# Essays on long-term care and hospital care

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# Abstract

This thesis consists of four empirical essays, contributing to the understanding of key policy issues related to the maximisation of the efficiency of health care provision. Two policy areas are considered and the English NHS is used as a case study throughout. Chapters 2-4 contribute to a growing literature around the interface between acute hospital care and long-term care. This is closely related to the debate around integrating care.

Chapter 2 evaluates the impact of long-term care supply on the discharge destination and hospital length of stay of hip fracture and stroke patients. The results indicate hospital stays are shorter for hip fracture patients when nearby care-home bed supply is high. No effect of care-home beds is found for the length of stay of stroke patients or the discharge destination of either patient group.

Chapter 3 models delayed discharges from hospital across local government areas (Local Authorities). The findings suggest there are fewer delays in Local Authorities with more care-home beds. Further, higher care-home bed supply and lower population in neighbouring Local Authorities also leads to fewer delayed discharges in the local area. Chapter 4 evaluates the impact of hospital characteristics on delayed hospital discharges. The results indicate that hospitals with more autonomy and a proven track record of good performance incur fewer delayed discharges.

The second policy area considered is the use of financial incentives to encourage a shift in patient care expected to improve efficiency. Chapter 5 evaluates a policy of paying hospitals a higher rate for same day discharges than overnight stays when treating specific conditions. The results indicate some positive effects from the policy introduced. Same day discharge rates are higher for eight out of 32 conditions. Considerable heterogeneity in response is also observed, some of which might be driven by features of the conditions.

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# Author's Declaration

I declare that this thesis represents original work, of which I am the primary author. Chapter 2 "Long-term care provision, hospital bed blocking, and discharge destination for hip fracture and stroke patients" is co-authored with Hugh Gravelle, Rita Santos and Luigi Siciliani. I prepared the major datasets and performed the empirical analysis for this paper. Data on long-term care within a 10km radius was constructed with the assistance of Rita Santos. I prepared the first draft of the manuscript. All authors assisted in the refinement of the text. This paper has been published in the International Journal of Health Economics and Management (2017), volume 17, issue 3, pages 311-331 .

Chapter 3 "Testing the Bed-Blocking Hypothesis: Does Nursing and Care Home Supply Reduce Delayed Hospital Discharges?" and Chapter 4 "Delayed Discharges and Hospital Type: Evidence from the English NHS" were co-authored with Hugh Gravelle and Luigi Siciliani. I constructed the datasets, performed the empirical analysis and prepared the first draft of these manuscripts. The theoretical model presented in Chapter 3 was prepared by Hugh Gravelle. Chapter 3 has been published in Health Economics (2015), volume 24(s1), pages 32-44. Chapter 4 has been published in Fiscal Studies (2017), volume 38(3), pages 415-519.

Chapter 5 "Paying for Efficiency: Incentivising Same-Day Discharges in the English NHS" was co-authored with Nils Gutacker, Katja Grašič, Noemi Kreif, Luigi Siciliani and Andrew Street. I prepared the dataset of planned conditions. Equivalent data for emergency conditions was prepared by Katja Grašič. I performed the extensive empirical analysis for this work and prepared the first draft of the manuscript. I also contributed to the theoretical description of hospital incentives. This manuscript was submitted and given a revise and resubmit at the Journal of Health Economics. The revised manuscript was accepted for publication in volume 68 of the journal. For this thesis the earlier version is presented, as the methods used are discussed in greater detail.

# Chapter 1

# Introduction

The provision of healthcare is a core focus of policy makers throughout Organisation for Economic Cooperation and Development (OECD) countries. In 2015, total government expenditure was around 40% of GDP in OECD countries. Within government spending, health represented the second largest budgetary item in the OECD as a whole at 18.7% and in many member states including France (14.3%), Germany (16.3%), Japan (19.4%), Norway (17.2%), the U.S. (24.2%) and the U.K. (17.8%). Public spending on hospital services in European OECD member states averaged 46.5% of expenditure on health in the same year and was largest in the U.K. at 75.2% (OECD, 2017). There is considerable upward pressure on health expenditure in general and hospital care in particular, due to ageing populations and technology development. At the same time, following the 2008 global financial crisis and subsequent recession, U.K. government health expenditure has grown more slowly than in previous decades. Real terms growth in health expenditure from 2009/10 to 2015/16 has been 1.3% on average, compared to an average of 4.1% from 1955/56 to 2015/16 (Stoye, 2017). These two trends reinforce a focus on maximising the efficiency of healthcare production.

However, the value of providing healthcare is ultimately derived from the additional health generated. Therefore, policy makers are also concerned with the quality of care, so far as higher quality leads to improved health outcomes. As such, a potential risk of policies incentivising greater efficiency of healthcare provision is that these policies will have negative consequences for care quality. For example, activity based payment systems give a fixed price for each patient treated. The price is driven by the type of patient, rather than treatment choices or health outcomes. Hospitals retain any surpluses and are liable for any costs of care exceeding these predetermined prices. This incentivises hospitals to minimise the cost of care and so improve the efficiency of healthcare production. However, concerns have been raised that such a strong cost minimising incentive, with no adjustment for quality, might lead to cutting costs by reducing the quality of care provided (Chalkley and Malcomson, 1998). This generates a trade off between maximising the efficiency and quality of care provided.

In this thesis, two areas of hospital care are considered. In both areas, efficiency can be increased by reducing hospital length of stay (LOS) to a clinically optimal level from the observed LOS. They might therefore represent efficiency improvements at a lower cost to care quality. The first area relates to the interface between long-term care (LTC) and hospital care. The provision of health and LTC in many OECD countries is managed and funded separately. In the U.K., hospital care is financed through general taxation and commissioned by Clinical Commissioning Groups (CCGs), formerly Primary Care Trusts (PCTs). The provision of the great majority of hospital care is through public hospitals and consumed free at the point of need. Long-term care is financed through a combination of out of pocket expenses and taxation in the form of subsidies. Local Authorities (LAs) are responsible for commissioning LTC, which is provided by a mix of private firms, charitable and public institutions. This division of responsibilities in providing hospital and long-term care can result in an externality problem in which incentives faced by individual organisations undermine overall system efficiency.

The availability and organisation of LTC is a necessary condition for many patients to be discharged from hospital care. In a first best optimum, patients would be discharged as soon as this was clinically optimal. As this part of the thesis is concerned with patients discharged to LTC, optimality can be thought of as the point where a patient would receive similar care and health benefit from being cared for in a hospital or in a LTC setting. Such discharges can be delayed when there is insufficient supply of LTC or specific packages of care have not been organised for the patient concerned. Where this occurs, hospital care acts as a more expensive substitute for LTC. Delayed discharges are also connected to the bed-blocking hypothesis. Where hospital beds are a binding constraint, reducing delayed discharges would allow for more prompt admissions to hospital. This may also reduce the cost of care in hospital, where delays in admission increase the risk of complications. Both of these mechanisms indicate an increase in the efficiency of healthcare provision. Even if hospital bed capacity is not a binding constraint, reducing delayed discharges allows more staff time to be spent with acutely ill patients, which may improve health outcomes for this patient group without increasing labour costs. This mechanism would suggest an improvement in care quality for hospital patients.

The consumption of both healthcare and LTC is strongly driven by morbidity (Kasteridis et al., 2015). The proportion of older people living with disability in England and Wales is expected to grow in coming years, largely due to an aging population (Guzman-Castillo et al 2015). In 2006/07, 10% of people aged over 75 consumed both health and LTC in that year (Bardsley et al., 2012). We can therefore expect substantive and increasing use of both health and LTC by the same patients in future years, enhancing the relevance of questions around the interface of the sectors. Chapters 2-4 of this thesis investigate whether the supply of LTC affects the discharge destination of hospital patients, their length of stay and delayed discharges. These analyses also consider whether the supply of LTC has spill-over effects on delayed discharges across geographic jurisdictions and how much variation in delays can be explained by hospital type (Teaching, Specialist, Mental Health and Foundation Trusts).

The second area, considered in chapter 5 of this thesis, is the potential for financial incentives to improve the efficiency of care in a hospital setting. This question is considered by evaluating a policy of paying a higher price if specific patients are admitted, treated and discharged on the same day. Adopting this treatment approach avoids an overnight stay in hospital and so reduces length of stay. Shorter stays are less costly to provide and so improve the efficiency of care provided. Shorter stays might represent an increase or decrease in the quality of care, depending on whether a faster discharge is clinically appropriate. As patients considered for this policy are discharged to their own home without LTC, an appropriate discharge implies the health gain from receiving additional treatment is negligible. This incentive is applied to patient groups where recommended rates of admission and discharge on the same day are higher than those observed nationally. It is therefore expected that average LOS can be shortened without reducing the quality of care of affected patients. In chapter 5 of the thesis, this change in incentives is used to investigate (i) whether providers respond to financial incentives regarding discharge choice, (ii) whether any response is consistent across different patient groups and (iii) whether any response is constant over time, following introduction of the incentive. The rest of this chapter is set out as follows. First, it provides a description of the key features of hospital care and LTC in England which have a bearing on the analysis performed in subsequent chapters. Second, it gives an overview of the empirical analyses performed in each chapter.

## 1.1 Institutional Framework

### *Hospital Care*

Hospital care in England is predominantly provided publicly, free at the point of need, by the National Health Service (NHS). Care is in turn largely financed from general taxation. Of £77.3bn spent on hospital care in the U.K. in 2015, £71.4bn (92%) was government financed. The remaining £5.9bn consisted of all non-government expenditure including: compulsory and voluntary insurance; charitable organisations; and out of pocket expenditure (ONS, 2017). In this thesis, the focus is on publicly financed healthcare. The administrative unit for providing care in NHS hospitals is the Hospital Trust. These Trusts employ medical professionals and manage the care at one or more hospital sites. Such hospitals are therefore generally referred to as NHS or public hospitals. While having the same core responsibilities, Trusts can be divided along two dimensions. First, around two thirds of Trusts have 'Foundation Trust' (FT) status. This status allows for a greater degree of independence from national policy. For example, FTs are able to borrow in order to invest in new equipment. As acquiring FT status requires meeting a series of targets and demonstrating financial viability, FT status can also be considered a general mark of quality for hospitals. Second, Trusts can be grouped into the mutually exclusive categories of Acute, Acute Teaching, Acute Specialist and Mental Health. Teaching Trusts have a connection with a University and have specific responsibilities to train medical students. Specialist Trusts focus on a specific area of medicine and provide care for the most complex cases in that area. Mental Health Trusts provide care for patients with mental, as opposed to physical, health conditions.

Reimbursement for acute hospital care is through a prospective payment system. A price is set in advance for a set of patient groups referred to as Healthcare Resource Groups, the English equivalent to Diagnosis Related Groups used in the U.S. and many other OECD countries. In general, prices are set based on the average cost of care for the patient group from three years previously. Patients are allocated to groups based on their diagnoses, procedures received and in some cases other characteristics such as age. Mental health care is reimbursed on a separate system to physical health. As this thesis explicitly related to reimbursement deals exclusively with care in an acute setting, details on mental health care are omitted.

### *Long-Term Care*

Long-term care in England encompasses assistance with day-to-day activities in a non-hospital setting. The provision of LTC takes a variety of forms and can be grouped into three types: informal care; formal homecare; and institutional care. Informal care is generally provided by a spouse or child in a patient's own home. Formal homecare generally takes the form of regular visits from a paid care worker. Institutional care is provided in a care home, which in some cases include nursing staff. In England, care homes without nursing care are frequently referred to as residential homes and those including nursing staff as nursing homes. The focus of this thesis is on the provision of LTC through care homes. This is the most intensive and costly form of LTC and the type for which the most detailed data is currently available for England.

In England, local government plays a major role in the provision of LTC. These bodies, referred to as Local Authorities (LAs), are responsible for performing an assessment when a potential need for LTC is identified. From this, a specific package of care is decided upon and LAs are responsible for commissioning this care from generally local providers. Care based on a needs assessment is predominantly provided based on major contracts agreed in advance between LAs and care providers. In the case of care home provision, the LAs offer specific placements to patients who have a final say on acceptance. LAs bear these responsibilities to people living within a specific geographic area, but their LTC can be provided in a location outside of this jurisdiction. That is, in a carehome within a different LA.

Care home services are predominantly provided by the private sector, with smaller numbers of homes run by the NHS, LAs or non-profit organisations. While authorities purchase care when need is identified, they can recoup an amount of this payment back from patients on a means test basis. Around 60% of care home users pay privately for the LTC they receive, either in full (37%) or as a top up payment (22%). People with low income or wealth are partially subsidised by the Local Authority. The level of subsidisation is a decision taken locally by authorities within nationally regulated minimums. Taken together, almost any consumer of LTC at a care home makes at least some payment at consumption (Forder, 2007). Further, as the proportion of people holding LTC insurance in England is minimal, these costs represent out of pocket expenses for the vast majority of users.

## 1.2 Chapters Overview

Chapter 2 investigates the impact of long-term care supply on the length of stay and discharge destination of hospital patients. Following a period of acute care, some patients require some form of long-term care. If appropriate care is not available, a patient may have to spend additional time in hospital. In this way, hospital care can act as a more costly substitute for LTC. The availability of LTC may also influence the discharge destination of hospital patients. For example, discharging a larger proportion of patients to institutional care when it is more readily available. The specific research questions addressed in chapter 2 are the impact of LTC supply on (i) the probability of a patient being discharged to a care home and (ii) patient length of stay in hospital.

The analysis uses a patient level dataset of hip fracture and stroke admissions in 2008/09. These are high volume conditions which frequently involve a mix of acute and LTC. The sample analysed includes all hip fracture and stroke patients admitted to an English hospital from their own home and discharged back to their own home or to a care home. Supply of long-term care is measured by the number of care home beds within 10km of the patient and the average price of care home beds in the same area. A small catchment area is used as the main analysis in this context as it is expected that nearby supply will have the greatest impact on patient decisions. Small catchment areas also highlight the differences in supply faced by patients treated in the same hospital. Other catchment areas, up to 30km, are also considered as sensitivity analyses. The dataset also includes a rich set of demographic and clinical factors which are used as covariates. The analysis employs linear probability and OLS models, both with hospital fixed effects to account for time invariant unobserved characteristics.

The results indicate no association between discharge destination and the supply or price of care home beds. However, there is evidence of bed-blocking. Length of stay is over 30% shorter among hip fracture patients discharged to a care home, when care home beds supply is in the highest quintile compared to those in the lowest quintile. Findings also indicate lower prices are associated with shorter hospital length of stay for hip fracture patients discharged to a care home.

The extent to which greater supply of care home beds or lower prices reduce delayed discharges is considered in chapters 3 and 4. Delays can increase the overall cost of treatment and may worsen patient outcomes. Delays in discharge might also lead to delays in admission for other patients, further increasing the average cost of care for this group through a higher risk of clinical complications. Chapter 3 focuses on delayed discharges attributed to Local Authorities. These local government bodies are responsible for providing needs assessments and for commissioning LTC for people living within their jurisdictions. However, capacity to fulfil this role may be constrained by the supply of LTC resources in the area, which are predominantly privately provided. Further, patients can receive care outside the jurisdiction of their LA. Therefore, the effects of LTC availability and need for care might spill-over across Local Authority boundaries. Chapter 3 specifically investigates (i) the impact of care home beds and prices on delayed discharges within an LA attributed to that LA (ii) whether need or LTC supply variables exhibit spill-over effects across LA boundaries.

The analysis uses a Local Authority level panel of hospital delayed discharges covering all English LAs in the period 2009 to 2013 inclusive. The supply of long-term care is captured by the number of care home beds and average prices within each LA. The empirical analysis employs linear models with hospital random effects to account for time invariant unobserved characteristics. It is possible that supply of LTC is influenced by the presence of delayed discharges in an area, a type of simultaneity problem. This concern is tackled by employing a set of instrumental variables in the model. The instruments used are one year lags of the potentially endogenous variables. The standard linear model is also extended by applying spatial econometric techniques to investigate potential spill-over effects. These are measured by the addition of spatially lagged population and care home beds variables to the model.

The results suggest that delayed discharges respond to the availability of care home beds, but the effect is modest: an increase in care home beds by 10% (250 additional beds in an LA) reduces delayed discharges attributed to Local Authorities by about 6–9%. There is also strong evidence of spill-over effects. Both population and care home beds in other LAs reinforce effects found in the local LA.

Chapter 4 investigates the role of hospital characteristics along with LTC supply in explaining variation in delayed discharges. Research about delayed discharges has generally focused on the role of local government as LTC commissioners. However, hospitals also play a role in the process of discharge. For example, it is necessary for hospitals to inform LAs of a potential need for LTC and when a patient is ready to be discharged. Delays might occur if this information is not provided in a timely matter or if there are bottlenecks of internal discharge procedures such as availability of consultants or provision of transport. Chapter 4 considers whether variation in delayed discharges can be explained by (i) hospital types of Acute Teaching, Acute Specialist or Mental Health (ii) autonomy of Trusts, as captured by Foundation Trust Status and (iii) the supply of LTC.

The analysis employs a Trust level panel of delays in all English NHS hospitals from 2011/12 to 2013/14 inclusive. The dataset also includes a set of patient characteristics along with the key variables under investigation. Long-term care is captured by the supply of care home beds within 10km of each Trust and the average price of care homes in the same area. The empirical strategy uses negative binomial models with hospital random effects. In common with chapter 3, results indicate that a greater local supply of long-term care is associated with fewer delays. It is also found that there are fewer delayed discharges from Foundation Trusts, which have greater autonomy than Trusts without this status, by 14-28%. Finally, there is indicative evidence that delays in leaving mental health hospitals are less frequently the responsibility of those hospitals than following acute care. Variation in overall delays is significantly associated with Mental Health Trusts while delays attributed to NHS hospitals is not.

Taken together, chapters 2-4 contribute to a growing literature on the impact of long-term care on hospital care. Previous studies of discharge destination which include long-term care supply as a factor have considered small numbers of hospitals (Bond et al., 2000), for the U.K., (Picone et al., 2003), for the U.S.). This work is extended in chapter 2 to include all hospitals in England. The analysis in chapter 2 also contributes to a wider strand of literature considering drivers of discharge destination (Aharonoff et al., 2004; Bond et al., 2000; Ellis and Trent, 2001; Gilbert et al., 2010; Picone et al., 2003) and hospital length of stay (Bond et al., 2000; Castelli et al., 2015; Clague et al., 2002; Holmas et al., 2010; Holmas et al., 2013; Picone et al., 2003) for hip fracture patients. Previous work on delayed discharges has considered local effects of long-term care at Local Authority level (Fernandez and Forder, 2008) or generally for a selected small geographic area in England (Bryan et al., 2006) and Norway (Holmas et al., 2010; Holmas et al., 2013). Work presented in chapters 3 and 4 consider the full set of English Local Authorities and Trusts respectively and investigate additional key features of spatial long-term care effects and the role of hospital type in delayed discharges.

