively constant over time, there is a large increase in the share of individuals living a residential institution in the last sample years and, to a smaller extent, in the share of individuals living alone and waiting for an adequate facility. This is in line with recent concerns about congestion in the LTC Network.

3.5 Entry of LTC providers

My empirical approach exploits the gradual contracting of providers, both over time and across geographic locations, to assess whether the roll-out of the LTC Network contributed to reduced bed-blocking inefficiencies. In this subsection I depict these sources of variation.

I start with NH facilities. Figure 3 plots the number of nursing home facilities and beds over time. Since the start of LTC Network in late 2006 there has been an almost steady growth in the number of NH contracted by the Ministry of Health. The stagnation during the period between 2011 and 2014 is the result of two main factors. First, the economic adjustment

Figure 2: text

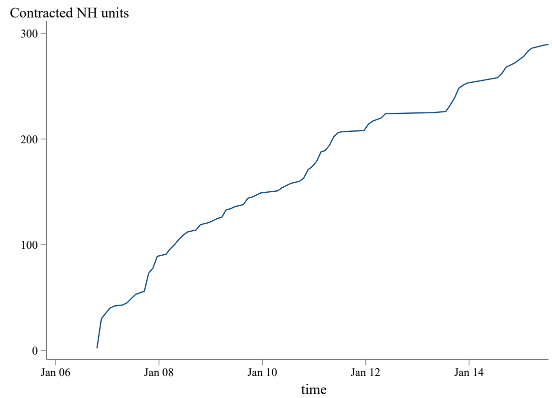


program negotiated in May 2011 between the Portuguese authorities and officials from the European Commission, the European Central Bank and the International Monetary Fund, which provided conditional financial assistance to Portugal and restrained public spending. Second, the fall in revenues from social gambling, which is one of the financing sources of the LTC Network (Lopes et al., 2018).

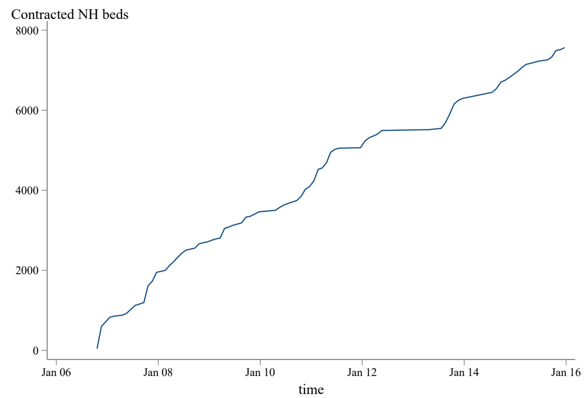
Figure 4 shows the distribution of contracted NH across ACES regions for three distinct points in time: 2006, the year when LTC Network was established; 2011; and 2015, the last year in the inpatient dataset. Most ACES regions experienced the entry of their first NH before 2011.

Similarly, figures 5 and 6 convey the expansion of contracted HCBS over time and across ACES regions, respectively.

Both for NH and HCBS, the capacities contracted with each provider are rather small, averaging 20 spots for HCBS teams and 25 beds for NH facilities. There exist, however, a few large providers that can accommodate over 70 individuals.



(a) Number of NH units



(b) Number of NH beds

Figure 3: Evolution of contracted nursing homes over time

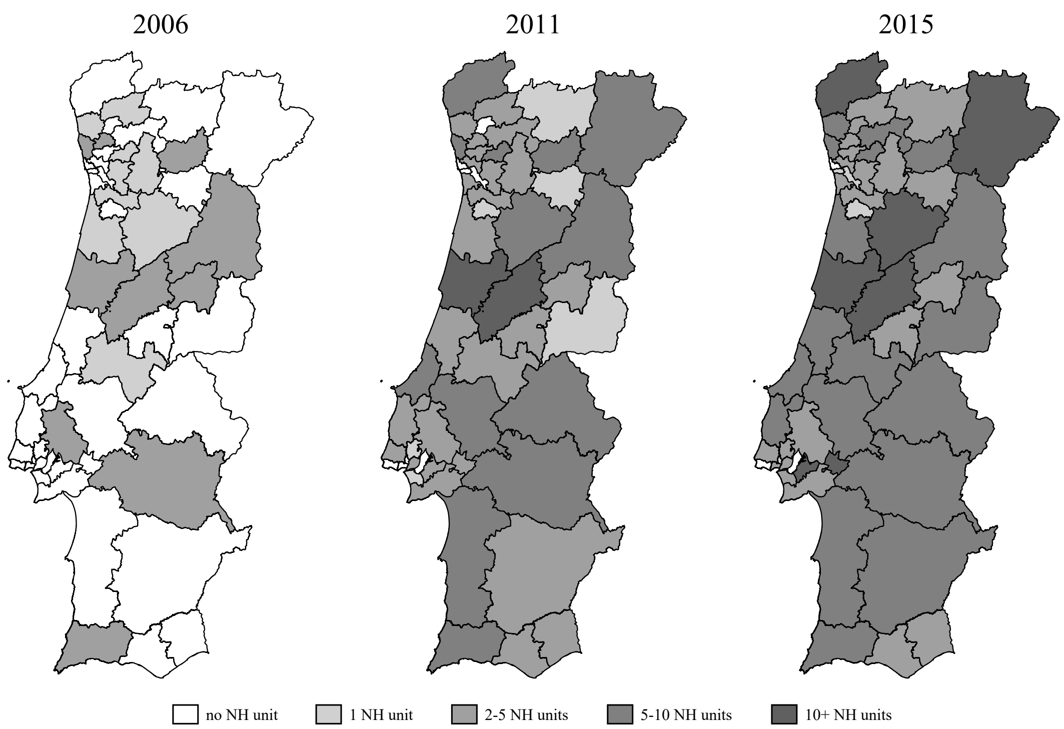
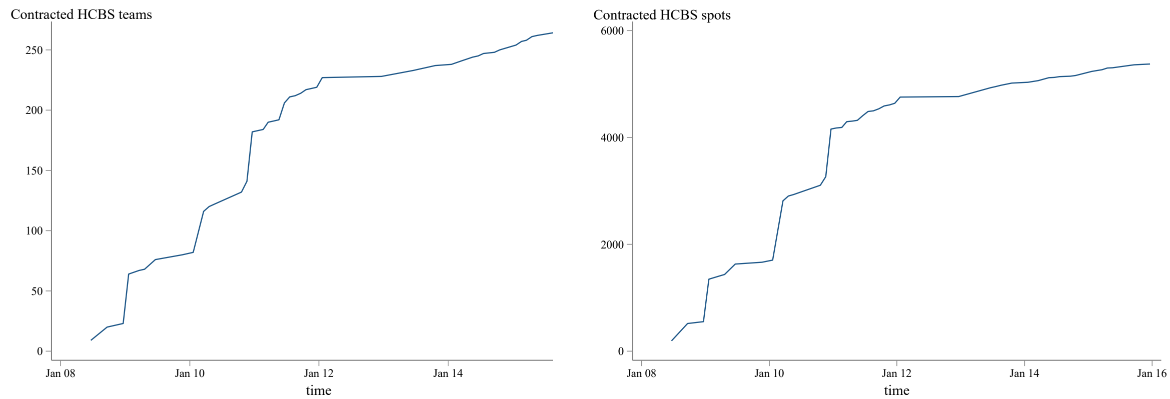