Chapter 5 considers the impact of financial incentives on the treatment of hospital patients. Reimbursement is one of the main tools used by policy makers in attempts to maximise the efficiency and quality of care provided to patients. Understanding the impact of past and current incentives can assist in refining incentives offered to achieve these objectives more effectively. Chapter 5 evaluates a policy with several unusual features which assist in providing useful insights. The incentive introduced encourages hospitals to admit and discharge patients on the same calendar day.

Where clinically appropriate, same day discharge is a more efficient form of patient care than overnight stays. In this context, appropriateness implies the health gain from an overnight stay in hospital is negligible compared to being discharged without an overnight stay. It is also profit maximising from the perspective of the provider, even before the evaluated policy is introduced. The cost of care is lower, while reimbursement is the same as for care with an overnight stay. The profit maximising incentive could therefore lead to patients being discharged too quickly. Therefore the policy, whereby a higher reimbursement is paid for same day discharge than overnight stay, is limited to specific patient groups with both a longer national average length of stay than is clinically recommended and where there is variation in that length of stay. The incentive is also high powered and adapted to different patient groups. The specific questions considered are (i) does hospital care respond to the financial incentives introduced? (ii), is the response consistent across conditions? And (iii) is the response consistent over time?

The analysis utilises a patient level dataset of all English patients treated for one of 191 conditions in 2006/07 to 2014/15 inclusive. All of the conditions included are amenable to admission and discharge on the same day at some recommended rate. An incentive of additional reimbursement for treating patients within a single day is attached to 32 of these conditions (13 planned and 19 emergency conditions). The incentivised conditions cover multiple clinical areas and the size of incentive is specific to each condition. The empirical strategy employed uses interrupted time series; differences-in-differences; and synthetic control models. The control groups used for differences-in-differences and synthetic control models are taken from the set of unincentivised conditions in the dataset.

Results indicate that the policy had a generally positive effect on planned conditions with a statistically significant effect in about a third of conditions and a median elasticity of policy response with respect to incentive size of 0.24. The results are more mixed for emergency conditions, indicating both positive and negative impacts and a median elasticity of 0.01. The median elasticity (across all 32 conditions) is 0.09 but above one for six conditions.

Considerable heterogeneity in response is observed across conditions and over time.

The analysis in chapter 5 contributes to two strands of literature. First, to literature on the impact of price changes on treatment choice. In general, previous research in this area has considered a change in reimbursement framework such as from block contracts to prospective payment (Farrar et al., 2009) or when within a common framework, focused on a single clinical procedure (Allen et al., 2016; Foo et al., 2017; Papanicolas and McGuire, 2015). Further, price differences have often been modest at less than 5% (Chandra et al., 2011; Papanicolas and McGuire, 2015), arising naturally from institutional circumstances instead of a deliberate policy (Foo et al., 2017; Papanicolas and McGuire, 2015) or limited to a short policy period (Allen et al., 2016). The chapter presents analysis on a series of similar incentives deliberately aiming to change clinical behaviour with an unusually large incentive and following its impact for 2 to 5 years. The work most directly extends the work of Allen et al. (2016), which investigates the same incentive following its first year of application to a single procedure of cholecystectomy.

Second, the chapter contributes to a wider literature on the impact of Pay for Performance (P4P) schemes, see Milstein and Schreyögg (2016) for a review of P4P in the hospital setting. Previous mixed results of this literature make it difficult to draw general conclusions. Analysis in chapter 5 provides insights into the generalisability of findings from a P4P scheme considering a narrow clinical area. It also sheds light on the hypothesis previously made that P4P schemes can be unsuccessful if the incentive concerned is modest (Milstein and Schreyögg, 2016).

# Chapter 2

# Long-Term Care Provision, hospital bed blocking, and discharge destination for hip fracture and stroke patients

## 2.1 Introduction

The provision of health care and long-term care for the elderly is a consistent focus of policy makers in the U.K. and other OECD countries (DH, 2001; DH, 2011b; Glendinning, 2003; OECD, 2011; Wanless, 2006). Around 10% of individuals over 75 years old used both health and long-term care in 2006/2007 in England (Bardsley et al., 2012). Longterm care has costs and outcome consequences on health care and vice versa (Fernandez and Forder, 2008; Forder, 2009; Vetter, 2003). In England, acute hospital care and long-term care are organised and funded separately and differently.

There is long standing concern over coordination for patients requiring health and long-term care, in particular the delayed discharge of patients from hospital (Baumann et al., 2007; Bryan et al., 2006; House of Commons Committee of Public Accounts, 2003; NAO, 2000). To improve integration policy makers need information about the effects of provision of one type of care on the other. In this paper we examine two questions where there is little quantitative evidence: the extent to which accessibility of long-term care affects the length of stay in hospital and the probability of a patient being discharged back to their homes rather than to a care home.

We focus on patients who suffer a hip fracture or stroke. The conditions are selected for their high incidence, impairing effects on patients, and the consequent need for long-term care for the elderly (Kasteridis et al., 2015; Meijer et al., 2011). The British Orthopaedics association reports there were around 70,000 hip fractures in the U.K. in 2007, including many older patients with complex clinical needs. The incidence is expected to rise (British Orthopaedic Association, 2007). Further, 10–20% of hip fracture patients admitted to hospital from their own home ultimately utilise some institutional care (National Clinical Guidelines Centre, 2011). The national stroke strategy published by the Department of Health in 2007 reports that there are approximately 110,000 strokes each year in England and that 75% of these occur among people aged 65 and over. Stroke is the single largest cause of disability, with a third of people suffering from a stroke having a long-term disability (DH, 2007a; NAO, 2005). Estimates of the proportion of care home residents who have had a stroke vary between 25 and 45% (CQC, 2011). Hip fracture and stroke patients are thus a policy concern (DH, 2001) and have been the focus of past research in England (Bond et al., 2000). Both require immediate hospital care and longer term rehabilitation. Such rehabilitation could take place in hospital but also at the patient's home or in a long-term care facility.

Higher care home bed supply, at given prices, implies a shorter waiting time for a bed to become available and may thus increase the probability of discharge to a care home. It may also imply a shorter hospital length of stay since patients will have shorter waits for a place in a care home. Higher prices will reduce the probability of the patient opting for a care home as opposed to returning to their own home and may induce patients to search for longer, thereby increasing hospital length of stay.

We examine two questions. First, we investigate whether access to long-term care in nursing and residential homes (as measured by beds and prices) influences the probability that patients who are admitted to hospital from their home are discharged to a care home. Second, we investigate the bed blocking hypothesis that the supply of long-term care influences length of stay in hospital.

### *Institutional Background*

Emergency hospital care in England is predominantly provided by the National Health Service (NHS) through 166 acute public hospitals, known as Trusts. NHS care is funded by general taxation, with 152 local health authorities (Primary Care Trusts, PCTs) receiving capitated budgets from the Department of Health from which they pay for hospital care provided to their populations. Patients do not pay for hospital care provided by NHS hospitals.

Long-term care is provided by over 18,000 care homes.[1] (Laing and Buisson, 2014). In

[1] "Care home" is the usual term in England for a residential institution providing long-term personal care such as help with bathing and dressing. Some care homes also provide nursing care and are referred to as nursing homes. A care home which does not provide nursing care has, in the past, been sometimes referred to as a residential home (Age UK, 2015). Other countries use a different terminology. For example, in the U.S. care homes might be referred to as Assisted Living, Personal Care Homes or Residential Care Facilities

2014 about 74% of care home beds were provided by for-profit firms, 17% by voluntary organisations and 8% by Local Authorities (LAs) (Jarret, 2016).[2] Providers are generally small and the supply and price of care home beds is largely driven by local demand, the cost of provision, and by competition (Forder and Fernandez, 2012; Allan and Forder, 2015).

Around 60% of care home users (Forder, 2007) are self-funders and pay at least in part privately for their long-term care. Those with low wealth are subsidised by their LA. The price charged for subsidised patients is lower than for self-funders because of the bargaining power of the LAs (OFT, 2011). This gives a financial incentive to care homes to give priority to self-funders, within the constraints of any locally negotiated contract with LA commissioners. Despite potentially considerable out-of-pocket expenses associated with long-term care, the proportion of individuals covered by private long-term care insurance in England is very small, with just under 22,000 people holding such insurance in 2008 (Comas-Herrera et al., 2009).

The majority of residents in care homes are long stay. Care homes also provide some rehabilitation services. Steventon and Roberts (2012) found that 39% of LA funded admissions to care homes in three English LAs in 2005/2006 were short stay but that the median length of stay was 18 months.

#### *Previous Literature*

Previous studies investigating discharge destination of hospital patients find that age, gender and living arrangements are key drivers of discharge to a care home as opposed to their own home. Other factors include comorbidities (Aharonoff et al., 2004; Gilbert et al., 2010), ethnicity (Aharonoff et al., 2004; Ellis and Trent, 2001), urbanisation (Gilbert et al., 2010) and income deprivation (Gilbert et al., 2010; Picone et al., 2003). Patients discharged to a care home are also likely to have a longer stay in hospital (Castelli et al., 2015; Wong et al., 2010).

Picone et al. (2003) investigates the determinants of hospital length of stay and discharge destination of 4,608 U.S. Medicare patients following hip fracture, stroke or heart attack. They show that potential supply of informal care (being married and number of children) increases the likelihood of being discharged home. They also find that supply of institutional care (concentration of skilled nursing home or rehabilitation hospital beds) is associated with shorter length of stay. The only patient level English study of discharge destination is (Bond

with precise definitions determined at the state level. Skilled Nursing Facilities or Nursing Homes perform the same general function as nursing homes in the U.K. (Pioneer Network, 2011) As this study uses English data, we use the English terminology definitions and so care homes include nursing and residential homes.

[2]The 152 Local Authorities (LAs) with responsibility for social care are elected political bodies funded by local taxes and central government grants. The 166 local acute health trusts are part of the NHS and are appointed by the Department of Health.

et al., 2000) who examine the discharge destination of 440 stroke and 572 hip fracture patients in six English NHS hospitals. They find that the probability of being discharged to a care home increases with the supply of care home beds. In line with these studies, we find a negative association between care home beds supply and length of stay in hospitals, and a positive but insignificant association between care home beds supply and the probability of being discharged to a care home.

Although there is an extensive literature on the substitution between informal and formal long-term care (Bolin et al., 2008; Bonsang, 2009; Grabowski et al., 2012; Houtven and Norton, 2004), there is limited evidence on the effect of care homes supply on health care utilisation, i.e. on the substitution between long-term social care and hospital care. Fernandez and Forder (2008) find that LAs with more home help hours and nursing and residential care beds have a lower rate of hospital delayed discharges and lower emergency readmission rates. Forder (2009) uses small area data on 8,000 census areas in England and finds that a £1 increase in spending on care homes reduces hospital expenditure by £0.35. Gaughan et al. (2015) use LA level data on all types of hospital patients and find that greater supply of care home beds in the LA is associated with a reduction in delayed discharge from hospital.

Holmas et al. (2010) investigate the effect of fining owners of long-term care institutions which prolong length of stay at hospitals in Norway. Surprisingly, hospital length of stay is longer when the fines are used, which they interpret as an example of monetary incentives crowding out intrinsic motivation. Holmas et al. (2013) find that greater expenditure on long-term care by Norwegian local authorities reduces both overall length of hospital stay and stay in hospital when medically ready for discharge.

Our study contributes to the literature on the relationship between long-term care and health care by using a large and rich individual patient level dataset for two disabling and high incidence conditions so that we can control more precisely for patient diagnoses, socioeconomic characteristics and hospital policies than previous English area level studies.

## 2.2 Data and Methods

### *Sample*

A detailed account of the data set construction is in the Data Appendix. We use cross-section administrative data from Hospital Episodes Statistics (HES). Our sample is all patients aged 65 or over, resident in England, treated in NHS hospitals, admitted from home as an emergency with a primary diagnosis of hip fracture or stroke, and discharged in the financial year April 2008–March 2009. We exclude patients who are admitted from a care home since they are very likely to return to the same care home. We analyse the two samples (hip fracture and stroke) separately. While coordination between acute and long-term care services is important for patients with either condition, the characteristics and needs of the two patient groups differ. As well as being treated in different hospital departments, which may have different policies about discharge, stroke is a potentially more severe condition and with a more varied prognosis.

Patients who die in hospital, are discharged to a penal institution or to a secure psychiatric unit, have incomplete spells, or for whom final discharge destination is not known, are excluded from the analysis. We also exclude patients at Hospital Trusts with less than 10 hip fracture and stroke patients per year. The estimation samples are 21,959 hip fracture patients and 33,101 stroke patients.

### *Dependent Variable*

Our dependent variables are the patient's hospital length of stay and whether the patient is discharged to a long-term care institution as opposed to returning home following hospitalisation. Patient length of stay is the number of days between admission and discharge from hospital at the end of their spell, allowing for patients to be transferred between hospitals during their spell.

### *Patient characteristics*

For each patient we have age, gender, number of diagnoses and procedures, day of discharge and whether the patient is transferred to a different provider during their hospital spell. HES diagnostic fields are used to construct three co-morbidity dummy variables based on the Charlson index (Charlson et al., 1987). We distinguish between (i) no Charlson comorbidities, (ii) a single non-severe co-morbidity, (iii) at least one severe or at least two non-severe co-morbidities. Since stroke is one of the Charlson co-morbidities we exclude it when constructing these variables for stroke patients.

We also distinguish between different types of hip fracture and stroke. The major types of hip fracture relate to the location of the fracture. The categories are femoral neck, peritrochanteric, and subtrochanteric, where the trochanters refer to protrusions of bone just below the ball of the hip. Prognosis and length of stay varies by type of fracture (Butelr et al., 2009; Clague et al., 2002). The most critical distinction for stroke patients is between strokes due to an infarction, where a vessel supplying blood to the brain is blocked and those due to a haemorrhage, where there is bleeding in or around the brain. Although patient outcome is driven by stroke severity as well as by type of stroke (Jorgensen et al., 1995) haemorrhagic strokes generally lead to worse outcomes in terms of disability and mortality.

### *Formal long-term care*

We have data on the number of registered beds and prices of different types of rooms for all providers in England whose main client group is patients aged 65 or over or with dementia (Laing and Buisson, 2014). We include these two categories of provider since they match with the age restrictions of our sample and it is these groups of patients most likely to require care in a care home following hip fracture or stroke. Care homes specialising in dementia are likely to cater to patients in our group given that its prevalence increases rapidly with age. Moreover, having a stroke might cause dementia and conversely a patient suffering with dementia might have a hip fracture from a fall.

While stroke is a more severe condition, the Stroke Association suggests that a patient can be accommodated in a residential home depending on need (Stroke Association, 2013). There are almost no specialist stroke care homes and at least 25% of patients in care homes have had a stroke (CQC, 2011). There is a small amount of specialist rehabilitation in the care home sector but these providers do not cater specifically for care following stroke or hip fracture.

We compute the number of beds and average prices in residential and nursing homes within a 10km radius of the centroid of each patient's small area of residence known as Lower Super Output Area (LSOA). LSOAs are small geographic areas with an average population of 1,500 in 2001. There are 32,482 LSOAs in England served by 166 acute hospital trusts. We also have a measure of average care home quality based on ratings by the sector regulator (the Care Quality Commission, (CQC)).

To allow for differences in population we use the mid-2008 population of retirement age (60 years and over for women; 65 years and over for men) living in LSOAs whose centroids are within 10km of each patient's LSOA centroid.

### *Socioeconomic characteristics of patient areas of residence*

Information on socioeconomic characteristics is not available at the individual level in HES. We attribute socioeconomic variables from the 2001 Census and the 2004 Index of Multiple Deprivation to patients by their LSOA of residence. The variables include the proportions of non-white residents, households with a single pensioner, and those reporting self-assessed health as "not good" from the three categories (good, fairly good and not good). The proportion of single pensioner households provides some adjustment for availability of informal care as much of this care is provided by a spouse or other relative living with the patient. We measure income deprivation as the proportion of the LSOA's population aged over 60 who are claiming income support, income related job seekers allowance, or pension credit guarantee. LSOAs are classified as urban, town or village.We include a dummy variable for patients resident in a London LSOA to allow for peculiarities of health and long-term care provision in the capital. Because of lack of information on acute care in Scotland and Wales, we include dummy variables indicating whether a patient's LSOA is within 10km of the English border with Scotland or Wales.

### *Methods*

We use models with the same explanatories for both patient discharge destination and patient length of stay except for using day of discharge in modelling length of stay. We estimate linear probability models for a patient being discharged to a care home as opposed to the patient's home, separately for hip fracture and stroke. The model is:

$$y_{ij} = \beta_1 m_{ij} + \beta_2 x_{ij} + \beta_3 B_{ij} + \beta_4 P_{ij} + h_j + \varepsilon_{ij} \tag{2.1}$$

where $y_{ij}$ is an indicator variable equal to one if the patient $i$ in hospital $j$ is discharged to a care home and zero if discharged to their own home. $m_{ij}$ is a vector of patient morbidity variables and $x_{ij}$ is a vector of patient demographic and socio-economic characteristics. $B_{ij}$ is care home beds supply in the 10km area around the centroid of the patient's LSOA of residence, and $P_{ij}$ is average care home prices in the same area. Notice that care home beds and prices vary across patients treated within the same hospital since each hospital will draw patients from many different LSOAs. We allow for non-linear effects by measuring price and beds supply as indicators for the quintiles of the national distribution of these variables across all LSOAs. $h_j$ is a hospital fixed effect. Except where otherwise stated, we estimate all models with cluster (hospital) robust standard errors.

For the investigation of patient length of stay we use the natural logarithm of length of stay as the dependent variable in (2.1). We estimate separate models for patients discharged to a care home and for those discharged to their home.

To choose between fixed or random hospital effects we estimate auxiliary regressions with the same explanatory variables as (2.1) but with hospital effects replaced by the hospital level means of the explanatories (Mundlak, 1978; Wooldridge, 2010). For all models we find that a joint Wald test rejects the null hypothesis that the coefficients on the hospital level means are zero. We therefore use the fixed effects specifications. Thus the reported coefficients on beds or prices show whether, within a given hospital, patients residing in LSOAs with a higher long-term care supply have greater length of stay and or probability of being discharged to a care home.

Care home beds and prices are measured for each patient as the sum (beds) and means (prices) for care homes within 10km of the patient's LSOA of residence. We argue that these are not correlated with unobservable factors affecting individual patient length of stay and discharge destination. First, we control for hospital fixed effects and these will pick any variations in hospital policies which might affect length of stay or discharge destination for all patients treated in the hospital and which might be correlated with care home supply and prices if care homes locate near hospitals which have a tendency to keep patients in longer or to discharge them to care homes. We identify the effect of care home beds and prices from their variation across patients treated within the same hospital but living in different LSOAs and thus facing different beds supply and prices. Second, we have good data on individual patient morbidity which might affect length of stay and discharge destination. We also include measures of LSOA level demographics, socioeconomic characteristics, morbidity, retirement, and single pensioner households which might affect area level demand for long-term care and hence supply and prices. Third, our dependent variables are for patients with two specific conditions whilst care homes cater for a much wider set of patients so it is unlikely that care home beds supply and prices will be driven by demand from stroke and hip fracture patients.