Figure 4: Location of contracted nursing homes



(a) Number of HCBS teams

(b) Number of HCBS spots

Figure 5: Evolution of contracted home-based care services over time

4 Empirical Strategy

4.1 Lengths of stay at the hospital

Inherent to the concept of bed-blocking is the idea that these individuals stay in the hospital longer than clinically needed. However, as previously discussed, potential bed-blockers are different from regular patients because they are older and have poorer health status. The first step of the analysis is to determine how much longer bed-blockers stay at the hospital as compared to regular patients, conditional on their health and demographic profiles. I estimate the additional length of stay at the hospital due to bed-blocking as follows:

$$y_{it} = \alpha BB_i + \beta X_i + \delta_d + \gamma_h + \tau_t + \varepsilon_{it}, \tag{1}$$

where i, d, h, and t index the patient, their DRG group, the hospital they are admitted to, and calendar time in quarters, respectively. The dependent variable y is the length of stay of the episode in days. BB_i is a vector of six binary indicators for each bed-blocking category; X_i is a vector containing 10-year age bins separately by gender and a set of dummies for

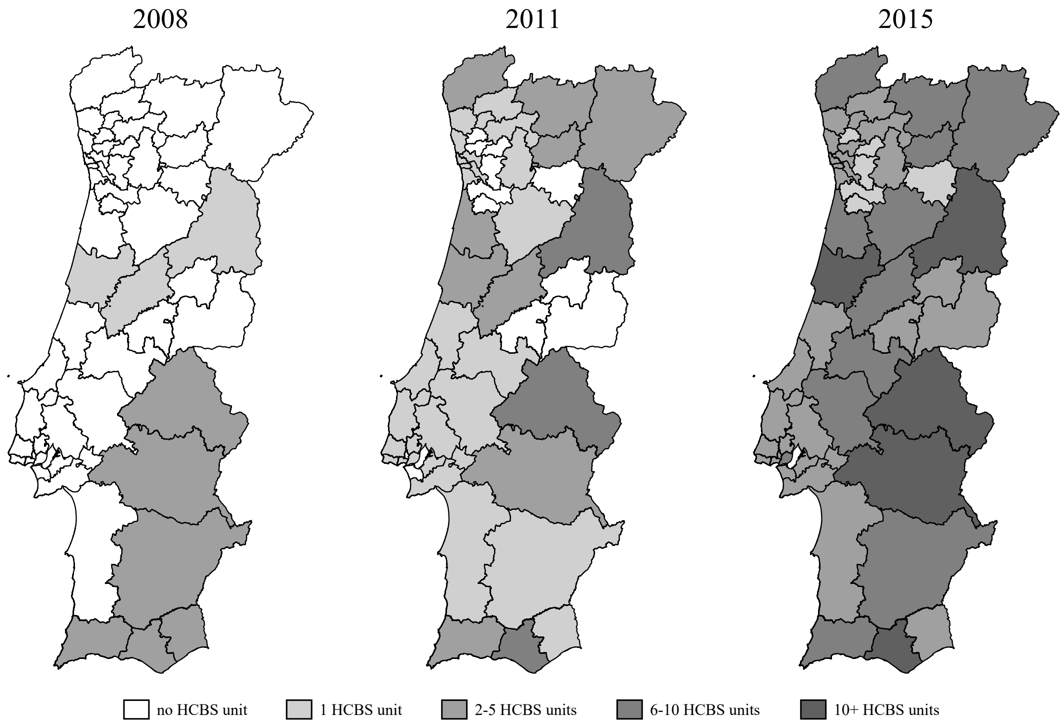


Figure 6: Location of contracted home care-based services

common comorbidities; δ_d, γ_h and τ_t are DRG, hospital, and calendar quarter fixed effects;[5], and ε_{it} is an error term. Vector α contains the parameters of interest, which measure the additional inpatient days of each bed-blocking category relatively to regular patients with similar demographics and clinical condition who are admitted to the same hospital in the same calendar quarter. Equation (1) is also estimated using the natural log of length of stay (+1, to deal with the about 3% of the observations whose length of stay equals zero days) as dependent variable to have an idea of how the potential bed-blockers compare to regular patients in relative terms.