Our models make the simplifying assumption that decisions on discharge destination and length of stay are independent. As a robustness check, we model the decisions jointly with a two-step selection model (Heckman, 1979) with a probit model for discharge destination and adding the inverse mills ratio derived from it to the linear length of stay models in the second stage. Using hospital fixed effects in the first stage probit model would yield biased estimates. Instead, we replace each explanatory variable with its hospital level mean and with patient level deviations from the mean. The hospital level means will pick up unobserved hospital effects. As an exclusion condition, we include the rate of discharge to care at the hospital level in the first stage but not in the second, arguing that the hospital rate of discharge to care will capture internal policies which affect patient probabilities of discharge to care but will not directly affect length of stay. We also run the model without this variable, relying on non-linearity for identification.

## 2.3 Results

### ***Summary statistics***

Table 2.1 provides descriptive statistics. Similar proportions of hip (14.5%) and stroke (13.5%) patients are discharged to a care home. The average hospital length of stay is 22 days for hip fracture and 29 days for stroke. Length of stay is shorter for patients returning to their home (20 days for hip fracture and 23 for stroke) than for those discharged to a care home (33 and 62 days). There are on average 2300–2400 care home beds within 10km with an average price around £524 per week. The average care home quality rating is ‘good’ (a score of 3).

Table 2.1: Summary Statistics

| | Hip Fracture | | | | Stroke | | | |
|---|---|---|---|---|---|---|---|---|
| | mean | SD | Min | Max | mean | SD | Min | Max |
| *Dependent variables* | | | | | | | | |
| Discharged to care home | 0.145 | 0.352 | 0 | 1 | 0.135 | 0.342 | 0 | 1 |
| Length of stay if discharged to care home | 32.68 | 27.98 | 2 | 167 | 62.07 | 44.16 | 1 | 460 |
| Length of stay if discharged home | 19.95 | 17.90 | 2 | 168 | 23.38 | 30.13 | 1 | 394 |
| *Patient characteristics* | | | | | | | | |
| Age group: 65-74 | 0.166 | 0.372 | 0 | 1 | 0.299 | 0.458 | 0 | 1 |
| Age group: 75-84 | 0.409 | 0.492 | 0 | 1 | 0.429 | 0.495 | 0 | 1 |
| Age group: 85plus | 0.425 | 0.494 | 0 | 1 | 0.271 | 0.445 | 0 | 1 |
| Male patient | 0.223 | 0.416 | 0 | 1 | 0.466 | 0.499 | 0 | 1 |
| Total diagnoses | 5.713 | 2.919 | 1 | 39 | 6.234 | 3.511 | 1 | 32 |
| Total procedures | 2.818 | 1.546 | 0 | 24 | 2.671 | 1.786 | 0 | 22 |
| Patient transferred in CIPS | 0.049 | 0.217 | 0 | 1 | 0.137 | 0.343 | 0 | 1 |
| Pertrochanteric fracture | 0.228 | 0.420 | 0 | 1 | | | | |
| Subtrochanteric fracture | 0.029 | 0.167 | 0 | 1 | | | | |
| Unspecified hip fracture | 0.743 | 0.437 | 0 | 1 | | | | |
| Stroke caused by a hemorrhage | | | | | 0.137 | 0.344 | 0 | 1 |
| Stroke caused by an infarction | | | | | 0.615 | 0.487 | 0 | 1 |
| Stroke not hemorrhage or infarction | | | | | 0.213 | 0.410 | 0 | 1 |
| Occluded cerebral vessels no infarction | | | | | 0.003 | 0.051 | 0 | 1 |
| Other stroke | | | | | 0.032 | 0.176 | 0 | 1 |
| No Charlson comorbidities | 0.493 | 0.500 | 0 | 1 | 0.515 | 0.500 | 0 | 1 |
| 1 minor Charlson comorbidity | 0.334 | 0.472 | 0 | 1 | 0.266 | 0.442 | 0 | 1 |
| >=2 minor or >=1 major Charlson comorbidity | 0.172 | 0.378 | 0 | 1 | 0.218 | 0.413 | 0 | 1 |
| Discharged on Monday | 0.152 | 0.359 | 0 | 1 | 0.174 | 0.379 | 0 | 1 |
| Discharged on Tuesday | 0.191 | 0.393 | 0 | 1 | 0.186 | 0.389 | 0 | 1 |
| Discharged on Wednesday | 0.190 | 0.392 | 0 | 1 | 0.185 | 0.388 | 0 | 1 |
| Discharged on Thursday | 0.180 | 0.385 | 0 | 1 | 0.180 | 0.385 | 0 | 1 |
| Discharged on Friday | 0.209 | 0.406 | 0 | 1 | 0.216 | 0.411 | 0 | 1 |
| Discharged on Saturday | 0.052 | 0.223 | 0 | 1 | 0.044 | 0.204 | 0 | 1 |
| Discharged on Sunday | 0.017 | 0.131 | 0 | 1 | 0.015 | 0.122 | 0 | 1 |

Table continues in following page.

Table 2.1: (continued)

| | **Hip Fracture** | | | | **Stroke** | | | |
|---|---|---|---|---|---|---|---|---|
| | mean | SD | Min | Max | mean | SD | Min | Max |
| *Socioeconomic characteristics of patient areas of residence* | | | | | | | | |
| % LSOA 60+ pop on income based benefit | 19.65 | 11.81 | 1 | 95 | 19.81 | 12.31 | 1 | 95 |
| % LSOA pop who are non-white | 6.21 | 11.20 | 0 | 90.45 | 7.09 | 13 | 0 | 94.8 |
| % LSOA pop with good SAH | 67.13 | 6.51 | 37.3 | 87.6 | 67.22 | 6.34 | 37.3 | 87 |
| % LSOA pop with fairly good SAH | 23.03 | 3.47 | 10.4 | 36.1 | 23.07 | 3.41 | 10.7 | 37.3 |
| % LSOA pop with not good SAH | 9.84 | 3.62 | 1.7 | 31.0 | 9.71 | 3.51 | 1.7 | 31.0 |
| % single pensioner households in LSOA | 16.09 | 6.01 | 0.5 | 51 | 15.92 | 6.00 | 0.0 | 51 |
| Patient resident in London | 0.089 | 0.284 | 0 | 1 | 0.103 | 0.304 | 0 | 1 |
| LSOA within 10km of Scottish boarder | 0.001 | 0.026 | 0 | 1 | 0.001 | 0.029 | 0 | 1 |
| LSOA within 10km of Welsh boarder | 0.012 | 0.109 | 0 | 1 | 0.015 | 0.121 | 0 | 1 |
| Urban > 10k people | 0.791 | 0.407 | 0 | 1 | 0.788 | 0.409 | 0 | 1 |
| Town and fringe | 0.111 | 0.314 | 0 | 1 | 0.114 | 0.318 | 0 | 1 |
| Village or hamlet and isolated dwellings | 0.098 | 0.297 | 0 | 1 | 0.098 | 0.297 | 0 | 1 |
| Total retired population within 10km (000s) | 67.2 | 62.1 | 0.5 | 328.7 | 70.9 | 67.1 | 348 | 328.2 |
| *Formal long-term care* | | | | | | | | |
| Care home beds within 10km (000s) | 2.31 | 1.79 | 0 | 7.81 | 2.41 | 1.92 | 0 | 7.82 |
| Beds within 10km/retired population | 0.037 | 0.01 | 0 | 0.116 | 0.037 | 0.01 | 0 | 0.116 |
| Average price within 10km | 523.21 | 93.05 | 232 | 971 | 525.25 | 91.49 | 232 | 961 |
| Average care home rating within 10km | 3.03 | 0.17 | 1 | 4 | 3.03 | 0.17 | 1 | 4 |
| Number of patients | 21959 | | | | 33101 | | | |

Notes: CIPS continuous in-patient spell, LSOA lower super output area, SAH self-assessed health

### *Discharge destination: hip fracture*

Table 2.2 reports the results from linear probability discharge destination models. The probability of being discharged to a care home is greater for patients who are older, female, and have more diagnoses. Compared to patients aged 65–74 years old, patients who are 75–84 and older than 84 years have 6.2 and 11.4% points higher probabilities of being discharged to a care home. Men have a 1.6% points smaller probability. An additional diagnosis or procedure increases the probability by 1.1 and 0.5% points.

Table 2.2: Determinants of discharge to care home

| | **Hip Fracture** | | **Stroke** | |
|---|---|---|---|---|
| | coef | p | coef | p |
| *Patient characteristics* | | | | |
| Age 75-84 | 0.062 | 0.000 | 0.054 | 0.000 |
| Age 85plus | 0.114 | 0.000 | 0.125 | 0.000 |
| Male | -0.016 | 0.005 | -0.043 | 0.000 |
| Number diagnoses | 0.011 | 0.000 | 0.018 | 0.000 |
| Number procedures | 0.005 | 0.021 | 0.002 | 0.11 |
| Patient transferred | 0.005 | 0.793 | 0.029 | 0.025 |
| Pertrochanteric fracture | 0.000 | 0.938 | | |
| Subtrochanteric fracture | 0.004 | 0.766 | | |
| Stroke caused by a hemorrhage | | | 0.014 | 0.035 |
| Stroke hemorrhage or infarction | | | -0.019 | 0.000 |
| Occluded cerebral no infarction | | | 0.009 | 0.776 |
| Other stroke | | | -0.074 | 0.000 |
| 1 minor Charlson comorbidity | 0.031 | 0.000 | 0.002 | 0.655 |
| >= 2 minor/>= 1 major Charlson comorbidity | 0.019 | 0.047 | -0.001 | 0.926 |
| *Socioeconomic characteristics of patient areas of residence* | | | | |
| LSOA 5th income deprivation quintile | -0.013 | 0.168 | -0.012 | 0.050 |
| % LSOA pop non white | 0.000 | 0.615 | 0.000 | 0.381 |
| % LSOA not good SAH | 0.000 | 0.788 | 0.004 | 0.002 |
| % LSOA single pensioner household | 0.001 | 0.278 | -0.001 | 0.08 |
| London LSOA | -0.031 | 0.364 | -0.027 | 0.371 |
| LSOA 10km of Scottish boarder | -0.012 | 0.897 | -0.069 | 0.252 |
| LSOA 10km of Welsh boarder | -0.003 | 0.923 | 0.024 | 0.238 |
| Town and fringe | -0.007 | 0.34 | -0.003 | 0.560 |
| Village, hamlet, isolated dwellings | -0.011 | 0.204 | -0.004 | 0.604 |
| Population within 10km (100000s) | 0.013 | 0.578 | 0.011 | 0.449 |
| *Formal long-term care* | | | | |
| **Beds within 10km second quintile** | 0.009 | 0.396 | 0.002 | 0.790 |
| **Beds within 10km third quintile** | 0.021 | 0.088 | -0.012 | 0.238 |
| **Beds within 10km fourth quintile** | 0.025 | 0.263 | 0.018 | 0.188 |
| **Beds within 10km top quintile** | 0.041 | 0.197 | 0.014 | 0.512 |
| **Price within 10km second quintile** | -0.010 | 0.339 | 0.002 | 0.855 |
| **Price within 10km third quintile** | -0.012 | 0.326 | 0.011 | 0.267 |
| **Price within 10km fourth quintile** | 0.006 | 0.739 | 0.019 | 0.127 |
| **Price within 10km top quintile** | -0.004 | 0.817 | 0.020 | 0.175 |
| **Care home ratings 10km mean** | -0.005 | 0.834 | 0.001 | 0.935 |
| Constant | -0.021 | 0.788 | -0.063 | 0.239 |
| Hospital effects | FE | | FE | |

Table continues in following page.

Table 2.2: (continued)

| | coef | p | coef | p |
|---|---|---|---|---|
| $R^2$ | 0.0327 | | 0.074 | |
| Observations | 21959 | | 33101 | |

Notes: Fixed effect panel data linear probability model of discharge to care home versus discharge to own home with cluster robust standard errors. The $\chi^2$ statistic for the auxiliary regression test (see (Methods) section) for the consistency of the random error specification is $\chi^2(29)=$ 28.15, p = 0.5097 for hip fracture and $\chi^2(31)$ = 125.85, p = 0.000 for stroke.

There is some, though weak, association of the probability of discharge to a care home with long-term care beds. Compared to patients in the lowest quintile of beds supply, the estimated probability of being discharged to care for patients in LSOAs in the second, third, fourth and fifth beds quintiles are 0.9, 2.1, 2.5 and 4.1% points greater. However, none of the coefficients achieves 5% statistical significance.

#### *Discharge destination: stroke*

The effects of covariates on the discharge destination of stroke patients are similar to those for hip fracture patients. Patients who are 75–84 years old and older than 84 years have 5.4 and 12.5% points higher probability of being discharged to a care home, compared to those aged 65–74. Men have a smaller probability (by 4.3% points) of being discharged to a care home.

An additional diagnosis increases the probability by 1.8% points. Transferred patients have 2.9% points higher probability. Compared to patients with cerebral infarction, the probability of discharge to care is 1.4% points higher if stroke is haemorrhagic.

The probability of stroke patients being discharged to care is not associated with the supply of care home beds, or with their price.

#### *Length of stay: hip fracture*

Since we use the logarithm of the length of stay as the dependent variable, the coefficients in Table 2.3 are the proportionate changes in length of stay in days from a one unit increase in the explanatory variable. Older patients have a longer length of stay. Among patients discharged to care, those who are older than 84 years have 12% longer stays than those aged 65–74. For patients discharged home, those aged 75–84 stay 21 and those aged over 84 stay 32% longer.

Table 2.3: Determinants of length of stay: hip fracture

| | **Discharged to care** | | **Discharged to home** | |
|---|---|---|---|---|
| | coef | p | coef | p |
| *Patient characteristics* | | | | |
| Age 75-84 | 0.065 | 0.128 | 0.209 | 0.000 |
| Age 85plus | 0.120 | 0.007 | 0.315 | 0.000 |
| Male | 0.067 | 0.026 | 0.008 | 0.464 |
| Number diagnoses | 0.089 | 0.000 | 0.081 | 0.000 |
| Number procedures | 0.077 | 0.000 | 0.080 | 0.000 |
| Patient transferred | 0.855 | 0.000 | 0.870 | 0.000 |
| Pertrochanteric fracture | -0.036 | 0.272 | -0.005 | 0.651 |
| Subtrochanteric fracture | 0.035 | 0.631 | 0.117 | 0.000 |
| 1 minor Charlson comorbidity | 0.009 | 0.769 | -0.039 | 0.001 |
| >= 2 minor/ >1 major Charlson comorbidity | -0.136 | 0.000 | -0.074 | 0.000 |
| Discharged on Tuesday | -0.087 | 0.037 | -0.076 | 0.000 |
| Discharged on Wednesday | -0.175 | 0.000 | -0.082 | 0.000 |
| Discharged on Thursday | -0.11 | 0.003 | -0.086 | 0.000 |
| Discharged on Friday | -0.141 | 0.000 | -0.116 | 0.000 |
| Discharged on Saturday | -0.154 | 0.006 | -0.189 | 0.000 |
| Discharged on Sunday | -0.197 | 0.057 | -0.135 | 0.000 |
| *Socioeconomic characteristics of patient areas of residence* | | | | |
| LSOA 5th income deprivation quintile | 0.023 | 0.547 | 0.075 | 0.000 |
| % LSOA pop non white | 0.000 | 0.844 | 0.001 | 0.281 |
| % LSOA not good SAH | -0.006 | 0.365 | -0.008 | 0.002 |
| % LSOA households single pensioner | -0.002 | 0.303 | 0.005 | 0.000 |
| London LSOA | -0.185 | 0.468 | -0.018 | 0.784 |
| LSOA 10km of Scottish boarder | 0.448 | 0.000 | 0.099 | 0.079 |
| LSOA 10km of Welsh boarder | -0.224 | 0.084 | -0.14 | 0.012 |
| Town and fringe | 0.009 | 0.849 | 0.000 | 0.989 |
| Village, hamlet isolated dwellings | -0.105 | 0.045 | -0.048 | 0.014 |
| Population within 10km (100000s) | 0.230 | 0.040 | 0.048 | 0.095 |
| *Formal long-term care* | | | | |
| **Beds within 10km second quintile** | -0.049 | 0.336 | -0.012 | 0.466 |
| **Beds within 10km third quintile** | -0.064 | 0.391 | 0.011 | 0.598 |
| **Beds within 10km fourth quintile** | -0.216 | 0.036 | 0.007 | 0.835 |
| **Beds within 10km top quintile** | -0.319 | 0.020 | -0.022 | 0.641 |
| **Price within 10km second quintile** | -0.014 | 0.769 | -0.030 | 0.178 |
| **Price within 10km third quintile** | 0.006 | 0.925 | -0.044 | 0.116 |
| **Price within 10km fourth quintile** | 0.162 | 0.030 | -0.031 | 0.342 |
| **Price within 10km top quintile** | 0.175 | 0.050 | -0.010 | 0.792 |
| **Care home ratings 10km mean** | 0.127 | 0.182 | 0.030 | 0.428 |
| Constant | 1.977 | 0.000 | 1.782 | 0.000 |
| Hospital effects | FE | | FE | |
| $R^2$ | 0.305 | | 0.311 | |

Table continues in following page.

Table 2.3: (continued)

| | coef | p | coef | p |
|---|---|---|---|---|
| Observations | 3175 | | 18784 | |

Notes: Dependent variable: natural logarithm of length of stay. Coefficients are the proportionate change in length of stay in days from a one unit increase in the explanatory variable. Fixed effects panel data models with cluster robust standard errors. The $\chi^2$ statistic for the auxiliary regression test (see (Methods) section) for the consistency of the random error specification is $\chi^2(35) = 115.56$, p = 0.000 for patients discharged to care and $\chi^2(35) = 100.87$, p = 0.000 for those discharged to their own home

Patients discharged to care stay 6.7% longer if male, 8.9% longer with an additional diagnosis, and 7.7% with an additional procedure. Patients transferred to a different hospital have more than 80% longer stays. Surprisingly, having Charlson comorbidities reduces length of stay. Patients discharged to care who live in villages and sparsely populated areas have 11% shorter stays than those living in urban areas. The fifth most income deprived quintile of the population have 8% longer length of stay than those in less deprived areas if discharged home. Patients discharged on Monday have longer stays compared with those discharged on other days of the week, perhaps because some could not be discharged during the weekend as relevant staff were not available.

The accessibility of long-term care beds is associated with shorter lengths of stay for patients discharged to a care home: patients in LSOAs in higher quintiles of long-term care beds have shorter hospital stay than those in lower quintiles. Those in the top two quintiles have lengths of stay which are 22 and 32% shorter than those in the bottom quintile, a difference which is quantitatively large and statistically significant at 5%. There is no association between beds supply and length of stay for hip fracture patients discharged home.

There is some indication that patients in areas with higher care home prices stay longer before being discharged to a care home. Patients in the fourth and fifth quintile of the price distribution have stays which are 16% (p = 0.030) and 18% (p = 0.050) longer than those in the bottom quintile. There is no association between prices and length of stay for hip fracture patients discharged to their home.

#### ***Length of stay: stroke***

Table 2.4 suggests that among patients discharged home, those who are 75–84 years old and older than 84 years have greater length of stay (respectively by 16 and 33%). Older patients discharged to care have shorter stays (by 7 and 23%). Men have 15% shorter stays if discharged home. An additional procedure increases length of stay by 5% if discharged to care and 10% if discharged home. An additional diagnosis increases length of stay by 7 and 13%. Length of stay for patients transferred to another hospital is 51% greater if discharged home and 91% greater if discharged into long-term care. Patients with Charlson comorbidities have a shorter length of stay whether discharged to their own home or to care. Patients living in areas in the fifth most income deprived quintile have 4% longer length of stay if discharged home. The type of stroke also affects length of stay: compared to patients whose stroke is caused by cerebral infarction, length of stay is shorter by 50 and 67% for patients discharged to care and those discharged to home whose cause of stroke is unspecified.

Greater supply of long-term care beds is not associated with the length of stay of patients discharged to a care home. In contrast, more long-term care beds reduces length of stay for patients discharged home (by 21% in the highest quintile) and the association is significant at 5% in the fourth and fifth quintiles. This is surprising since we would not expect beds supply to affect the hospital length of stay of patients discharged to their own home. Length of stay is not associated with the care home prices whether patients are discharged home or to care home.

### *Robustness checks*

We tested the sensitivity of our results to different estimation methods and specifications. We interacted income deprivation with the supply and price variables and found that their effect did not vary with deprivation. We measured long-term care supply using patient areas of 20 and 30km radii instead of 10km.We estimated models with beds per capita, rather than entering beds and population separately. We estimated Cox proportional hazard models for length of stay. The key results were not affected and are reported in Gaughan et al. (2013).

Table 2.4: Determinants of length of stay: stroke

| | **Discharged to care** | | **Discharged to home** | |
|---|---|---|---|---|
| | coef | p | coef | p |
| *Patient characteristics* | | | | |
| Age 75-84 | -0.074 | 0.035 | 0.160 | 0.000 |
| Age 85plus | -0.225 | 0.000 | 0.327 | 0.000 |
| Male | 0.027 | 0.282 | -0.146 | 0.000 |
| Number diagnoses | 0.069 | 0.000 | 0.129 | 0.000 |
| Number procedures | 0.052 | 0.000 | 0.099 | 0.000 |
| Patient transferred | 0.509 | 0.000 | 0.909 | 0.000 |
| Stroke caused by a hemorrhage | -0.080 | 0.010 | 0.026 | 0.293 |
| Stroke hemorrhage or infarction | -0.087 | 0.005 | -0.202 | 0.000 |
| Occluded cerebral vessels no infarction | 0.083 | 0.569 | -0.192 | 0.106 |
| Other stroke | -0.497 | 0.000 | -0.672 | 0.000 |
| 1 minor Charlson comorbidity | -0.128 | 0.000 | -0.077 | 0.000 |

Table continues in following page.

Table 2.4: (continued)

| | coef | p | coef | p |
|---|---|---|---|---|
| >=2 minor or >=1 major Charlson comorbidity | -0.207 | 0.000 | -0.045 | 0.041 |
| Discharged on Tuesday | -0.075 | 0.024 | -0.156 | 0.000 |
| Discharged on Wednesday | -0.080 | 0.019 | -0.170 | 0.000 |
| Discharged on Thursday | -0.102 | 0.008 | -0.164 | 0.000 |
| Discharged on Friday | -0.099 | 0.008 | -0.313 | 0.000 |
| Discharged on Saturday | -0.223 | 0.000 | -0.423 | 0.000 |
| Discharged on Sunday | -0.203 | 0.117 | -0.675 | 0.000 |
| *Socioeconomic characteristics of patient areas of residence* | | | | |
| LSOA fifth income deprivation quintile | 0.022 | 0.530 | 0.043 | 0.038 |
| % LSOA pop non white | 0.001 | 0.461 | 0.001 | 0.211 |
| % LSOA not good SAH | -0.013 | 0.020 | 0.003 | 0.352 |
| % LSOA households single pensioner | 0.004 | 0.103 | -0.001 | 0.334 |
| London LSOA | 0.179 | 0.112 | -0.126 | 0.103 |
| LSOA within 10km of Scottish boarder | 0.860 | 0.000 | -0.008 | 0.899 |
| LSOA within 10km of Welsh boarder | 0.022 | 0.765 | 0.002 | 0.981 |
| Town and fringe | 0.040 | 0.259 | -0.039 | 0.051 |
| Village or hamlet and isolated dwellings | 0.007 | 0.879 | -0.005 | 0.833 |
| Population within 10km (100000s) | 0.044 | 0.667 | 0.184 | 0.000 |
| *Formal long-term care* | | | | |
| **Beds within 10km second quintile** | 0.020 | 0.655 | -0.026 | 0.289 |
| **Beds within 10km third quintile** | -0.052 | 0.411 | -0.050 | 0.153 |
| **Beds within 10km fourth quintile** | -0.061 | 0.522 | -0.111 | 0.035 |
| **Beds within 10km top quintile** | -0.196 | 0.167 | -0.209 | 0.003 |
| **Price within 10km second quintile** | -0.013 | 0.786 | -0.024 | 0.449 |
| **Price within 10km third quintile** | -0.060 | 0.247 | 0.018 | 0.617 |
| **Price within 10km fourth quintile** | -0.046 | 0.53 | -0.016 | 0.678 |
| **Price within 10km top quintile** | -0.051 | 0.624 | -0.032 | 0.477 |
| **Care home ratings within 10km mean** | 0.122 | 0.206 | -0.073 | 0.144 |
| Constant | 3.069 | 0.000 | 1.678 | 0.000 |
| Hospital effects | FE | | FE | |
| $R^2$ | 0.253 | | 0.337 | |
| Observations | 4465 | | 28636 | |

Notes: Dependent variable: natural logarithm of length of stay. Coefficients are the proportionate change in length of stay in days from a one unit increase in the explanatory variable. Fixed effects panel data models with cluster robust standard errors. The $\chi^2$ statistic for the auxiliary regression test (see (Methods) section) for the consistency of the random error specification is $zchi^2(37)= 114.35$, p = 0.0001 for patients discharged to care and $\chi^2(37)= 450.81$, p = 0.0001 for those discharged to their own home

Table 2.5 has results from the selection correction model which allows for the interdependence of decisions on length of stay and discharge destination. They are very similar to those from the simpler separate linear models and indicate that accounting for selection does not alter the main findings.

## 2.4 Discussion

### *Discharge destination*

As expected, and in line with earlier findings (Bond et al., 2000) older patients and those with greater morbidity are more likely to be discharged to a care home when they leave hospital. Other things equal, men are less likely to enter a care home on discharge. This may be because they are more likely to have a spouse or a partner who can provide informal care at home since women have longer life expectancy and tend to be younger than their partners (Wilson and Smallwood, 2008).

There is only very weak evidence in our results that accessibility of long-term care affects the discharge destination for hip fracture or stroke patients.We find that hip fracture patients who live in areas with higher care home beds supply are more likely to be discharged to a care home. The magnitude of the effects are quite large (4.1% points in the highest quintile compared with an unconditionalmean probability of 14.5%) but is not statistically significant at the conventional (5%) level.

There is no association between beds supply and discharge destination for stroke patients, who are arguably more severely impaired than hip fracture patients and therefore less able to substitute formal care with informal care at home.

Prices are not associated with discharge destination for either hip fracture or stroke patients. This suggests that the demand for a care home is at most determined by non-monetary costs, such as the waiting time.

In summary, our results suggest that discharge destination is mostly driven by patient characteristics such as severity, age and comorbidities rather than by care home prices and bed supply. Stroke patients discharged to a care home have on average been diagnosed with two additional conditions, received 0.3 more procedures, are more likely to have the more serious haemorrhagic stroke, and to have more comorbidities. Hip fracture patients discharged to care are diagnosed with around one additional condition, receive 0.2 more procedures and have a rate of comorbidity 5 or 6% points higher than those discharged home.

### *Length of stay*

Patient severity is also a key determinant of length of stay. More secondary diagnoses and procedures are associated with significantly longer stays. The primary diagnosis is also important. The effect of age is similar for hip fracture and stroke patients discharged to their own homes: length of stay is over 30% greater for patients over 85. Older hip fracture patients

Table 2.5: Comparison of selection correction and seperate linear models

| | Discharge Destination | | | | Ln Length of Stay if discharged to care | | | | Ln Length of Stay if discharged to home | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Linear FE** | | **Selection correction 1st stage** | | **Linear FE** | | **Selectin correction 2nd Stage** | | **Linear FE** | | **Selection correction 2nd Stage** | |
| | coef | p | coef | p | coef | p | coef | p | coef | p | coef | p |
| **Hip Fracture Models** | | | | | | | | | | | | |
| **Beds within 10km 2nd quintile** | 0.009 | 0.396 | 0.042 | 0.335 | -0.049 | 0.336 | -0.036 | 0.445 | -0.012 | 0.466 | -0.013 | 0.426 |
| **Beds within 10km 3rd quintile** | 0.021 | 0.088 | 0.105 | 0.070 | -0.064 | 0.391 | -0.028 | 0.669 | 0.011 | 0.598 | 0.012 | 0.602 |
| **Beds within 10km 4th quintile** | 0.025 | 0.263 | 0.114 | 0.159 | -0.216 | 0.036 | -0.181 | 0.046 | 0.007 | 0.835 | 0.008 | 0.799 |
| **Beds within 10km top quintile** | 0.041 | 0.197 | 0.176 | 0.141 | -0.319 | 0.020 | -0.246 | 0.061 | -0.022 | 0.641 | -0.022 | 0.635 |
| **Price within 10km 2nd quintile** | -0.010 | 0.339 | -0.065 | 0.173 | -0.014 | 0.769 | -0.024 | 0.643 | -0.030 | 0.178 | -0.031 | 0.086 |
| **Price within 10km 3rd quintile** | -0.012 | 0.326 | -0.086 | 0.143 | 0.006 | 0.925 | -0.010 | 0.883 | -0.044 | 0.116 | -0.044 | 0.043 |
| **Price within 10km 4th quintile** | 0.006 | 0.739 | 0.009 | 0.906 | 0.162 | 0.030 | 0.203 | 0.015 | -0.031 | 0.342 | -0.030 | 0.270 |
| **Price within 10km top quintile** | -0.004 | 0.817 | -0.035 | 0.703 | 0.175 | 0.050 | 0.211 | 0.040 | -0.01 | 0.792 | -0.009 | 0.789 |
| Inverse Mills ratio | | | | | | | 0.233 | 0.000 | | | -0.324 | 0.035 |
| **Stroke Models** | | | | | | | | | | | | |
| **Beds within 10km 2nd quintile** | 0.002 | 0.790 | 0.019 | 0.598 | 0.020 | 0.655 | 0.023 | 0.596 | -0.026 | 0.289 | -0.022 | 0.346 |
| **Beds within 10km 3rd quintile** | -0.012 | 0.238 | -0.061 | 0.204 | -0.052 | 0.411 | -0.075 | 0.213 | -0.050 | 0.153 | -0.065 | 0.045 |
| **Beds within 10km 4th quintile** | 0.018 | 0.188 | 0.091 | 0.162 | -0.061 | 0.522 | -0.048 | 0.551 | -0.111 | 0.035 | -0.092 | 0.036 |
| **Beds within 10km top quintile** | 0.014 | 0.512 | 0.079 | 0.410 | -0.196 | 0.167 | -0.174 | 0.143 | -0.209 | 0.003 | -0.199 | 0.002 |
| **Price within 10km 2nd quintile** | 0.002 | 0.855 | 0.004 | 0.929 | -0.013 | 0.786 | -0.004 | 0.932 | -0.024 | 0.449 | -0.025 | 0.349 |
| **Price within 10km 3rd quintile** | 0.011 | 0.267 | 0.059 | 0.206 | -0.060 | 0.247 | -0.032 | 0.572 | 0.018 | 0.617 | 0.030 | 0.335 |
| **Price within 10km 4th quintile** | 0.019 | 0.127 | 0.092 | 0.116 | -0.046 | 0.530 | -0.028 | 0.696 | -0.016 | 0.678 | 0.003 | 0.936 |
| **Price within 10km top quintile** | 0.020 | 0.175 | 0.088 | 0.235 | -0.051 | 0.624 | -0.037 | 0.698 | -0.032 | 0.477 | -0.014 | 0.770 |
| Inverse Mills ratio | | | | | | | 0.334 | 0.076 | | | -0.778 | 0.082 |

Notes: There are 21,959 hip fracture observations and 33,101 stroke observations. Linear FE model coefficients are from the models in Tables 2, 3 and 4. Selection correction models include hospital means of patient level variables and deviations from means. Coefficients are those on the deviations also have longer stays if discharged to care homes, though the effects of age are around one third as large as for patients discharged to their own homes. Counter-intuitively, older stroke patients discharged to a care home have shorter hospital stays. These most complex patients may have the highest priority for nursing home care and have least access to potential substitutes with care at home, a hypothesis supported in part by the significantly longer stay for older patients who are discharged home.

Patients in areas with greater income deprivation who are discharged to their own home stay longer in hospitals. Cookson and Laudicella (2011) also find that English elective hip replacement patients in poorer areas have greater length of stay. Since poorer individuals are generally in worse health, income deprivation may also be a proxy of poor health and hospitals may want patients discharged home to be in better health than those discharged to a care home where there will be more support.

Within a given hospital, hip fracture patients who are discharged to a care home have a shorter hospital stay if they live in an area with a greater supply of long-term care beds. The results are consistent with bed blocking: once patients are medically fit for discharge their length of stay is determined by factors outside the control of the hospital, such as local care home supply.

We also find that hip fracture patients living in areas with higher long-term care prices have longer hospital stays. This suggests that patients intending to enter a care home take longer to search for a place when bed prices are higher.

The difference between the length of stay of patients discharged home and to a care home is particularly marked for stroke patients. This is expected as stroke is in general a more severe condition. Most critically, the prognosis following a stroke ranges widely from a very short stay of a few days to a protracted stay extending into months. The latter case, involving extensive rehabilitation in a hospital setting, is where patients ultimately discharged to care are concentrated. Patients discharged to their own home quickly are likely to have been less severe and have been treated most promptly as these are important factors in determining outcomes. Stroke patients discharged to a care home are much more likely to have a severe comorbidity (28% compared to 21%) and also more likely to have had a stroke caused by haemorrhage (16% compared to 13%).

The length of stay of stroke patients discharged to a care home is not affected by the availability of beds, their price or the quality of care homes in their area. The differences in results between stroke and hip fracture may be explained by stroke being a more impairing condition for which patients require much more intensive post hospital care. The demand for long-term care for stroke patients may therefore be less affected by beds supply and prices. Note however that the coefficients in the top quintiles are negative and for the top quintile the coefficient is quantitatively large (a reduction in length of stay by 20%) though not statistically significant (p = 0.17).

In contrast to hip fracture patients, we find that for stroke patients, greater availability of beds reduces length of stay of those discharged to their own home: patients in the highest quintile of beds supply have a 21% shorter stay than those in the lowest quintile. This may be due to care homes beds supply being positively correlated with provision of assistance for stroke patients in their homes.

As in the case of discharge destination decision, patient severity is the key determinant of length of stay. However, for hip fracture patients the availability of formal long-term care also appears to have an important impact for those discharged to institutional care. For patients discharged to their own home the availability of informal care from relatives is also likely to affect length of stay. We do not have patient-level data on the home circumstances of hospital patients but do use a small area measure of the proportion of pensioners living alone. We find, in line with Picone et al. (2003), that hip fracture patients discharged to their home have longer hospital stays in small areas with a higher proportion of single pensioners.

## 2.5 Concluding remarks

Our results suggest that accessibility of long-term care matters for hip fracture patients. Greater long-term care supply and lower prices are associated with shorter hospital length of stay for patients discharged to care homes. The effect can be quantitatively large with 20–30% shorter length of stay for patients with most availability (at the highest bed quintiles).

The results are substantially different for stroke patients. Hospital length of stay is not associated with price (in contrast to hip fracture patients). Counter-intuitively, those discharged home have a shorter length of stay if availability of long-term care beds is high. The differences between stroke and hip fracture may be that stroke results in more severe and longer lasting impairment.

Overall, for hip fracture patients we find evidence consistent with the ‘bed-blocking’ hypothesis that availability of long-term care affects the length of stay of patients who no longer need to be in acute hospital and are ready to be discharged. Caring for such patients in hospital is more costly than long-term care. Our results suggest that for hip fracture patients an expansion of the long-term care sector can reduce hospital length of stay and reduce the total cost of caring for these patients.

# Chapter 3

# Testing the bed-blocking hypothesis: Does nursing and care home supply reduce delayed hospital discharges?

## 3.1 Introduction

Hospital bed-blocking occurs when a patient is medically ready to be discharged and cared for in another setting. Because hospital care is more expensive than nursing or residential home care, bed-blocking is a signal of allocative inefficiency. There is concern about bed-blocking in countries including Australia, Austria, the Netherlands, Sweden and the U.K. (Brown et al., 2011; Mur-Veeman and Govers, 2011; NAO, 2000).

We investigate the extent to which greater supply of nursing and care home beds reduces delays in hospital discharges (i.e. the degree of substitution between formal long-term care (LTC) and health care). Whether policy makers should encourage such increases in supply to reduce delayed discharges depends, inter alia, on the elasticity of the number of delayed discharges with respect to the availability of care home beds. If the elasticity is high, then an increase in care home supply will have a significant positive externality on the hospital sector.

The rate at which hospital patients are discharged into a nursing home may depend not only on the supply of beds but also on their price. Unlike health care, which is free or heavily subsidised in most Organisation for Economic Cooperation and Development countries, there is limited insurance for nursing home costs (Cremer et al., 2012). Hence, higher prices may prolong search and make patients more reluctant to be transferred to a nursing home and hence increase bed-blocking. If so, policy interventions, which reduce prices for nursing homes (such as encouraging competition, (Forder and Allan, 2014)) may also have beneficial effects in the hospital sector.

We also explore whether the supply of care homes in a Local Authority (LA) affects delayed discharges in other LAs. This is important for policy. If spillover effects across LAs are negligible, then policymakers will have to pay more attention to variations in care homes availability across LAs, because they will also imply variations in delayed discharges. But variation in provision across LAs may be of less concern if patients are willing to accept a bed in other LAs. Spillover effects across LAs may also raise coordination issues by weakening incentives to expand care home capacity.

To answer our research questions, we first provide a theoretical framework for understanding hospital delayed discharges. The empirical analysis then uses a new English 2009–2013 panel dataset on delayed discharges (DH, 2011a) and a mix of econometric approaches. To control for unobserved heterogeneity at LA level, we use panel-data models, which reduce the risk of omitted variable bias due to time-invariant unobservables correlated with both hospital delays and availability of care homes. Unobserved heterogeneity is likely to be important because LAs differ in needs, geography, population size, policies and controlling political party. We also allow for possible simultaneity bias, arising because social care beds supply, prices and delays in hospital discharges are jointly determined, by instrumenting current social care beds and prices with their 1 or 2-year lagged values. To test for spillover effects across LAs (our second research question), we use spatial econometrics methods, which allow for spatial dependence across geographical units (Moscone and Tosetti, 2014).