[5]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.

4.2 Effect of LTC entry

I exploit variation in entry timing of LTC providers in a local market to assess the effects of LTC availability on the length of stay of bed-blockers relative to regular patients. As previously described, there are two main types of LTC providers, nursing homes and teams providing home-based care services.

My first specification is a difference-in-differences model comparing each of the bed-blocking categories with regular patients, before and after the entry of each type of LTC provider in a market. Specifically, I estimate the following equation:

$$\begin{aligned} y_{it} =& \alpha_1 BB_i + \alpha_2 PostNH_{mt} + \alpha_3 PostNH_{mt} \times BB_i + \\ & \alpha_4 PostHCBS_{mt} + \alpha_5 PostHCBS_{mt} \times BB_i + \beta X_i + \delta_d + \gamma_m + \tau_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

, where i, d, and t index the patient, their DRG group, and the calendar quarter of hospital admission, and m indexes the local market where the patient lives. The dependent variable is the length of stay of patient i admitted in calendar quarter t in days. $PostNH_{mt}$ is an indicator variable taking value 1 in periods after the first NH provider is contracted by the Government in local market m. Similarly, $PostHCBS_{mt}$ is an indicator variable taking value 1 in periods after the first HCBS team is contracted by the Government in local market m. All remaining variables are as previously defined. The estimates of interest are in the vectors α_3 and α_5, and capture the change in the length of stay of each bed-blocking category after the entry of NH and HCBS, respectively, in their local market, compared to regular patients. At baseline, I define the local markets as the ACES regions. Because most ACES regions experience the entry of a several NH and HCBS, the estimates of α_3 and α_5 capture the effect of having *at least one* NH and HCBS in the local market of residence on hospital lengths of stay.

I analyze the robustness of the baseline results to different model specifications, local market definitions, and functional forms of the outcome variable. In terms of model specification, I alternatively add region-specific time trends and hospital fixed-effects to the baseline specification. I assess the robustness of the results to different definitions of local market. Because the areas of the ACES regions can be very different, I alternatively use 15 and 30km radii around the centroid of a patient's municipality of residence as definition of local market. Finally, I analyze the robustness of the results to alternative definitions of the outcome variable by using the natural logarithm of the length of stay (+ 1), and binary variables for being over certain percentiles of the distribution of length of stay pooled across all sample years.

To analyze potential heterogeneity of effects over time I restrict the sample to the periods 2000-2012, 2005-2012, and 2012-2015. To analyze heterogeneity across different populations, I estimate the baseline model restricting the sample to individuals over 65 years old and to those admitted with a stroke diagnosis. Finally, I analyze heterogeneity with respect to the entry of different types of nursing homes (for short, medium, and long-term stays) and to different ownership of nursing homes (private non-profit, religious non-profit, public, and private for-profit).

The identifying assumption in equation (2) is that in the absence of the entry of long-term care providers, any trends in lengths of stay of both bed-blockers and regular patients would have been similar across regions. There are potential threats to this assumption. For example, it might be that regions where there were more concerns about bed-blocking experienced earlier entry of nursing homes and home care-based services, there might be changes in the patient-mix, among others. In order to assess the plausibility of the common trend assumption in greater detail, I use an event-study approach. The event-study framework is less restrictive than equation (2) in that it allows the effect of LTC availability on the length of stay of bed-blockers to vary over time. I specify the event-study in a window of six years around the entry of the first LTC provider of each type (NH and HCBS) in each region. The event-study specification takes the following form:

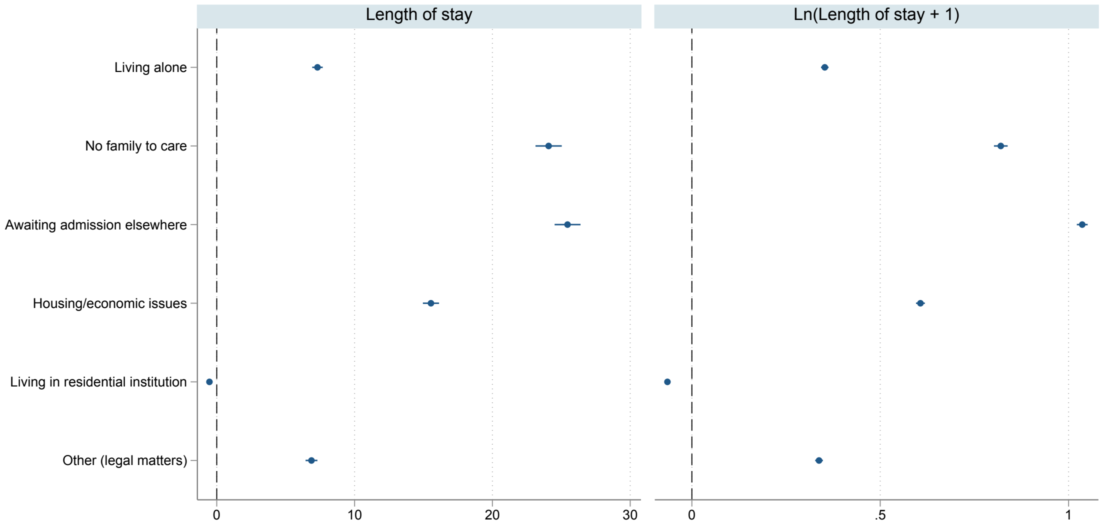
$$y_{it} = \theta_r BB_i^j f(r) + \beta_1 BB_i^j + \beta_2 f(r) + \beta_3 X_i + \delta_d + \gamma_m + \tau_t + \varepsilon_{it}, \tag{3}$$