We find that delayed discharges do respond to the availability of care home beds. The response is modest: an increase in care home beds of 10% (250 additional beds per LA) would reduce social care delayed discharges by 6–9%. Although their estimated effects are less robustly estimated, higher prices also contribute to increasing delayed discharges.

We also find spillover effects across LAs. Higher availability of care home beds in other LAs reduces delayed discharges, although higher prices in other LAs have no statistically significant effect. Higher population in other LAs increases delayed discharges, suggesting that patients are willing to cross LA boundaries to secure a care home bed.

### ***Related Literature***

There is an extensive literature on substitution between informal care and formal long-term care, but few studies on substitution between care homes (formal long-term care) and delayed hospital discharges (health care).[1] Forder (2009) used cross-section electoral ward level data in England and found that increasing spending on care homes by £1 reduces hospital expenditure by £0.35. Holmas et al. (2010) investigated the effect of fining owners of long-term care institutions who prolong length of stay at hospitals in Norway. Oien et al. (2012) investigated the effect of long-term financing on the composition of long-term services at municipality level in Norway. Picone et al. (2003) investigated the simultaneous determinants of hospital length of stay and discharge destination of U.S. Medicare patients following hip fracture, stroke or heart attack. The study that is closest to ours is Fernandez and Forder (2008) who use 1998/1999 and 1999/2000 data for English LAs and find that LAs with more home help hours, and nursing and residential care beds, had a lower rate of hospital delayed discharges and lower emergency readmission rates.

Our study makes several innovations. Our theoretical model augments stochastic queuing theory with endogenous demand (baulking) to explain social care market equilibria with positive waiting times for care home places. Our data set is recent (2009–2013) and has measures for hospital delays, which distinguish between delayed patients and the number of days of delay, and between total delays and those due to social care. We also have data on the numbers of beds, prices and quality for all nursing and care homes. We exploit the panel-data to control for endogeneity due to unobserved heterogeneity at LA level and to construct instruments for the potentially endogenous supply of social care beds and prices. We also use spatial econometrics regressions to test for spillover effects across LAs.

## 3.2 Institutional Setting

Hospitals and nursing and care homes in England have different organisational arrangements and funding. Hospital care is provided by 164 public hospitals paid by a mix of nationally set prospective prices and block contracts negotiated with local health authorities. National Health Service patients do not pay for hospital care. By contrast, there are over 18,000 providers of social care (nursing and residential homes) (Laing and Buisson, 2014), which are a mix of for-profit, nonprofit and public organisations. Around 60% of users pay for social care (Forder, 2007), with those on low income or wealth being subsidised. LAs provide means tested personal social services, including home help.

Long-standing concerns about the coordination of health and long-term care for patients discharged from hospital led to the Community Care (Delayed Discharges) Act (2003).[2] The Act requires LAs and hospitals to collaborate around the discharge of patients from hospital.

[1] See Norton (2000), Grabowski et al. (2012), Costa-Font and Courbage (2012), Cremer et al. (2012), and Siciliani (2013) for comprehensive literature reviews on the economics of long-term care

[2] Baumann et al. (2007), DH (2003), DH (2011b), House of Commons Committee of Public Accounts (2003), and NAO (2000)

LAs must reimburse hospitals for delayed discharges for which they are solely responsible.

## 3.3 A model of patients waiting for hospital discharge

We observe the number of patients waiting for hospital discharge at a census date. Assume that all patients with a delayed hospital discharge (i.e. medically ready for discharge but still in hospital) are waiting to find a place in a nursing home. We require a model that explains why patients are waiting given that nursing homes could raise prices and reduce waiting times. To explain such equilibria with positive waiting times, we assume that demand and patient length of stay in a nursing home are uncertain: we use a stochastic queuing model with endogenous demand (baulking).

Suppose, initially, that there is a single nursing home with $k$ beds and that the number of patients who complete their hospital treatment and are ready to be discharged follows a Poisson distribution with mean rate $\gamma$.[3] A proportion $\theta$ of these patients wish to enter a nursing home, so that the flow rate of demand for a nursing home place is also Poisson distributed with mean $\lambda = \gamma\theta$ (the arrival rate). Patient length of stay in the nursing home is exponentially distributed with a mean of $1/k\mu$, where $\mu$ is the 'service' rate in bed.[4] The expected waiting time (delay) before a nursing-home bed becomes available depends on the number waiting in hospital and the rate at which beds become available. The expected waiting time is:[5]

$$\bar{w} = \bar{w}(k, \mu, \lambda)\bar{w}_k < 0, \bar{w}_\mu < 0, \bar{w}_\lambda > 0 \tag{3.1}$$

By Little's Law (Little, 1961), the expected number of patients waiting for a place is:

$$L = \bar{w}\lambda \tag{3.2}$$

We assume that patients know the expected waiting time and that patient expected utility from a nursing home place after a delay of $\bar{w}$ is $v(m–p, \bar{w}, x)$ ($v_p < 0$, $v_w < 0$) where $m$ is income, $p$ is the price of a care home bed and $x$ is a vector of patient characteristics. Utility from the alternative of discharge to the patient's home is $v^0(m, x)$. The proportion of patients $\theta$ who opt for a nursing home place (i.e. who have $v(m–p, \bar{w}, x)–v^0(m, x) \geq 0$) depends on the expected delay $\bar{w}$, nursing home price $p$, and the joint distribution of income and other characteristics:

$$\theta = \theta(\bar{w}, p, F) \tag{3.3}$$

[3] This is the number in the Local Authority, which is our unit of analysis. Patients may be in several hospitals serving the Local Authority's patients.

[4] For example, suppose that patients exit a nursing home only on death.

[5] See Gross et al. (2008) for the complicated expression for $\bar{w}(k, \mu, \lambda)$.

where $F$ is a vector of parameters affecting patient preferences and characterising the joint distribution of $m$ and $x$. Ceteris paribus, higher prices and longer expected waiting times reduce the proportion of patients who demand a nursing home bed: $\theta_p < 0$ and $\theta_w < 0$.

The arrival rate for patients demanding a nursing home bed satisfies the implicit function:

$$g = \lambda - \gamma\theta(\bar{w}, p, F) = \lambda - \gamma\theta(\bar{w}(k, \mu, \lambda), p, F) = 0 \tag{3.4}$$

which can be solved explicitly for the arrival rate as:

$$\lambda = \lambda(k, p, \mu, \gamma, F) \tag{3.5}$$

With:

$$\lambda_k = \gamma\theta_{\bar{w}}\bar{w}_k/g_\lambda > 0, \lambda_p = \gamma\theta_p/g_\lambda < 0, \lambda_\mu = \gamma\theta_{\bar{w}}\bar{w}_\mu/g_\lambda > 0, \lambda_\gamma = \theta/g_\lambda > 0 \tag{3.6}$$

Where $g_\lambda = 1 - \gamma\theta_{\bar{w}}\bar{w}_\lambda > 0$

The care home chooses beds and price to maximise expected profit:

$$\pi = (p\text{–}c)\lambda(k, p, \mu, \gamma, F) \tag{3.7}$$

so that equilibrium beds supply $k(\mu, \gamma, F)$ and price $p(\mu, \gamma, F)$ are also functions of the exogenous factors entering patient preferences and the cost function.[6] From Little's Law, the expected number of patients waiting for discharge to a nursing home is:

$$L = \lambda((k, p, \mu, \gamma, F)\bar{w}(k, \mu, \lambda(k, p, \mu, \gamma, F)) = L(k(\mu, \gamma, F), p(\mu, \gamma, F), \mu, \gamma, F) \tag{3.8}$$

We want to estimate the effects of beds and prices on delay and so estimate (3.8), rather than the reduced form $L^0(\mu, \gamma, F)$. But, as (3.8) makes clear, in the empirical analysis, we need to take account of the fact that prices and beds are endogenous, so that prices, beds and the number waiting are jointly determined. Section 3.4 discusses how we allow for this using LA effects and instruments for prices and beds.

[6]If the queueing model was deterministic, as in Lindsay and Feigenbaum (1984), with demand function $D(p, w)$ and output $S$, then waiting time $w(p, S)$ is determined by $D(p, w) - S = 0$ for $w > 0$ and $D(p, 0) - S \leq 0$ for $w = 0$, with $w_p < 0$, $w_S < 0$ if $w > 0$. It can never be profit maximising to have a positive queue: if $w > 0$, the care home can raise price, keeping output constant and letting the waiting time fall, thereby increasing profit because revenue is increased and costs unchanged. Thus, nonstochastic waiting time models cannot explain the existence of positive queues, that is, of people waiting to be discharged.

### *Comparative statics*

The expected number waiting $L$ is decreasing in nursing home prices: a ceteris paribus increase in $p$ reduces the proportion of patients who opt for nursing homes ($\lambda_{p<0}$ and the expected wait:

$$\partial\bar{w}(k,\mu,\lambda)/\partial p = \bar{w}_\lambda\lambda_p < 0 \tag{3.9}$$

Thus, both parts of $L = \lambda\bar{w}$ are reduced by an increase in $p$ and $\partial L/dp < 0$. The effect of an increase in the number of beds $k$ is ambiguous:

$$\partial L/\partial k = \lambda_k\bar{w} + \gamma[\bar{w}_k + \bar{w}_\lambda\lambda_k] \tag{3.10}$$

because it increases demand via its effect on waiting time, but it also reduces the waiting time so that $\lambda\bar{w}$ could increase or decrease. It is possible to show that the number waiting increases or falls depending on whether the demand for nursing home places is elastic or inelastic with respect to expected waiting time. If demand is inelastic, the expected number waiting will fall.[7]

Conditional on $p$ and $k$, an increase in throughput ($\mu$) in nursing homes also has an ambiguous effect because it affects waiting time directly and via its effect on demand. LAs with a larger or sicker population will have higher $\gamma$ and will have more patients waiting for discharge because $\partial L/\partial\gamma = (\bar{w}_\lambda\lambda + \bar{w})\lambda_\gamma = (\bar{w}_\lambda\lambda + \bar{w})\theta > 0$.

### *Extensions to the model*

We can generalise the model for there to be more than one nursing home. Let the proportion of patients choosing nursing home $h$ be $\theta_h = \theta_h(\bar{w}_h, p_h, \bar{w}_{-h}, p_{-h}, F)$, where $\bar{w}_{-h}$ and $p_{-h}$ are vectors of expected waiting times and prices at other nursing homes. The expected number waiting for a place at home $h$ is again determined by Little's Law as $L_h = \lambda_h\bar{w}_h = \gamma\theta_h\bar{w}_h$ where $\bar{w}_h = \bar{w}_h(k_h, \mu_h, \lambda_h)$ and so the expected total number waiting to be discharged to a nursing home is:

$$L = \sum_h L_h = \sum_h \lambda_h(\boldsymbol{k},\boldsymbol{p},\boldsymbol{\mu},F)\bar{w}_h(\boldsymbol{k},\boldsymbol{p},\boldsymbol{\mu},F) = L(\boldsymbol{k},\boldsymbol{p},\boldsymbol{\mu},F) \tag{3.11}$$

where $\boldsymbol{k}$, $\boldsymbol{p}$, $\boldsymbol{\mu}$ are vectors of beds and so on in all homes.[8]

[7] Intuitively, Little's Law ($L = \bar{w}\lambda$) is analogous to the expression for revenue (price times demand) and revenue falls if price is reduced if and only if demand is inelastic with respect to price. There is no evidence on the effect of waiting times on the demand for nursing home places, but most studies of the effect of hospital waiting times report that demand for hospital care is inelastic with respect to hospital waiting times (Gravelle et al., 2003; Martin et al., 2007).

[8] The arrival rates $\lambda_h$ and expected waiting times are found by solving $\lambda - \gamma\theta_h(\bar{w}_h, p_h, \bar{w}_{-h}, p_{-h}, F) = 0$, and $\bar{w}_h(k_h, \mu_h, \lambda_h)$ simultaneously for all $h$. The equilibrium beds $k_h$ and prices $p_h$ are found as the Nash

## 3.4 Econometric Models

We use LA-level data and estimate three types of model based on (3.11).

### *Panel data*

Our first regression model is:

$$L_{it} = \alpha_t + \delta_i + \beta_1 s_{it} + \beta_2 x_{it} + u_{it} \tag{3.12}$$

where $L_{it}$ is a measure of hospital delayed discharges for patients resident in LA $i$ in year $t$, $s_{it}$ is a vector measuring supply of care homes in LA $i$ in year $t$ (total beds and average bed prices) and $x_{it}$ is a vector of control variables, such as the elderly population. $\delta_i$ is a LA effect, which controls for unobserved heterogeneity at LA level and $\alpha_t$ is the year effect. We estimate (3.12) by random effects (RE) with robust standard errors and clustering on LAs. To test whether the random-effects model is preferred to a fixed-effects model, we add the mean of the time-varying variables to (3.12) and test for its significance (Mundlak, 1978; Wooldridge, 2010). If the means are jointly insignificant, then the random-effects specification is preferred.

### *Spatial effects*

To test whether the effect of care homes supply spills over across LA boundaries, we estimate spatial econometric models:

$$L_{it} = \alpha_t + \delta_i + \beta_1 s_{it} + \beta_2 x_{it} + \phi_1 \sum_j \omega_{ij} s_{jt} + \phi_2 \sum_j \omega_{ij} x_{jt} + \rho \sum_j \omega_{ij} y_{jt} + \psi \sum_j \omega_{ij} u_{jt} + \varepsilon_{it} \tag{3.13}$$

where $L_{it}$, $s_{it}$ and $x_{it}$ are specfied as in (3.12). $\omega_{it} \geq 0$ is a distance (spatial) weight. The coefficients $\phi$ on the spatially lagged regressors test whether supply of care homes or covariates such as elderly population in nearby LAs affect delayed discharges in a given LA, that is, they test for spillovers. The coefficient $\rho$ on the spatially lagged dependent variable allows for higher delays in nearby LAs to be associated with more delayed discharges in a given LA. For example, unobserved local demand factors could affect delays in the LA and in its neighbouring LAs. The inclusion of the spatially lagged dependent variable therefore helps to control for omitted-variable bias. The coefficient $\psi$ on the spatial error term allows for correlation between delay in the LA and the error terms in neighbouring LAs.

We use four versions of (3.13). The simplest is the spatially lagged Xs (SLX) model, which applies spatial weights to only the explanatory variables. The spatially autoregressive

equilibrium where each nursing home maximises profit given $\lambda_h = \lambda_h(\boldsymbol{k}, \boldsymbol{p}, \boldsymbol{\mu}, F)$ and $w_h(k_h, \mu_h, \lambda_h)$.

model includes the spatially lagged dependent variable. The spatial Durbin model has spatial lags of the dependent and independent variables. The spatial Durbin error model includes spatially lagged errors and independent variables.[9] We row-standardise the weight matrix.[10]

### *Instrumental variables*

As we noted in discussing the theoretical model, beds supply, prices and delayed discharges are jointly determined in equilibrium. Thus, failing to include variables that affect demand will bias the estimated effects of beds and prices on delay. If these omitted variables are time invariant, then the inclusion of LA effects in the model will remove potential bias. But the omitted variables may be time varying or delays may affect supply (simultaneity) so that potential bias is not removed by the LA effects in the estimated models. We therefore also estimate models in which we instrument beds and prices with their 1 or 2-year lagged values.

## 3.5 Data

### *Dependent variables*

The delays data are from the 'Acute and Non-Acute Delayed Transfers of Care' dataset (DH, 2011a) for 5 years 2009–2013. The Community Care (Delayed Discharges) Act (2003) requires LAs to reimburse National Health Service hospitals for each day an acute patient's discharge is delayed if the sole reason for that delay is the responsibility of the LA Social Services department either in making an assessment of the patient for community care services or in prhoviding those services. Hospitals have to keep records of the number of patients delayed, days of delay and the institution responsible for the delays.[11]

The dataset records delays in the transfer of patients from hospital care to social care in England by each of 147 LAs. The relevant LA is the council with responsibility for adult social care where the patient resides. We use two dependent variables (i) delayed patients: the number of patients who are ready to be discharged from hospital into social care but have not been discharged at midnight on the last Thursday of each month, averaged over the year;

[9] We estimate (3.13) by maximum likelihood (Moscone and Tosetti, 2014).

[10] Define $d_{ij}$ as the distance between LA $i$ and LA $j$. The weights are given by $\omega_{ij} = 0$, if $i = j$, $\omega_{ij} = (d_{ij}^{-1})/(\sum_j d_{ij}^{-1})$ if $i \neq j$. The inverse distance specification gives a lower weight to the delayed discharges of LAs that are more distant from Local Authority $i$. Row standardisation permits us to interpret $WL$ as a weighted average delayed discharges across LAs, where the weights are inversely related to the distance between LAs centroids. Similarly, we can interpret $W$s as the weighted average LTC supply and $W_x$ as the average population or demand shifter.

[11] A patient is considered delayed if 'a clinical decision has been made that patient is ready for transfer and a multidisciplinary team decision has been made that patient is ready for transfer and the patient is safe to discharge/transfer'. In this context, a multidisciplinary team includes 'nursing and other health and social care prhofessionals caring for that patient in an acute setting'. A delay can only be attributed to social care if the relevant Trust (hospital) notifies the relevant Local Authority that a patient may require community care and 24 hours notice of the actual need of that care. Delay may be also attributed to both National Health Service and the Local Authority or to the National Health Service. There is a formal procedure for disputes.

and (ii) days delayed during the month experienced by all patients with delayed discharges, not just those waiting at census date, averaged over the year.

The data distinguish between delays attributed to the hospital, to social care (which is the responsibility of the LA in which the patient lives) and to both. To allow for the possibility of misclassification, we estimated models for (i) delays officially attributed to social care and (ii) all delays.[12] The results were qualitatively very similar and so in the text, we report results for delays officially attributed to social care, relegating results for models of all delays to Appendix B.

### *Supply of long-term care*

We measure for each LA the number of care home beds and the average price charged by care homes and their quality rating. Data on individual care (residential/nursing) homes were aggregated to LA level by mapping the postcode of each provider to a LA. We include only prhoviders whose 'primary client' is people aged 65 years and over. We use Laing and Buisson data (Laing and Buisson, 2014) to obtain care homes prices per week and take the unweighted average price of beds acrhoss eight categories.

As a robustness test, we include the quality of care homes as a covariate in some models. The Care Quality Commission rates care homes as Poor, Adequate, Good or Excellent. We measure the quality of care homes in an LA as the percentage rated Excellent. The data are only available for 1 year (2010), and we use this value for all years.

### *Conrol variables*

We control for the population within each LA who are aged 65 years and over using Office of National Statistics (ONS, 2011) mid-year population estimates for 2009–2013. We also use the percentage of people aged 65 years and over receiving social security benefits as a control for deprivation in a LA. This variable is measured only for 2010 and treated as time-invariant. To control for population health, we use the number of deaths among people aged 65 years and over. We use 2-year lagged values of these variables to avoid the 'bad control' problem (Angrist and Pischke, 2009).