$$f(r) = \begin{cases} a & \text{if } r < -6 \\ I_r & \text{if } -6 \geq r \leq 6 \\ b & \text{if } r > 6 \end{cases}$$

, where r indexes time in years relative to the first entrant in a region and $f(r)$ is a function of relative time that includes binary indicators for each of the relative years inside the event-window but also includes two other binary indicators: one for relative years prior to $r = -6$ and other to relative quarters after $r = 6$. That is, I assume that outside the six-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 year where entry occurred to zero, $f(-1) = 0$.

BB_i^j is a binary indicator for patient i being classified in bed-blocking category j and all the remaining notation is as before. The coefficients in θ_r corresponding to years before the year of entry are informative about the plausibility of the common trend assumption. Equation (3) is estimated 12 times for the 2 distinct events (entry of a NH and entry of a HCBS team) and each of the six j categories. In each of the estimations, the sample consists of the patients classified in category j and of regular patients, thus excluding patients classified in one of the five categories other than j.

Figure 7: Estimates of α from equation (1)



NOTES: The figure shows the estimates of α from equation (1) and their corresponding 95% confidence intervals. In the left panel the dependent variable is length of stay in days and in the right panel it is ln(length of stay + 1). All models include individual demographics and comorbidities, calendar quarter fixed-effects, diagnosis-related group fixed-effects, and hospital fixed-effects.

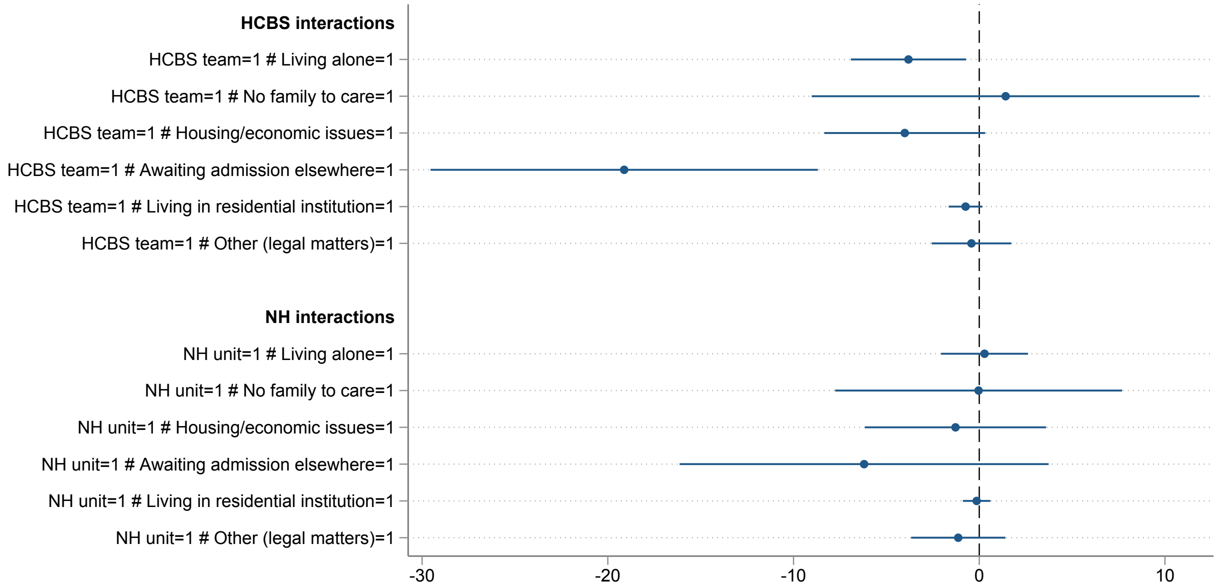
5 Results

5.1 Lengths of stay at the hospital

Figure 7 shows the estimates of α from equation (1). Individuals living in a residential institution have lengths of stay slightly shorter than regular patients and do not block beds. All the remaining categories have lengths of stay considerably longer than regular patients. For example, individuals living alone have hospital stays that are, on average, 7 days (35%) longer than regular patients. Individuals awaiting admission to an adequate facility have stays about 25 days (104%) longer than regular patients, on average.

We can therefore conclude that, despite their older age and more complex clinical status, bed-blockers still stay considerably longer at the hospital when compared to regular patients.

Figure 8: Estimates of α from equation (2)



NOTES: The figure shows the estimates of α 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, calendar quarter fixed-effects, diagnosis-related group fixed-effects, and region (ACES) fixed-effects. Standard errors clustered at the region level.

5.2 Effects of LTC entry

5.2.1 Difference-in-differences

Figure 8 shows the estimates of the interaction terms in equation (2). Hospital length of stay falls by 3.8 days for individuals living alone, by 4 days for those with inadequate housing, and by 19 days for those awaiting vacancy in an adequate facility after the entry of a HCBS team in their region. The estimates associated with the entry of NH providers are too noisy to allow drawing any conclusion. Importantly, for both HCBS and NH entry, the estimates for the two placebo groups are well estimated at zero, as expected.

Table 2 reports the results of robustness checks to the baseline specification. For convenience, column 1 reproduces the baseline results. The baseline results are unchanged when adding region-specific time trends and hospital fixed-effects. In columns 4 and 5, I redefine the relevant market to the 15 and 30km radius around the centroid of the patient's municipality, respectively, and find very similar results.

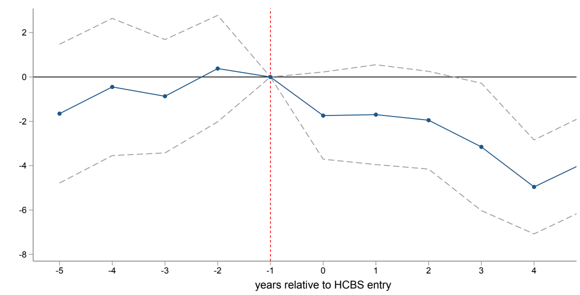
The baseline results are robust to alternative definitions of the outcome variable, as shown in Table 3.

Finally, I report the results from the heterogeneity analysis in Table 4. Restricting the sample to individuals over 65 leaves my results roughly unchanged. Focusing on patients with a stroke diagnosis, I find a significant reduction in the length of stay of bed-blockers after the entry of a NH. This reduction in length of stay amounts to 4 days for individuals living alone and to 0 days for individuals with housing and other economic issues. The fact that these results did nor show up for the baseline sample of patients indicates that NH specifically cater to highly dependent patients and that the average patient may simply not be at risk. Regarding the heterogeneity of the results to different sample periods, the length of stay reductions seem to be concentrated around the introduction of the LTC Network, where there is also more variation to be exploited. The fact that length of stay reductions are not found when using the later sample years suggests that there might be other effects taking place, for example, related to capacity constrains that may become binding after the initial entry periods.

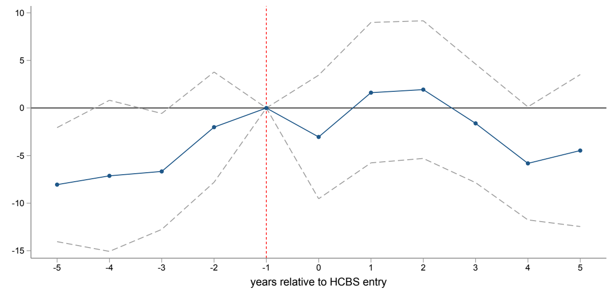
5.2.2 Event-study

I report the results from the events-study analysis in figures 9 and 10, respectively for the entry of HCBS teams and NH facilities. For each bed-blocking category, the figures plot the estimates of θ_r from equation (3) and the corresponding 95% confidence intervals.

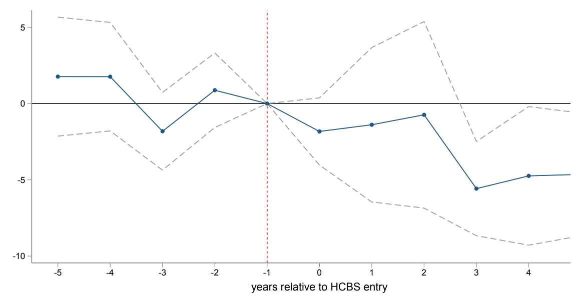
The event-study estimates are more noisy because I estimate a different coefficient for each relative year and bed-blockers amount to a rather small share of admissions. Nevertheless, they convey similar results to the difference-in-differences: HCBS entry seems to lead to modest reductions in length of stay for individuals living alone and those with housing/economic issues. NH entry, in turn, does not typically lead to reductions in length of stay for the average patient, the exception being the group of patients awaiting for a vacancy at an adequate facility. The advantage of the event-study specification is that it is informative about pre-trends in