[12]Delays attributed to social care can include, in addition to those waiting for a bed in a care home, patients who are to be discharged to their own home but are delayed because their LA Social Services department has not yet made arrangements for a care package to be provided at home or for necessary equipment or adaptions to be supplied. Because some delays are attributed both to the NHS and to the LA, the all delays category will include all delays solely or partly attributable to social care. Thus, while both types of dependent variable will include delays for patients who are waiting for a place in a nursing or care home, they will also include delays for patients who are to be discharged to their home. This measurement error in the dependent variable will add noise to the model but should not lead to bias in the estimated coefficients.

## 3.6 Results

### *Descriptive statistics*

Table 3.1 shows that 28 patients are delayed at the monthly census day in an average LA of which 8.5 are attributed solely to social care. In an average calendar month, 785 bed days are lost because of patients not being discharged when ready, of which 236 days are classified as the responsibility of social care. The average LA has population aged 65 years and over of 60,000 and 2,500 residential or nursing home beds. The average LA price for a week of care is £550, although it can reach over £1000.

Table 3.1: Summary statistics

| Variable | Mean | SD (Overall) | SD (Between) | SD (Within) | Min | Max |
|---|---|---|---|---|---|---|
| Delayed patients (all patients) | 28.44 | 28.12 | 27.17 | 7.522 | 1.08 | 155.67 |
| Days of delay (all patients) | 784.9 | 816.4 | 788.8 | 218.6 | 36.33 | 4911 |
| Delayed patients attributed to social care | 8.505 | 11.39 | 10.83 | 3.627 | 0 | 100.8 |
| Days of delay attributed to social care | 236.1 | 330.9 | 316 | 101.1 | 0 | 2908 |
| Care-homes beds | 2506 | 2335 | 2327 | 263.4 | 233 | 12496 |
| Care-homes price | 546 | 112.7 | 107.3 | 35.37 | 364.8 | 1081 |
| Population over 65 | 59700 | 52460 | 52500 | 3295 | 7455 | 286310 |
| % Care-homes rated excellent in 2010 | 20.34 | 12.38 | 12.42 | 0 | 0 | 70 |
| % age 65+ on Income Benefit | 20.89 | 7.86 | 7.88 | 0 | 7.26 | 51.98 |
| Deaths in population over 65 | 2603 | 2195 | 2200 | 77.02 | 281 | 11503 |

Notes: SD, stands for Standard Deviation
Data are for 147 Local Authorities over 2009-2013. Mean, min, max are over five years. Delayed patients: number waiting for discharge on monthly census date. Days of delay: total days of delay experienced by all delayed patients during a month. Delayed patients and delayed days are averages of monthly data over the year. Deaths are lagged by two years.

Both the dependent and explanatory variables are measured in logs so that reported coefficients are elasticities.[13,14]

[13] A log-log specification passed the RESET using a quartic function of the predicted dependent variable.

[14] For variables that have 0 values for some LAs, we use the inverse hyperbolic sine transformation $y = f(z) = \ln(z + (z^2+1)^{1/2})$ where $z$ is the raw variable (Burbidge et al., 1988). $y \approx \ln z + \ln 2$ for $z \geq 0$, so that the coefficients can still be interpreted as elasticities.

### *Regression results*

Table 3.2 reports results from the baseline RE and SLX models of patients whose delays are attributed officially to social care. We estimate models for the number of patients delayed on a census day (patients delayed) in an average month and the total number of bed days lost because of delays (days of delay). All models in Table 3.2 pass the Mundlak and Hausman tests, supporting the use of random rather than fixed-effects specification. The SLX models include spatial lags of beds and of the elderly population in other LAs.[15] Results for models where the dependent variables are patients delayed or days delayed for all causes are very similar to those where delays are officially attributed to social care. They are reported in Table B.1 of Appendix B.

Table 3.2: Delayed discharges attributed to social care

| | Patients delayed | | | | Days of delay | | | |
|---|---|---|---|---|---|---|---|---|
| | RE | | SLX | | RE | | SLX | |
| | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.670*** | 0.001 | -0.578*** | 0.008 | -0.921*** | 0.001 | -0.784*** | 0.007 |
| Care-homes price | 0.697** | 0.031 | 0.603 | 0.156 | 0.983** | 0.014 | 0.851* | 0.098 |
| Pop 65+ | 1.738*** | 0.000 | 1.599*** | 0.000 | 2.229*** | 0.000 | 2.020*** | 0.000 |
| 2010 | -0.0851** | 0.031 | -0.161*** | 0.001 | -0.208*** | 0.001 | -0.323*** | 0.000 |
| 2011 | -0.174*** | 0.006 | -0.193*** | 0.007 | -0.185** | 0.027 | -0.214** | 0.022 |
| 2012 | -0.313*** | 0.000 | -0.254** | 0.012 | -0.320*** | 0.001 | -0.234* | 0.052 |
| 2013 | -0.423*** | 0.000 | -0.480*** | 0.000 | -0.404*** | 0.000 | -0.493*** | 0.001 |
| Beds spatial lag | | | -2.844*** | 0.003 | | | -4.262*** | 0.005 |
| Pop 65+ spatial lag | | | 4.878*** | 0.001 | | | 7.332*** | 0.002 |
| Constant | -15.54*** | 0.000 | -45.08*** | 0.000 | -17.56*** | 0.000 | -62.10*** | 0.000 |
| $R^2$ | 0.488 | | 0.524 | | 0.441 | | 0.485 | |
| Mundlak Test | 3.852 | 0.278 | 4.353 | 0.500 | 2.649 | 0.449 | 3.045 | 0.693 |
| Hausman Test | 5.671 | 0.579 | 5.773 | 0.762 | 4.983 | 0.662 | 4.359 | 0.886 |

Notes: Dependent variable and continuous explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. Spatial models: SLX (Spatially Lagged Xs). Observations: 735 = 5x147. *p<0.1, **p<0.05, ***p<0.01.

The coefficient on beds in the LA is significant and negative in all the random-effects models. Allowing for spatial lags reduces significance and the magnitude of the coefficient somewhat but the beds coefficient is always highly significant. The coefficient on prices is much more variable across the models. It has the expected positive effect but is only

[15] We also estimated models, which included the spatial lag of prices. This variable made little difference and was never significant.

significant at 5% when spatial lags are not included.

The spatially lagged beds and population are statistically significant with the expected negative sign on beds and positive sign on the elderly population in other LAs. The coefficient on spatially lagged beds is much larger than the coefficient on beds in the LA. This is to be expected because there will be a much larger supply of beds in the LAs surrounding an LA than in it.

### *Other spatial specifications*

We also investigated variants of the spatial specification (3.13). The spatial Durbin error model includes spatially lagged errors as well as spatially lagged beds and elderly population. The spatial Durbin model adds spatially lagged dependent variable to the spatial lags of beds and elderly population, and the spatially autoregressive model has spatial lags of the dependent variable rather than spatial lags of beds and elderly population. The estimated coefficients are similar to those from the models with spatially lagged beds and elderly population in Table 3.2 (see Tables B.3 and B.4 of Appendix B).

### *IV models*

The first two models presented in table 3.3 provide the results from instrumental variable (IV) models in which beds and prices are instrumented with their 1-year lagged values.[16] The F statistics on the instruments from the first-stage regressions are very large, indicating that lagged beds and prices are strong instruments. The coefficient on beds is generally larger (in absolute value) compared with Table 3.2.

### *Sensitivity analyses*

We estimated models with additional explanatory variables suggested by the theoretical model and the institutional structure. The quality of nursing and care homes in the LA may affect demand for care homes. We therefore included the percentage of care homes in the LA, which were rated Excellent in 2010 as a quality measure.

We also added the LA mortality rate for the over 65 population. To allow for the possibility that longer delays in hospital could affect mortality, we use the 2-year lag of death rate of population over 65 years. Mortality has an a priori ambiguous effect. LAs with sicker populations may have more demand for social care beds (corresponding to higher $\gamma$ in the theory model), and this will increase the number waiting. But, with higher death rates,

[16]See Table B.2 for the results when delays for all causes are included. Results from models using 2-year lagged values as instruments were very similar and are in Table B.5. Table 3.3 includes spatial lags of beds and population. The results are similar if the spatial lags are excluded (Table B.6).

Table 3.3: Patients Delayed and Days of Delay (attributed to Social Care)

| | IV models | | | | Augmented models | | | |
|---|---|---|---|---|---|---|---|---|
| | Patients delayed | | Days of delay | | Patients delayed | | Days of delay | |
| | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.807** | -0.015 | -0.913** | -0.040 | -0.689*** | -0.003 | -1.010*** | -0.001 |
| Care-homes price | 1.165** | -0.025 | 1.452** | -0.039 | 1.226*** | -0.009 | 1.413*** | -0.007 |
| Pop 65+ | 1.818*** | 0.000 | 2.134*** | 0.000 | 0.765 | -0.107 | 0.285 | -0.674 |
| 2010 | -0.187*** | -0.002 | -0.352*** | 0.000 | -0.191*** | 0.000 | -0.353*** | 0.000 |
| 2011 | -0.249*** | -0.001 | -0.273*** | -0.007 | -0.182** | -0.024 | -0.131 | -0.253 |
| 2012 | -0.348*** | -0.001 | -0.330** | -0.025 | -0.230* | -0.056 | -0.0821 | -0.602 |
| 2013 | -0.598*** | 0.000 | -0.617*** | 0.000 | -0.460*** | -0.001 | -0.307 | -0.110 |
| SD Care-homes price | | | | | -0.0055 | -0.952 | 0.092 | -0.549 |
| % care-homes rated excellent | | | | | 0.00099 | -0.824 | -0.0014 | -0.840 |
| % 65+ on income benefit | | | | | 0.445*** | -0.006 | 0.580*** | -0.002 |
| Price*(% 65+ on income benefit) | | | | | -0.0659*** | -0.009 | -0.0877*** | -0.002 |
| Deaths in pop 65+ | | | | | 1.088** | -0.035 | 2.116*** | -0.008 |
| Beds spatial lag | -2.385** | -0.013 | -3.950*** | -0.005 | -2.931*** | -0.001 | -4.514*** | -0.002 |
| Pop 65+ spatial lag | 4.828*** | 0.000 | 7.464*** | -0.001 | 5.317*** | 0.000 | 7.815*** | 0.000 |
| Constant | -52.02*** | 0.000 | -69.76*** | 0.000 | -60.83*** | 0.000 | -77.30*** | 0.000 |
| $R^2$ | 0.523 | | 0.486 | | 0.585 | | 0.541 | |
| F Test (Beds) | 102.37 | 0.000 | 98.51 | 0.000 | | | | |
| F Test (Price) | 128.61 | 0.000 | 123.37 | 0.000 | | | | |
| F Test (Beds spatial lag) | 1364.27 | 0.000 | 1308.15 | 0.000 | | | | |
| Hausman Test | 2.388 | 0.984 | 1.810 | 0.994 | | | | |
| Mundlak Test | | | | | 17.88 | 0.0221 | 13.82 | 0.0865 |

Notes: IV and Augmented Models, SD, standard deviation
Dependent variable and continuous explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. F tests are for the joint significance of the instruments in each first stage model. The instruments are one year lag of care-homes beds, one year lag of care-homes price, and one year spatially lagged care-homes beds. % 65+ on income benefit is the proportion of the population aged 65 and over who are receiving income support in 2010. Observations: 735 = 5x147. *$p<0.1$, **$p<0.05$, ***$p<0.01$.

length of stay ($1/\mu$) in the theory model) in care homes may be shorter so that more beds become available in a given period, and the theory model shows that this could reduce or increase the number waiting.

Patients with low income or wealth are entitled to subsidies to reduce the cost of a care home bed. We therefore included the proportion of the population aged over 65 years who were in receipt of income-related social security benefits in 2010. We incorporate this variable in the model in two ways. First, because poorer individuals are more likely to be in poor health, we could regard it as another proxy for morbidity, and we therefore add it to the model. Second, the higher the proportion of poor elderly in the LA, the less sensitive will demand for care homes are to the price of beds. We therefore add the interaction of income deprivation with beds price to the model.

Finally, we conjectured when discussing extensions to the theory model that patients (or their relatives) are likely to spend longer searching for a care home bed the greater the dispersion of prices. We therefore include the standard deviation of care home prices in the LA to the model.

The results for the third and fourth models in Table 3.3 show that the inclusion of these additional variables does not qualitatively affect the estimates of the effects of care home beds and prices. The Mundlak tests suggest, however, that the RE specification may be less appropriate for these augmented models than for the baseline models. Quality rating and the standard deviation of care home prices are always insignificant. Higher needs, as proxied by mortality, increase delays (but are significant only when delays are attributed to social care; see Table B.2 in Appendix B for all delays). The effects of income deprivation are as anticipated. The main effect of deprivation (as a proxy for morbidity) is to increase delays, and the effect of price on delay is reduced in absolute value when patients are more income deprived.

### ***Quantitative effects***

The theory model indicated that the effect of an increase in supply on delays is in principle indeterminate. Higher supply reduces the expected waiting time but also increases demand. Whether the number waiting increases or falls depends on whether the demand for nursing home places is elastic or inelastic with respect to expected waiting time. Our results generally suggest that delays reduce with larger supply implicitly suggesting that the demand for nursing home places is relatively inelastic.

Our preferred models in Table 3.2 yield an elasticity of the number of patients delayed with respect to beds supply of -0.58 to -0.67. Thus, an increase in care home beds of 10% (from 2500 to 2750 in an average LA) would reduce the number of patients delayed each month by 5.8-6.7%. Given a monthly average number of 8.5 delayed patients, this corresponds to a reduction of less than one patient per month (0.49–0.57 patients) in an average LA. In terms of delays measured in hospital bed days in Table 3.2, a 10% increase in home-care beds would reduce delayed bed days by 7.8–9.2%, which, given an average of 236 delayed bed days in a month, corresponds to a reduction of 18–22 days per month in an average LA. The quantitative effect appears therefore to be relatively modest. When all delays are used as dependent variable, the elasticities with respect to beds are smaller -0.36 to -0.44 for delayed patients and -0.32 to -0.39 for delayed bed days (Appendix B Table B.1). Given a monthly average number of 28.44 (785) delayed patients (bed days), this corresponds to a reduction of 1–1.2 patients (25–30 bed days) per month in an average LA. The quantitative effect appears therefore to be larger when the more inclusive definition of delays is used but remains qualitatively similar and still relatively modest.[17] The small effect on delays suggests that increasing the supply of care home beds will not be cost reducing,[18] although a full evaluation of such policies would need to take account of the possible gains to patients from a more rapid transfer to a more appropriate care setting and the use of the extra social care beds by people who enter care-homes directly rather than via hospital.

## 3.7 Conclusions

Coordination between the health and long-term care sectors is critical to address concerns about hospital bed blocking. This study has investigated the extent to which expanding the supply of nursing and care home beds can reduce delayed discharges. The results suggest that delayed discharges in hospitals do respond to the availability of care home beds but that the response is relatively modest: an increase in care home beds of 10% (250 additional beds per LA) would reduce social care delayed discharges by 6–9%. Although less robustly estimated, we find some evidence of positive effect of care home prices on delayed discharges. These may arise because patients spend longer searching in markets with higher average prices. Policies aimed at encouraging competition across care homes and at reducing prices may therefore bring further reductions of hospital delays.

We find spillover effects across LAs with respect to both care home beds and elderly population. Higher availability of care homes in other LAs reduces delayed discharges. Similarly, higher population in other LAs increases delayed discharges. This suggests that patients are willing to cross boundaries in order to secure a bed in a care home.

[17] Effects are only slightly larger when the IV results are used.

[18] Using the average price of a care home bed (£546 per week) as a measure of the average cost, a 10% increase in beds in the average Local Authority (250 beds) would cost about £546*4*250 = £546,000 per month. Assuming a reduction in hospital bed days of 30 per month and a hospital hotel cost of £150 per day, a 10% increase in care home beds for a month would reduce National Health Service costs by £4,500.

A key implication is that policies aimed at specific LAs need to take account of these spillovers, which could otherwise lead to free riding and 'races to the bottom' in the absence of coordination across authorities. For example, a LA would have a weaker incentive to encourage an expansion of care home capacity if some of the benefits in terms of reductions in delayed discharge accrue to neighbouring LAs or if the needs of the elderly population of a LA can be satisfied by neighbouring capacity. The presence of such spillover effects, with patients in one LA willing to accept beds in nearby LAs, implies that inequalities in care home availability across LAs may be of less concern than the total supply of care home beds.

# Chapter 4

# Delayed discharges and hospital type: Evidence from the English NHS

## 4.1 Introduction

Over 1.2 million bed-days were lost in the National Health Service (NHS) in England in 2013–14 because patients remained in hospital after they were medically ready to be discharged. The annual cost of patients aged 65 and over occupying hospital beds but no longer in need of acute treatment has been estimated at £820 million (NAO, 2016). Such delayed discharges, often referred to as bed-blocking, are a long-standing policy concern. In the U.K., the issue is as old as the NHS. Lowe and McKeown (1949) noted that the creation of the NHS divided the responsibility for health and other forms of care and that the allocation of patients to appropriate care settings began to increase in importance.[1]

Despite subsequent changes in the provision and organisation of health and long-term care (LTC) services, including attempts to improve integration between the sectors (Glasby et al., 2011), the problem of delayed discharges persists. As the King's Fund has reported (Appleby et al., 2013), delayed discharges remain an important concern among NHS managers. A recent report of the House of Commons Health Committee pointed to delayed discharges as one of the reasons for hospital accident and emergency departments missing their access targets (House of Commons Health Committee, 2013).

[1]Before the creation of the NHS, Poor Law Authorities were responsible for the social (long-term care) and medical (hospital) needs of people in their area. The difference in cost between caring for an elderly person in hospital and elsewhere may have been small, due to the limited differences between settings in terms of equipment and staff at the time. The National Health Service Act in 1946 specifically set the remit of the new hospital boards created to be providers of hospital care, creating a division of responsibility for the different services.

Concern about delays is also not limited to the U.K.. In many member countries of the Organisation for Economic Co-operation and Development (OECD), hospital and long-term care provision is frequently divided between different sets of institutions. The funding and organisation of these two sectors often differ, with each acting independently of the other. The separation of responsibilities can lead to delays due to lack of communication and coordination. The supply of long-term care is not controlled by the hospitals. But if a care-home bed is not available when a hospital patient is ready to be transferred, the patient is forced to remain in hospital until a bed becomes free or they are sufficiently recovered to go home. Delays may be the result of poor hospital management and protocols. For example, a patient may have a delayed discharge because a consultant (senior doctor) is not on duty to authorise the discharge or because the patient is waiting for a transfer to non-acute NHS community care.