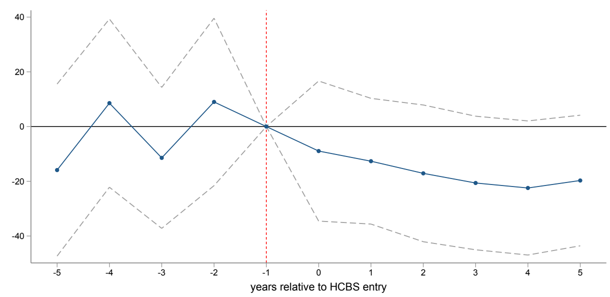
(a) Living alone



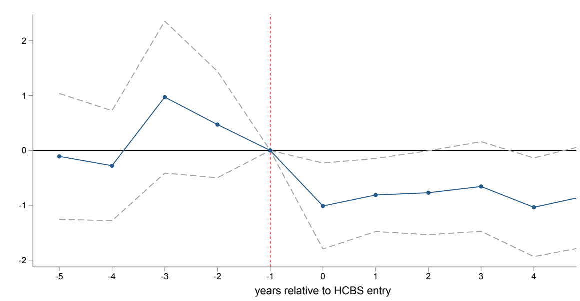
(b) No family to care



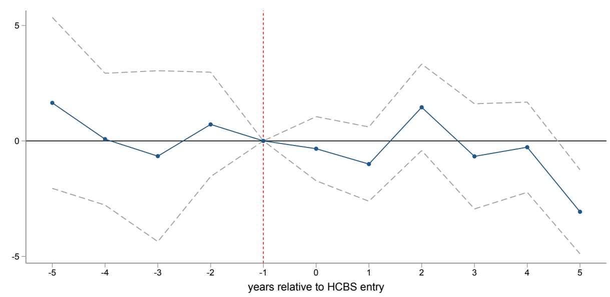
(c) Housing/economic issues



(d) Awaiting adequate facility



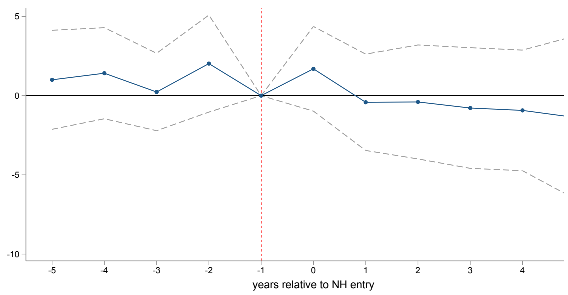
(e) Living in residential institution



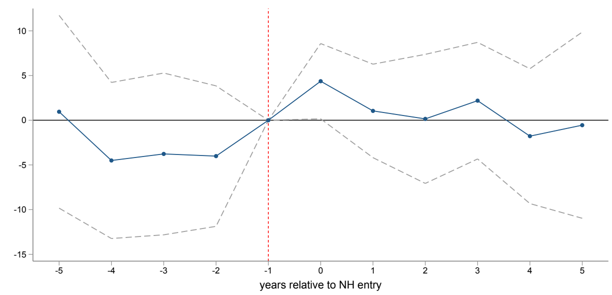
(f) Other (legal matters)

Figure 9: Event-study results for HCBS entry

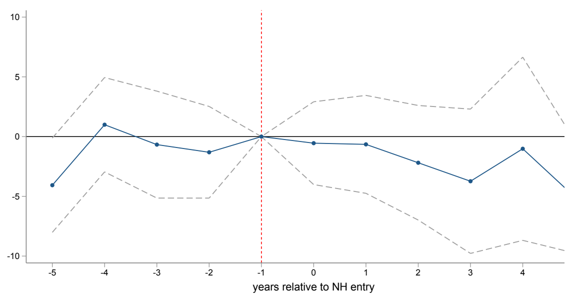
NOTES: Each panel in the figures plots the estimates of θ_r from equation (3) and the corresponding 95% confidence intervals for a specific group of patients in the sample. In each panel, the vertical axis is length of stay in days and the horizontal axis is time in years relative to the entry of the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



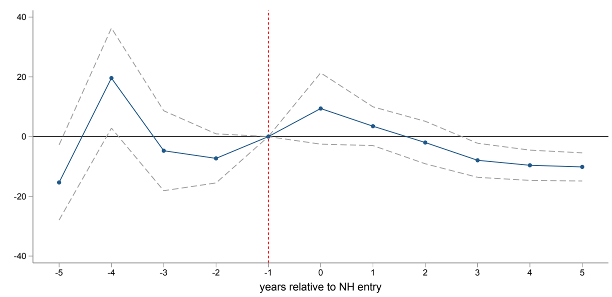
(a) Living alone



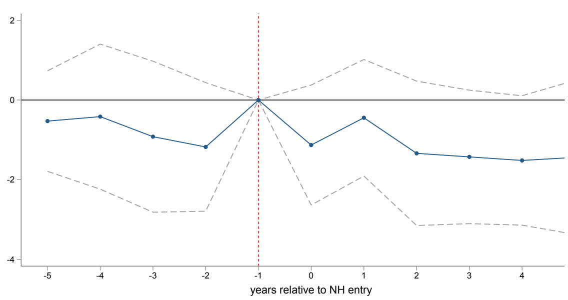
(b) No family to care



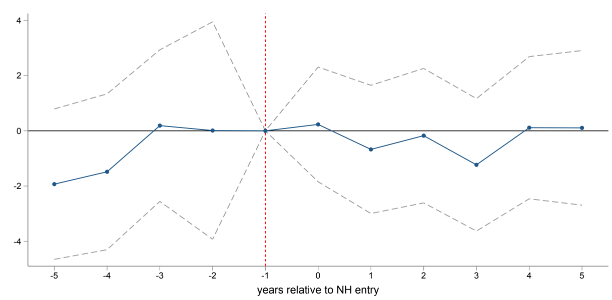
(c) Housing/economic issues



(d) Awaiting adequate facility



(e) Living in residential institution



(f) Other (legal matters)

Figure 10: Event-study results for NH entry

NOTES: Each panel in the figures plots the estimates of θ_r from equation (3) and the corresponding 95% confidence intervals for a specific group of patients in the sample. In each panel, the vertical axis is length of stay in days and the horizontal axis is time in years relative to the entry of the first nursing home in the region. The coefficient on the year just before entry was normalized to zero. All models include individual demographics and comorbidities, calendar quarter fixed-effects, diagnosis-related group fixed-effects, 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.

lengths of stay for each fo the patient groups analyzed. In most of the event-study plots the confidence intervals are wide and the pre-entry estimates are not statistically significant (the exception being panel (b) in Figure 9, corresponding to individuals with no family to care, for which there seems to be a slight upwards pre-trend).

Overall, both the difference-in-differences and the event-study analyses suggest modest effects of LTC availability on bed-blocking.

6 Conclusion

I analyze whether LTC provision can alleviate bed-blocking in Portuguese public hospitals. To do so, I exploit the roll-out of the public LTC network, which started in 2006 and included both nursing home facilities and teams providing home and community-based services.

Preliminary results from a difference-in-differences and an event-study approach suggest that HCBS teams are somewhat successful at reducing bed-blocking. For example, individuals living alone and those with inadequate housing have, on average, about 4-day shorter lengths of stay at the hospital after the entry of a HCBS team in their region of residence. For individuals waiting for a vacancy the reductions amount to 19 days. The entry of a nursing home provider, in turn, is not associated with length of stay reductions for the average bed-blocker but it leads to significant bed-blocking reductions among patients with high levels of dependency.

In general, LTC provision does not fully eliminate bed-blocking. A gap between the length of stay of stay of bed-blockers and regular patients still persists. Going forward, I want to assess the importance of capacity constraints and coordination frictions as mechanisms for explaining my findings.

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

	(1) Baseline	(2) Region-specific trends	(3) Hospital FE	(4) 15km radius	(5) 30km radius
HCBS team=1 × livingAlone=1	-3.811**	-3.645**	-3.810**	-2.957***	-2.670**
	(1.546)	(1.513)	(1.547)	(1.093)	(1.245)
HCBS team=1 × noFamilyToCare=1	1.421	1.419	1.403	0.310	0.834
	(5.201)	(5.164)	(5.195)	(3.521)	(3.361)
HCBS team=1 × housingIssues=1	-4.010*	-4.024*	-3.975*	-4.527***	-4.217**
	(2.157)	(2.144)	(2.161)	(1.731)	(1.828)
HCBS team=1 × awaitingAdequateFacility=1	-19.118***	-18.977***	-19.165***	-9.145***	-18.647***
	(5.194)	(5.165)	(5.185)	(3.247)	(4.605)
HCBS team=1 × Living in residential institution=1	-0.735	-0.676	-0.753	-0.297	-0.655*
	(0.453)	(0.417)	(0.455)	(0.343)	(0.392)
HCBS team=1 × otherSocialAdmission=1	-0.420	-0.384	-0.379	-1.059	-0.991
	(1.067)	(1.065)	(1.063)	(0.813)	(0.759)
NH unit=1 × livingAlone=1	0.285	0.086	0.310	0.006	-1.176
	(1.165)	(1.142)	(1.171)	(1.128)	(1.249)
NH unit=1 × noFamilyToCare=1	-0.036	-0.149	-0.035	3.215*	0.070
	(3.848)	(3.825)	(3.847)	(1.920)	(2.130)
NH unit=1 × housingIssues=1	-1.277	-1.217	-1.300	-0.081	-2.434
	(2.430)	(2.399)	(2.411)	(1.356)	(1.504)
NH unit=1 × awaitingAdequateFacility=1	-6.199	-6.385	-6.110	1.606	-7.762
	(4.949)	(4.857)	(4.925)	(2.942)	(11.311)
NH unit=1 × Living in residential institution=1	-0.140	-0.225	-0.110	-0.149	-0.340
	(0.369)	(0.240)	(0.369)	(0.210)	(0.317)
NH unit=1 × otherSocialAdmission=1	-1.131	-1.136	-1.135	-0.119	-0.669
	(1.264)	(1.264)	(1.261)	(0.942)	(1.313)
Observations	7962717	7962717	7962717	7962717	7962717
R^2	0.214	0.215	0.215	0.215	0.215

NOTES: The table shows the estimates of α^j 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, calendar quarter fixed-effects, diagnosis-related group fixed-effects, and region (ACES) fixed-effects. Column 2 includes region-specific time trends. Column 3 includes hospital fixed-effects. Columns 4 and 5 use the 15 and 30km radius around the centroid of the patient's municipality as the relevant region, respectively. Standard errors in parenthesis are clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

	(1) Baseline	(2) Ln(LOS+1)	(3) 1(LOS¿p50)	(4) 1(LOS¿p75)	(5) 1(LOS¿p90)	(6) 1(LOS¿p95)	(7) 1(LOS¿p99)
HCBS team=1 × livingAlone=1	-3.811**	-0.168***	-0.049***	-0.087***	-0.069***	-0.048***	-0.025**
	(1.546)	(0.053)	(0.018)	(0.024)	(0.021)	(0.017)	(0.010)
HCBS team=1 × noFamilyToCare=1	1.421	0.023	-0.005	0.002	0.019	0.008	0.015
	(5.201)	(0.123)	(0.022)	(0.039)	(0.049)	(0.049)	(0.035)
HCBS team=1 × housingIssues=1	-4.010*	-0.159***	-0.048***	-0.068***	-0.057**	-0.044*	-0.019
	(2.157)	(0.058)	(0.013)	(0.019)	(0.024)	(0.023)	(0.017)
HCBS team=1 × awaitingAdequateFacility=1	-19.118***	-0.135**	0.002	0.029	0.002	-0.021	-0.091***
	(5.194)	(0.061)	(0.013)	(0.021)	(0.030)	(0.035)	(0.022)
HCBS team=1 × Living in residential institution=1	-0.735	-0.028	0.002	-0.025*	-0.019**	-0.011**	-0.003*
	(0.453)	(0.036)	(0.018)	(0.015)	(0.008)	(0.005)	(0.001)
HCBS team=1 × otherSocialAdmission=1	-0.420	-0.054	-0.025	-0.034*	-0.016	-0.004	0.002
	(1.067)	(0.047)	(0.026)	(0.017)	(0.015)	(0.013)	(0.007)
NH unit=1 × livingAlone=1	0.285	0.056	0.021	0.035	0.028*	0.019	0.002
	(1.165)	(0.051)	(0.020)	(0.025)	(0.017)	(0.012)	(0.009)
NH unit=1 × noFamilyToCare=1	-0.036	0.060	0.016	0.048	0.042	0.041	0.009
	(3.848)	(0.095)	(0.019)	(0.032)	(0.037)	(0.035)	(0.025)
NH unit=1 × housingIssues=1	-1.277	0.013	0.007	0.020	0.024	0.009	-0.010
	(2.430)	(0.069)	(0.014)	(0.022)	(0.025)	(0.023)	(0.017)
NH unit=1 × awaitingAdequateFacility=1	-6.199	-0.081	0.015	0.004	-0.030	-0.065	-0.046
	(4.949)	(0.062)	(0.012)	(0.016)	(0.038)	(0.043)	(0.031)
NH unit=1 × Living in residential institution=1	-0.140	-0.047	-0.027	-0.001	0.004	0.002	0.001
	(0.369)	(0.039)	(0.019)	(0.016)	(0.008)	(0.005)	(0.001)
NH unit=1 × otherSocialAdmission=1	-1.131	0.017	-0.016	0.041**	0.041*	0.016	-0.007
	(1.264)	(0.048)	(0.026)	(0.019)	(0.023)	(0.018)	(0.008)
Observations	7962717	7962717	7962717	7962717	7962717	7962717	7962717
R^2	0.214	0.317	0.306	0.215	0.169	0.139	0.088