A growing elderly population, measured both absolutely and as a proportion of the total population (European Commission Economic Policy Committee, 2009), suggests that the problem is likely to become worse because use of health and LTC services is concentrated among the elderly (Meijer et al., 2011). Bardsley et al. (2012) found that 10 per cent of people aged 75 and over in 2005–06 used both hospital and LTC services in the same year. This demand pressure increases the importance of allocating patients to the appropriate care setting. See Kuhn and Nuscheler (2011) for a theoretical analysis.

The cost of delays in discharging patients from hospital is financial and clinical. Since hospital care is more expensive than care in other settings, a patient who can be appropriately cared for in another setting, such as an LTC institution (residential home or nursing home) or with support in their own home (home care), will be less costly to treat if discharged from hospital. There are also some greater clinical risks to the patient of being in hospital when medically ready to be discharged, including hospital-acquired infection and pressure sores (Health Foundation, 2013).

Previous research suggests that provision of LTC affects the extent of bed-blocking (Fernandez and Forder, 2008; Gaughan et al., 2015). But hospitals can also reduce bed-blocking through good discharge planning and communication with LTC providers. For example, an internal analysis of delays in the Sheffield Teaching Trust (Health Foundation, 2013) resulted in changes in procedure, which reduced delays without increasing readmissions – an indication that the prompter discharges were appropriate.

### *Aims and hypotheses*

We investigate how delayed discharges vary by type of NHS hospital. NHS hospitals are classified for administrative and regulatory purposes in two main ways. First, depending on their patient group and functions, they are designated as Acute, Specialist, Teaching or Mental Health. Second, depending on their governance structure, they may have Foundation Trust (FT) status, which gives them greater autonomy.

We focus on hospital type since it is readily observed and many existing NHS policies are defined in terms of hospital type. For example, Specialist hospitals receive top-up payments over and above the standard payments for each patient treated[2]. Mental Health providers have different payment rules from other providers, with a greater proportion of their funding coming from block contracts with local health care budget holders and less varying with the number of patients treated. Teaching hospitals receive additional payments for teaching services. Hospitals with FT status face a less constraining regulatory regime than other hospitals: they do not have to break even each year, they can borrow to invest and they have greater freedom in paying their staff. Hospital types with fewer delays could be used as examples of good practice. Those with more delays could be targeted by specific policy interventions. Moreover, our data on delayed discharges are at hospital rather than individual patient level.

We compare differences in delays across types of provider before and after controlling for a range of factors such as patient demographics, case mix, size and the availability of long-term care. Any remaining differences across hospital types after allowing for these factors may be due to the different types of organisation (due to specialisation or greater autonomy), different services (acute, mental health) or additional responsibilities (such as teaching).

The a priori effect of hospital type on delays is unclear. Foundation Trust status requires that the hospital demonstrates quality of care and financial viability (Monitor, 2007; Monitor, 2013). FT status can be considered a label of good-quality care. Higher quality, driven by more efficient management of patient pathways, may reduce discharge delays but might also attract more severe and complex patients with a higher risk of suffering delay.

Specialist Trusts may obtain efficiency gains and provide higher quality by focusing on a narrower range of patients, such as those with cardiovascular or orthopaedics conditions. This may lead to fewer delays for these patients. But specialist hospitals may also attract more complex patients who may have more requirements for post-treatment long-term care services, which may take longer to arrange. Teaching Trusts educate medical students as well as treating patients and this reduces the amount of attention that senior staff can devote to patient care once immediate medical needs are met. Teaching hospitals may also attract more complex patients who are more prone to delays.

[2]Acute NHS hospitals are paid by a prospective payment system with price per patient treated varying with the patient's Healthcare Resource Group (HRG), which is defined by diagnosis and procedure. Similar grouping-with-tariff systems, referred to as Diagnosis Related Group (DRG) payment systems, are used in many other European and OECD countries.

Mental Health Trusts treat patients with serious mental illness rather than physical health problems. These patients are often managed partly by community facilities such as Crisis Resolution Teams and Home Treatment Teams. Thus they may have better links to community and long-term care than other types of hospital, but their patients may be more difficult to place in suitable facilities outside hospital. There is also concern that mental health services are relatively underfunded. Where this results in insufficient resources in the hospital or provision of community care for mental health conditions, this could increase delayed discharges.

***Related literature***

Forder (2009) investigated the degree of substitution between hospital and LTC services in 8,000 English electoral wards and estimated that a £1 increase in spending on care homes was associated with a £0.35 fall in hospital costs. Fernandez and Forder (2008) and Gaughan et al. (2015) found that English patients living in local authorities with fewer care-home and nursing-home beds were more likely to have a delayed discharge. Hospital readmissions are also higher in local authorities with lower care-home or home-help supply (Fernandez and Forder, 2008).

Our study contributes to the literature on the substitution between hospital and LTC. The analyses in Fernandez and Forder (2008) and Gaughan et al. (2015) were at local authority level and could not examine the impact of hospital characteristics on hospital delays since patients resident in a local authority are likely to be treated in one of several hospitals. We believe our study is the first that attempts to examine variations in delayed discharges across hospitals. It is also relevant for the extensive empirical literature on quality and efficiency differences across hospital types (for-profit versus nonprofit, specialised versus non-specialised, etc.) as surveyed in Eggleston et al. (2008).

Section 4.2 details the data. Section 4.3 provides the methods. Section 4.3 reports descriptive statistics and regression results. Section 4.4 discusses potential mechanisms underlying the findings. Section 4.5 concludes.

## 4.2 Data

We employ a new database which measures delays at hospital Trust level and includes all NHS hospital Trusts in three financial years – 2011–12, 2012–13 and 2013–14.

### *Dependent variable*

Information on hospital delays are reported at hospital, rather than individual patient, level. The 'Acute and Non-Acute Delayed Transfers of Care' data set (NHS England, 2014b) contains monthly information submitted by Trusts to the Department of Health on the number of delayed transfers of patients, as required by the Community Care (Delayed Discharges etc.) Act 2003.[3] Since the Act only covers delays among adults, specialist children's hospitals are not included in the analysis. We also exclude hospitals specialising in maternity, gynaecology and neonatal care, sometimes referred to as 'women's hospitals', as they serve relatively young patients who are unlikely to require long-term care and who have a negligible number of delayed discharges. We have information on delays for all English Acute and Mental Health Trusts in three financial years.

A delay is defined as occurring when a clinical decision has been made that a patient is ready for discharge from hospital and a multidisciplinary team agrees with this decision. The multidisciplinary team includes 'nursing and other health and social care professionals caring for that patient in an acute setting' (NHS England, 2010). When a delayed discharge occurs, it is attributed to the NHS Trust where the patient was treated, to the local authority where the patient resides or to both. There is a formal dispute procedure for cases where agreement over attribution is not reached between the institutions concerned.

We measure delayed discharges as the total number of bed-days lost per year due to delayed patients. We measure both the total number of delayed days (Delays), whether attributed to the NHS or not, and those attributed to the NHS only (Delays attributed to the NHS).

### *Types of Trust*

Information on type of Trust is from the National Reporting and Learning System (NHS England, 2013). There are four mutually exclusive types of Trust: Acute Trusts,[4] Acute Specialist Trusts, Acute Teaching Trusts and Mental Health Trusts (Manhaes et al., 2013).

Acute Trusts provide acute hospital care without a specific focus on teaching or a specific type of patient or condition. Acute Teaching Trusts are generally large providers with a wide

[3] The Act allows NHS Trusts to claim reimbursement from local authorities in charge of care home and community care provision in their area, if necessary services are not provided in time for the discharge of an acute patient and this is solely the responsibility of the local authority. A Trust can only claim such reimbursement if it gives at least three days' notice that a patient is likely to require LTC on discharge and at least 24 hours' notice of the discharge (DH, 2003; NHS England, 2010). Trusts must report all delays that occur, irrespective of whether they are entitled to reimbursement for them.

[4] Within the set of Acute Trusts that are not categorised as Acute Specialist or Acute Teaching, there are three subsets: Small Acute, Medium Acute and Large Acute. Size in this instance is defined by income (HSCIC, 2013c). We ignore these subsets so that size is measured by beds for all Trust types (Acute, Acute Specialist, Acute Teaching and Mental Health Trusts).

range of departments, linked to a university and providing training for medical students as well as treating a full range of patients. Acute Specialist Trusts are a regional or national centre for a particular field of medicine, such as cancer or orthopaedics. They treat the most complex cases in a field and are generally small compared with Acute Trusts. Mental Health Trusts provide hospital care to patients with mental health conditions. In this, they are similar to Acute Specialist Trusts, but they are similar in size to Acute Trusts and there are far more Mental Health Trusts than there are Acute Specialists in a specific field.

Trusts of all four types can also have Foundation Trust status, (Monitor, 2014) the requirements for which are the same for all Trust types. There were only small changes in the number of Trusts with FT status and in their distribution across the four Trust types over the study period.

### *Control variables*

We control for the number of beds in a Trust, taking data from 'Quarterly bed availability and occupancy' submitted to the Department of Health and published by NHS England (NHS England, 2014a). The average number of beds is given at Trust level for each quarter of a financial year. (NHS England, 2014a). We use the average of the sum of the number of available and occupied beds reported for the four quarters of each financial year. To account for potential non-linearity in the relationship between beds and delays, beds are also measured as categorical variables: 200–399, 400–599, 600–799, 800–999, 1,000–1,499 and 1,500+ beds. The base case is 0–199 beds.

We use four Trust-level case-mix variables: the percentages of admissions that are emergencies, for males, patients aged 60–74 and patients aged 75+ (HSCIC, 2013b). We include risk-adjusted emergency readmission rates within 28 days of discharge from hospital as a measure of hospital quality[5]. The data are from the Indicator Portal of the Health and Social Care Information Centre (HSCIC) website (HSCIC, 2014) and are indirectly standardised by age, gender, method of admission, diagnoses and procedures. The denominator for the emergency readmission rate is all patients discharged alive in the year, except those with a primary specialty of mental health or any diagnosis of cancer. The latter are excluded since their readmissions are much less likely to be a signal of poor care and are not used as a performance indicator (HSCIC, 2013a).

A higher readmission rate might be associated with more delays if it reflects poorer quality of care in the hospital or a greater proportion of patients with unobserved greater morbidity. However, bed-blocking may increase subsequent emergency readmissions if pressure on beds

[5] Other measures of clinical quality, such as case-mix-adjusted mortality, are not available for all types of Trust.

leads to premature discharge or worse care for other patients. We therefore use two-year lags of the emergency readmission rate to reduce simultaneity bias.

If no bed is available in a care home, then a patient may have to remain in hospital despite being clinically ready to be discharged into long-term care. Most patients have to pay, at least in part, for long-term care and so it may take longer to find an LTC bed at a price they can afford if prices are higher. We therefore measure the accessibility of long-term care in the area served by a hospital Trust using data on care-home beds and prices for June 2011 (Laing and Buisson, 2014). We measure the number of care-home beds and their average price within 10 kilometres[6] of a hospital for care homes whose primary clients are people aged 65+ or with dementia. The primary client group of a care home is the group for which the largest number of beds is registered with the Care Quality Commission, which regulates the sector.

There were eight mergers between Trusts during the study period. We compute annual values for dependent and explanatory variables for Trusts that merged at some point in a year as if they were a single Trust at the start of the year.

## 4.3 Methods

Since days of delay are non-negative, are integer-valued and have a right skewed distribution, we estimate negative binomial count data models in which the mean number of days of delay, $\mu_{it}$, is given by:

$$\ln \mu_{it} = \beta_0 + \boldsymbol{H}_i'\boldsymbol{\beta}_1 + \beta_2 F_{it} + \beta_3 \ln b_{it} + \boldsymbol{x}_{it}'\beta_4 + v_t \tag{4.1}$$

$\boldsymbol{H}_i$ is a vector of dummy variables for hospital types (Specialist, Teaching, Mental Health) with Acute as the baseline type. $F_{it}$ is a dummy variable for the hospital having Foundation Trust status. No hospital changed its type over the period but three became FTs, so $F_{it}$ does vary over time. $\boldsymbol{x}_{it}$ is a vector of covariates. $v_t$ are year dummies. The coefficients $\beta$ are the proportionate changes in the number of days of delay from a one-unit change in the explanatory variable if it is continuous or from a change from 0 to 1 for a dummy variable such as hospital type. We enter the logarithms of LTC beds and prices in the models so that their coefficients are the percentage change in delays associated with a 1 per cent increase in beds or prices.

$b_{it}$ is the number of beds in the hospital. We estimate equation 4.1 with beds as an exposure term, i.e. with $\beta_3 = 1$. This is equivalent to standardising the dependent variable

[6] The location of a Trust is defined by the postcode of its headquarters. The postcode of the care-home provider defines the location of LTC. Postcodes are mapped to lower super output areas (LSOAs), which have a mean population of 1,500. The straight-line distance between the centroids of LSOAs is used to determine which care homes are within 10km of each Trust.

for the hospital size. We could have used the number of patients (rather than beds) as the exposure term, but this raises concerns about simultaneity if hospitals with more delayed discharges admit fewer patients because no beds are available. We therefore, as in Propper et al. (2004) and Kolstad and Kowalski (2012), use beds to measure hospital size.

To allow for the possibility that the number of delays is not proportional to hospital size, with larger hospitals being better or worse at managing delays, we also include in $\boldsymbol{x}_{it}$ a vector of bed size categories (200–399 etc.), as listed in Section 4.2 with unconstrained coefficients.

We use the NB2 negative binomial model (Cameron and Trivedi, 1986) in which the variance is a quadratic function of the mean. The main alternative count model, the Poisson, assumes that the variance is equal to the mean and we find that this strong assumption does not hold in our data.

We estimate five versions of equation 4.1 for all delays and then for delays due to the NHS. The first version includes only the hospital type categories. We then allow for hospital size by adding beds as an exposure term and the bed size categories. Next we add the number and price of local care-home beds and then the case-mix and readmission variables. These models are estimated with robust standard errors clustered at Trust level. Our fifth model includes time-invariant random hospital effects.

Finally, we estimate three models as robustness checks for our main findings. The first of these includes interactions of FT status and hospital type. The second excludes Mental Health Trusts from the sample. Both of these models investigate whether the effect of FT status is consistent across Trust types. The third robustness check includes a variable for Trusts with another Trust in the same local authority and an interaction of this variable with FT status. This model is included to consider whether LTC providers prefer caring for patients discharged from a Foundation Trust and so affect the number of delays from FTs.

## 4.4 Results

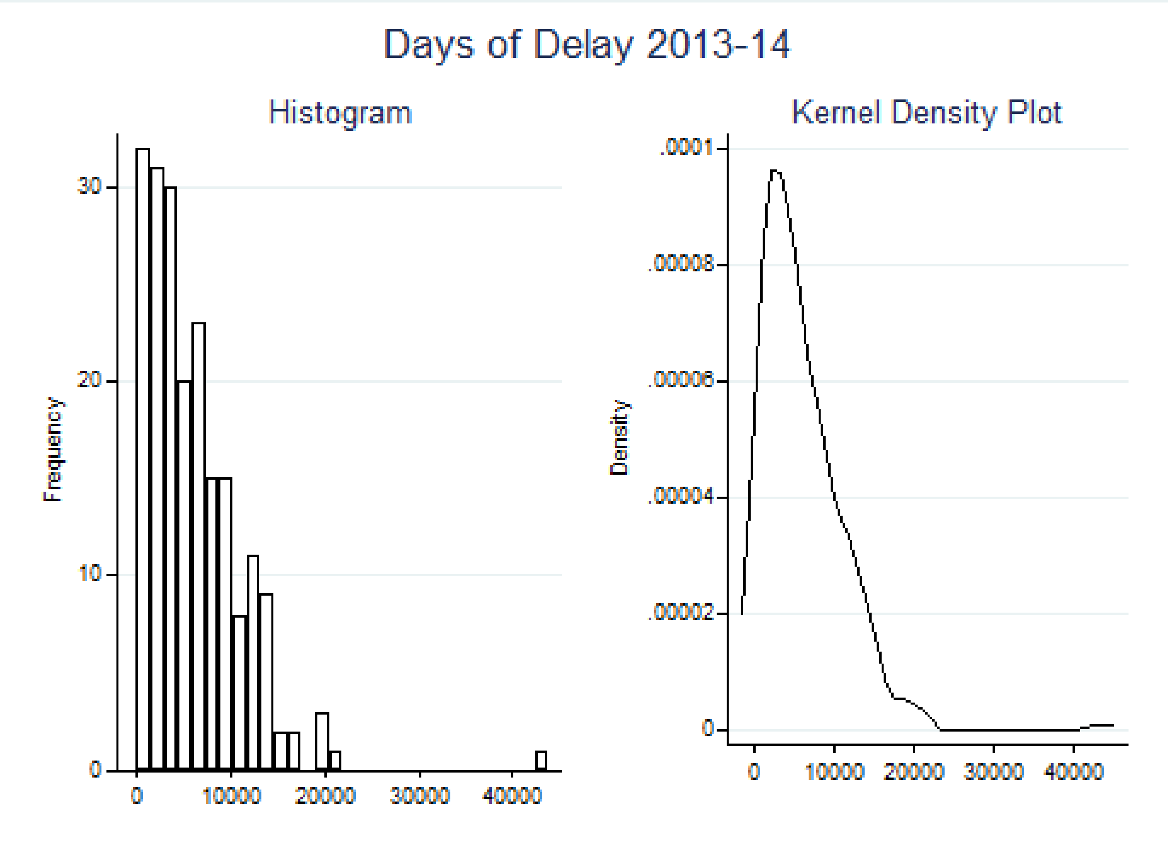
### *Descriptive statistics*

The average Trust has around 6,000 bed-days lost due to delays, of which 4,000 are attributed to the NHS. Delays increased by 3.8 per cent per year, from 5,742 days in 2011–12 to 6,182 days in 2013–14. Delays due solely to the NHS increased more quickly than delays due to other institutions and rose from 64 per cent to 69 per cent of all delays over the period.

Figure 4.1 shows the distribution of the number of days of delay across Trusts in 2013–14. The distribution is right-skewed, with a small proportion of providers having a large number of delays. The distributions are similar for the other years.