NOTES: The table shows the estimates of α from robustness checks to equation (2). In the baseline model in column 1 the dependent variable in length of stay in days. In column 2 the dependent variable is the natural logarithm of length of stay plus 1, $\ln(LOS+1)$. In columns 3 to 7 the dependent variable is a binary indicator taking value 1 in case individual i is above a certain percentile of the distribution of length of stay. All models include individual demographics and comorbidities, calendar quarter fixed-effects, diagnosis-related group fixed-effects, and region (ACES) fixed-effects. Standard errors in parenthesis are clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Results from estimating equation (2) in alternative time periods and samples

	(1) Baseline	(2) Periods 2000-2011	(3) Years 2005-2011	(4) Years after 2011	(5) Individuals over 65	(6) Stroke diagnosis
HCBS team=1 × livingAlone=1	-3.811**	-1.797	-1.530	2.963***	-3.166*	-3.753
	(1.546)	(1.327)	(1.255)	(0.651)	(1.701)	(2.650)
HCBS team=1 × noFamilyToCare=1	1.421	5.770	6.171	0.150	0.448	1.197
	(5.201)	(5.035)	(4.710)	(2.501)	(5.136)	(8.351)
HCBS team=1 × housingIssues=1	-4.010*	-1.804	-1.401	0.244	-2.886	0.539
	(2.157)	(2.043)	(2.084)	(1.341)	(2.399)	(3.982)
HCBS team=1 × awaitingAdequateFacility=1	-19.118***	-11.021***	-9.405**	5.235***	-15.830**	-2.461
	(5.194)	(4.099)	(4.118)	(1.543)	(6.320)	(5.942)
HCBS team=1 × Living in residential institution=1	-0.735	-0.386	-0.343	0.695***	-0.589	-1.410*
	(0.453)	(0.347)	(0.342)	(0.165)	(0.434)	(0.750)
HCBS team=1 × otherSocialAdmission=1	-0.420	0.865	0.865	3.569***	4.994*	-3.217
	(1.067)	(1.143)	(1.089)	(0.730)	(2.911)	(8.816)
NH unit=1 × livingAlone=1	0.285	-0.249	0.745	0.674	-0.237	-4.416**
	(1.165)	(1.553)	(1.322)	(1.795)	(1.083)	(1.841)
NH unit=1 × noFamilyToCare=1	-0.036	-4.369	-3.123	11.754**	2.104	-0.918
	(3.848)	(3.490)	(4.471)	(4.770)	(3.398)	(6.905)
NH unit=1 × housingIssues=1	-1.277	-2.042	-0.108	1.491	-1.757	-10.382***
	(2.430)	(2.143)	(2.163)	(4.272)	(2.382)	(3.860)
NH unit=1 × awaitingAdequateFacility=1	-6.199	-12.590	-9.597	-3.458	-7.027	-12.056
	(4.949)	(7.743)	(7.299)	(3.953)	(5.311)	(8.053)
NH unit=1 × Living in residential institution=1	-0.140	-0.581	-0.420	-0.127	-0.119	-0.040
	(0.369)	(0.365)	(0.316)	(0.239)	(0.323)	(0.593)
NH unit=1 × otherSocialAdmission=1	-1.131	-1.814	-1.957	2.026	-5.367*	-4.973
	(1.264)	(1.532)	(1.712)	(1.488)	(2.789)	(7.268)
Observations	7962717	6011594	3477098	1951119	3782917	281243
R^2	0.214	0.209	0.230	0.241	0.170	0.087

NOTES: The table shows the estimates of α in equation (2) for alternative time periods and age groups. Column 1 reproduces the baseline results. Column 2 restricts the analysis to individuals admitted to the hospital between the years 2000 and 2011. Columns 3 and 4 restrict the time window of analysis to the period between 2005 and 2011, and 2012 onward, respectively. Finally, columns 5 and 6 restricts the sample to individuals over 65 years old and to individuals admitted for stroke (DRG 14). All models include individual demographics and comorbidities, calendar quarter fixed-effects, diagnosis-related group fixed-effects, and region (ACES) fixed-effects. Standard errors in parenthesis are clustered at the region level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$