Without accounting for size, total delays are largest in Teaching Trusts and smallest in

Figure 4.1: Days of Delay

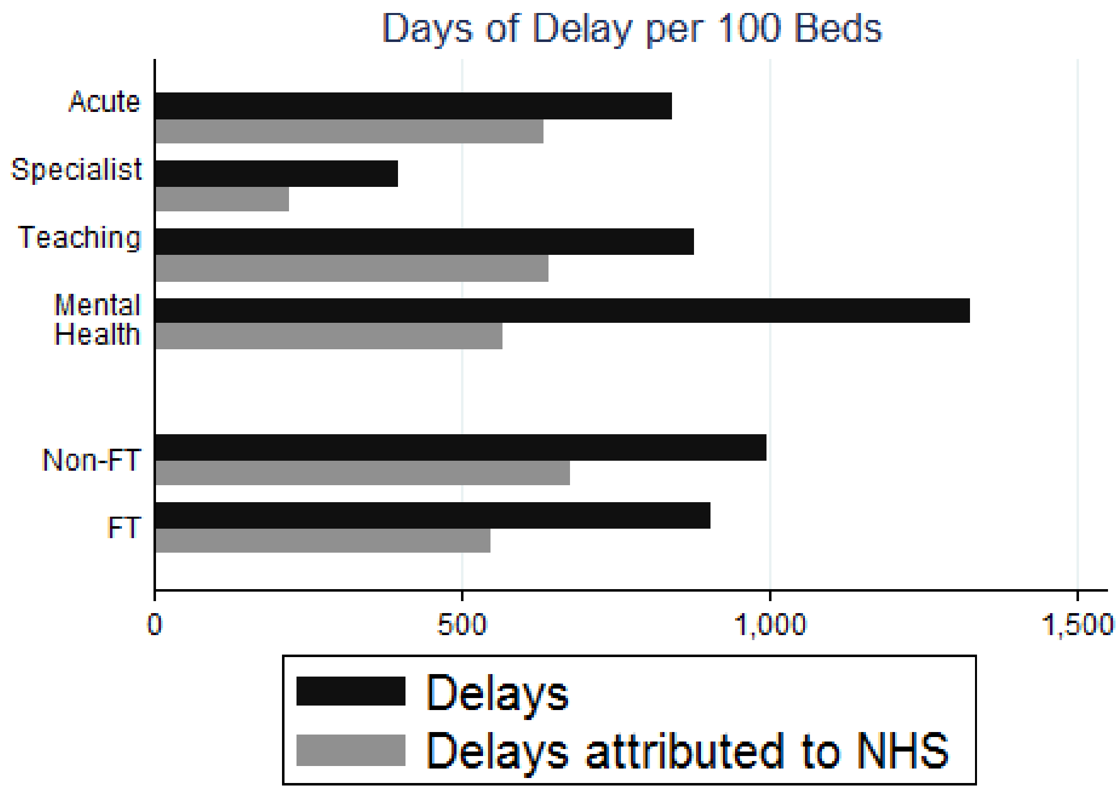



Specialist Trusts. Acute and Mental Health Trusts have similar numbers of days of delay. However, Teaching Trusts are larger hospitals while Acute Specialist and Mental Health providers tend to be smaller. Figure 4.2 shows days of delay per 100 beds for the different types of Trust and by FT status. Mental Health Trusts have the highest number of days of delay per bed, around 50 per cent more than Acute and Teaching Trusts. Specialist Trusts have the smallest number of days of delay per bed. Mental Health Trusts have a much smaller proportion of delays that are attributed to the NHS (44 per cent versus over 55 per cent for Specialist and 70 per cent for Acute and Teaching Trusts).

Figure 4.2 also indicates that there are fewer days of delay per 100 beds in Trusts with FT status than in non-FT Trusts, particularly for delays attributed to the NHS. Overall, delays per 100 beds are 9 per cent smaller and delays attributed to the NHS are 19 per cent smaller in Foundation Trusts.

As Table 4.1 shows, 57 per cent of Trusts are Acute (i.e. non-teaching, non-specialist hospitals), 13 per cent are Acute Teaching Trusts and 25 per cent are Mental Health Trusts. Only 6 per cent are Specialist Trusts. FT status applies to 63 per cent of Trusts. On average, Trusts have 643 beds. Around 22 per cent of patients admitted to hospital are aged 75+ and around 40 per cent are admitted as emergencies. The standardised readmission rate is 9 per

Figure 4.2: Days of Delay per 100 Beds by Trust Type




cent on average. The average Trust has about 3,100 care-home beds within 10 kilometres of the Trust headquarters. Within the same radius, the average price for a week's stay in a care home is £550.

Table 4.2 presents the number of Trusts with and without FT status. The highest proportion of Foundation Trusts is amongst Acute Specialist Trusts: 11 out of the 12 Specialist Trusts have FT status. Mental Health Trusts and Acute Teaching Trusts also have high FT rates, of 72 per cent and 60 per cent respectively. Acute Trusts with no additional responsibilities, such as teaching, have the lowest FT rate, of 56 per cent.

### *Regression results*

Table 4.3 reports results for models with total bed-days lost as the dependent variable. Model 4.1 includes only year and Trust type dummy variables, with 2011–12 and Acute Trusts as the baseline categories. In model 4.2, we add a hospital beds exposure term with a coefficient equal to 1, which standardises delays by beds, and we also add bed size categories. 4.3 adds measures of LTC availability (beds and prices) and model 4.4 also has case-mix and quality (emergency readmission) variables. Model 4.5 includes the same explanatory variables as model 4.4 but allows for unobserved random hospital effects.

Table 4.1: Descriptive statistics

| | Mean | SD | Obs | Min | Max |
|---|---|---|---|---|---|
| **Days of delay** | | | | | |
| All Trusts | 5,997 | 5,294 | 614 | 0 | 43,899 |
| Acute Trusts | 5,654 | 4,050 | 349 | 97 | 18,363 |
| Acute Specialist Trusts | 613.0 | 632.0 | 36 | 0 | 2,427 |
| Acute Teaching Trusts | 9,820 | 9,067 | 78 | 291 | 43,899 |
| Mental Health Trusts | 6,096 | 4,396 | 151 | 228 | 23,641 |
| Foundation Trusts | 5,488 | 4,737 | 385 | 0 | 23,641 |
| **Days of delay attributed to NHS** | | | | | |
| All Trusts | 4,002 | 3,869 | 614 | 0 | 25,494 |
| Acute Trusts | 4,262 | 3,415 | 349 | 33 | 17,297 |
| Acute Specialist Trusts | 348.0 | 491.0 | 36 | 0 | 2,115 |
| Acute Teaching Trusts | 7,071 | 6,034 | 78 | 161 | 25,494 |
| Mental Health Trusts | 2,688 | 2,321 | 151 | 23 | 12,528 |
| Foundation Trusts | 3,494 | 3,526 | 385 | 0 | 17,297 |
| **Trust type** | | | | | |
| Acute Trust | 0.568 | 0.496 | 614 | 0 | 1 |
| Acute Specialist Trust | 0.059 | 0.235 | 614 | 0 | 1 |
| Acute Teaching Trust | 0.127 | 0.333 | 614 | 0 | 1 |
| Mental Health Trust | 0.246 | 0.431 | 614 | 0 | 1 |
| Foundation Trust | 0.627 | 0.484 | 614 | 0 | 1 |
| **Covariates** | | | | | |
| Hospital beds | 642.8 | 352.3 | 614 | 7.532 | 2,165 |
| Care-home beds | 3,129 | 2,182 | 614 | 118.0 | 7,496 |
| Care-home price/week (£) | 550.3 | 90.79 | 614 | 414.4 | 722.1 |
| % patients aged 60–74 | 20.60 | 6.319 | 614 | 0.977 | 47.00 |
| % patients aged 75+ | 21.96 | 8.833 | 614 | 0 | 60.36 |
| % male patients | 45.73 | 5.843 | 614 | 1.554 | 77.35 |
| % emergency admissions | 39.78 | 14.75 | 614 | 0 | 97.73 |
| Standardised readmission rate (%) | 8.622 | 4.832 | 614 | 0 | 17.10 |

Notes: SD = standard deviation, Sample is 614 Trusts (208, 203 and 203 for 2011–12, 2012–13 and 2013–14 respectively). Mean, SD, observations, minimum and maximum are over three years. 'Days of delay' is totaldaysofdelayexperiencedbyalldelayedpatients-duringayear.'DaysofdelayattributedtoNHS'istotal days of delay experienced by delayed patients during a year attributed to the NHS. 'Hospital beds' is the annual average daily number of available or occupied beds. 'Care-home beds' is the number of beds in care homes within 10km of the Trust's headquarters in 2011 whose primary clients are patients aged 65+ or with dementia. 'Care-home price/week' is the average weekly price in care homes within 10km of the Trust's headquarters in 2011 whose primary clients are patients aged 65+ or with dementia. 'Standardised readmission rate' is the annual indirectly standardised rate of emergency readmission within 28 days, lagged by two years.

Table 4.2: Number of Foundation Trusts, by type and year

| | 2011–12 | | 2012–13 | | 2013–14 | |
|---|---|---|---|---|---|---|
| | Non-FT | FT | Non-FT | FT | Non-FT | FT |
| Acute Trusts | 54 | 65 | 50 | 65 | 48 | 67 |
| Acute Specialist Trusts | 1 | 11 | 1 | 11 | 1 | 11 |
| Acute Teaching Trusts | 11 | 15 | 10 | 16 | 10 | 16 |
| Mental Health Trusts | 15 | 36 | 14 | 36 | 14 | 36 |
| Total | 81 | 127 | 75 | 128 | 73 | 130 |

In all models, we find that there is overdispersion, rejecting the Poisson specification relative to the negative binomial model. The goodness-of-fit measures (AIC and BIC) broadly indicate that additional variables improve the explanatory power of the models, though the AIC indicates that the improvement from adding all the case-mix and readmission controls (model 4.4 versus model 4.3) is small. The BIC, which has a stronger penalty for additional explanatory variables, suggests a deterioration in model performance when the case-mix and readmission variables are added, even though one of them is statistically significant.

Foundation Trust status is associated with 14–15 per cent fewer bed-days lost after standardising for beds and controlling for long-term care, case mix and readmission rates (models 4.3 and 4.4).[7] After controlling for unobserved heterogeneity (model 4.5), the difference is even larger (28 per cent).

Once bed numbers are allowed for, Teaching Trusts have similar delays to Acute Trusts. Specialist Trusts have around 52 per cent fewer delays per bed than Acute Trusts (model 4.2) but the difference is not statistically significant, even at 10 per cent, once long-term care availability has been controlled for (models 4.3 to 4.5).

Mental Health Trusts are associated with 58–85 per cent more delayed days after accounting for size (models 4.2 to 4.4). However, this effect is smaller and insignificant after controlling for unobserved heterogeneity (model 4.5).

The availability of long-term care beds is consistently associated with fewer delays. We use the logarithms of LTC beds and prices in the models, so their coefficients are the percentage change in delays associated with a 1 per cent increase in beds or prices. Thus the results in models 4.3 to 4.5 suggest that a 1 per cent increase in long-term care beds is associated with 0.27–0.29 per cent fewer delays. Higher prices for long-term care beds are positively

[7] When the explanatory variable is continuous (for example, the percentage of patients aged 75 or over), the percentage change in the dependent variable from a one-unit change in the explanatory variable is $100 * [exp(coefficient)–1]$. For dummy variables (for example, Specialist Trust status), the percentage change from changing from Acute to Specialist status is computed as $100 * [exp(coefficient)–1]$. When the explanatory variable is the logarithm of a continuous variable (for example, the logarithm of the number of care-home beds), the percentage change in the dependent variable from a 1 per cent change in the explanatory variable is the coefficient.

Table 4.3: Days of Delay

| | Model (4.1): Hospital type only | | Model (4.2): (1) plus exposure and size categories | | Model (4.3): (2) plus care home beds and prices | | Model (4.4): (3) plus case-mix and readmissions | | Model (4.5): (4) with random hospital effects | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | p | Coef | p | Coef | p | Coef | p | Coef | p |
| Acute Specialist Trust | -2.177*** | 0.000 | -0.727** | -0.045 | -0.625 | -0.138 | -0.620 | -0.187 | 0.040 | -0.886 |
| Acute Teaching Trust | 0.540*** | -0.002 | 0.097 | -0.602 | 0.122 | -0.430 | 0.121 | -0.430 | -0.138 | -0.344 |
| Mental Health Trust | 0.098 | -0.394 | 0.481*** | 0.000 | 0.615*** | 0.000 | 0.457** | -0.015 | 0.205 | -0.218 |
| Foundation Trust | -0.128 | -0.196 | -0.125 | -0.118 | -0.163** | -0.039 | -0.147* | -0.065 | -0.329*** | 0.000 |
| 2012-13 | 0.052* | -0.084 | 0.044 | -0.154 | 0.035 | -0.273 | 0.026 | -0.434 | 0.021 | -0.539 |
| 2013-14 | 0.0545 | -0.174 | 0.056 | -0.175 | 0.049 | -0.243 | 0.042 | -0.344 | 0.043 | -0.224 |
| Hospital Beds 200-399 | | | -0.027 | -0.931 | -0.234 | -0.534 | -0.353 | -0.350 | -0.255 | -0.239 |
| Hospital Beds 400-599 | | | -0.060 | -0.850 | -0.181 | -0.636 | -0.335 | -0.377 | -0.319 | -0.152 |
| Hospital Beds 600-799 | | | -0.011 | -0.974 | -0.082 | -0.833 | -0.215 | -0.580 | -0.274 | -0.232 |
| Hospital Beds 800-999 | | | -0.025 | -0.940 | -0.043 | -0.912 | -0.172 | -0.663 | -0.175 | -0.447 |
| Hospital Beds 1000-1499 | | | 0.043 | -0.897 | 0.012 | -0.976 | -0.121 | -0.756 | -0.159 | -0.501 |
| Hospital Beds 1500+ | | | -0.426 | -0.259 | -0.306 | -0.465 | -0.407 | -0.323 | -0.687** | -0.029 |
| Ln Care Home Beds | | | | | -0.270*** | 0.000 | -0.266*** | 0.000 | -0.288*** | 0.000 |
| Ln Care Home Price/Week | | | | | 0.166 | -0.530 | 0.214 | -0.438 | 0.417* | -0.081 |
| % of patients aged 60-74 | | | | | | | -0.013 | -0.495 | -0.041*** | 0.000 |
| % of patients older than 75 | | | | | | | 0.0127** | -0.026 | 0.0221*** | 0.000 |
| % of male patients | | | | | | | 0.015 | -0.105 | 0.015** | -0.021 |
| % of emergency admissions | | | | | | | 0.001 | -0.685 | 0.003 | -0.352 |
| % standardised readmissions | | | | | | | -0.0005 | -0.973 | -0.001 | -0.872 |
| Constant | 8.676*** | 0.000 | 2.192*** | 0.000 | 3.298** | -0.047 | 2.359 | -0.254 | -4.782*** | -0.007 |
| Ln alpha | -0.401*** | 0.000 | -0.712*** | 0.000 | -0.790*** | 0.000 | -0.806*** | 0.000 | | |
| Ln r | | | | | | | | | 1.150*** | 0.000 |
| Ln s | | | | | | | | | 7.406*** | 0.000 |
| Exposure | | | Ln Beds in Trust | | Ln Beds in Trust | | Ln Beds in Trust | | Ln Beds in Trust | |
| AIC | 11747.9 | | 11539.1 | | 11489.4 | | 11488.3 | | 11183.7 | |
| BIC | 11783.2 | | 11601 | | 11560.1 | | 11581.1 | | 11280.9 | |
| s.e. | Cluster | | Cluster | | Cluster | | Cluster | | OIM | |

Notes: Negative binomial models: (1) to (4) pooled, (5) random effects. Dependent variable: total days of delay experienced by all delayed patients during a year. Coefficients are proportionate change in days of delay from one unit increase in explanatory variable. Standardised readmissions are lagged by two years. Exposure term has a coefficient of 1. Ln alpha: log of overdispersion. Ln r and Ln s: shape parameters of the beta (r, s) distribution of random effects. AIC: Akaike Information Criterion. BIC: Bayesian Information Criterion. s.e.: standard errors. Cluster: cluster robust standard errors. OIM: observed information matrix standard errors. Observations: 614 = 208, 203 and 203 for 2011-12, 2012-13 and 2013-14. *p < 0.1, **p < 0.05, ***p < 0.01

associated with delays but the coefficient is at most weakly significant (model 4.5).

Trusts with a higher percentage of patients aged 75+ have more delays (models 4.4 and 4.5). Treating one unit (i.e. 1 per cent) more patients in this age category is associated with 1–2 per cent more delays. A higher proportion of male patients is also positively associated with more delays, though the association is statistically significant only in the random effects model (4.5). Given that the models condition on age and that men have shorter disability-free life expectancy, this variable may capture a greater likelihood of non-acute health problems that make it more difficult to discharge male patients.

To capture economies or diseconomies of scale, we include hospital bed number categories with the omitted category being fewer than 200 beds. Since we also include beds as an exposure term with a coefficient of unity, the generally negative coefficients on the bed number categories imply that delays increase less than proportionately with beds. However, the coefficients are only statistically significant in the random effects specification (model 4.5) and only for the largest size category (1,500 or more).

### *NHS delays*

Table 4.4 provides the results for delays attributed to the NHS. Unlike the Table 4.3 results for all delays, Mental Health Trusts do not differ significantly from Acute Trusts after accounting for size, long-term care, case-mix and readmissions variables. As in Table 4.3 for all delays, there are no significant differences between other Trust types and Acute Trusts after controlling for long-term care. A 1 per cent increase in long-term care beds is associated with 0.23–0.27 per cent fewer NHS delays, a similar result to that for all delays.

The effect of FT status is again negative, statistically significant and large in magnitude. Foundation Trusts incur 17–20 per cent fewer delays after accounting for size, long-term care, case mix and readmission rates in models 4.3 and 4.4. Allowing for unobserved heterogeneity (model 4.5) again increases the size of the effect (to 32 per cent).

### *Interaction of FT status and Trust type*

Models 4.1 to 4.5 assume that having Foundation Trust status has the same implications for all types of Trust. We also estimated specifications similar to models 4.4 and 4.5 but with the addition of interactions between FT status and Trust type. The results are reported in Table C.1 in Appendix C. They are broadly in line with those in Tables 4.3 and 4.4 and do not suggest that the association between FT status and delays varies by type of Trust. There is a large positive and highly significant coefficient on the interaction of Specialist Trust and Foundation Trust for NHS days of delay, but this is driven by the only Specialist Trust that does not have FT status and which had a very small number of delays attributed to the NHS

Table 4.4: Days of Delay Attributed to NHS

| | Model (4.1): Hospital type only | | Model (4.2): (1) plus exposure and size categories | | Model (4.3): (2) plus care home beds and prices | | Model (4.4): (3) plus case-mix and readmissions | | Model (4.5): (4) with random hospital effects | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | p | Coef | p | Coef | p | Coef | p | Coef | p |
| Acute Specialist Trust | -2.429*** | 0.000 | -0.717 | -0.104 | -0.503 | -0.364 | -0.723 | -0.241 | -0.172 | -0.599 |
| Acute Teaching Trust | 0.491*** | -0.003 | 0.052 | -0.784 | 0.106 | -0.520 | 0.0694 | -0.689 | -0.025 | -0.874 |
| Mental Health Trust | -0.433*** | -0.001 | -0.049 | -0.626 | 0.087 | -0.432 | -0.326 | -0.174 | -0.200 | -0.312 |
| Foundation Trust | -0.171 | -0.125 | -0.171* | -0.064 | -0.229** | -0.013 | -0.190** | -0.040 | -0.393*** | 0.000 |
| 2012-13 | 0.097*** | -0.004 | 0.109*** | -0.002 | 0.098*** | -0.007 | 0.086** | -0.021 | 0.054 | -0.169 |
| 2013-14 | 0.122** | -0.011 | 0.151*** | -0.002 | 0.148*** | -0.003 | 0.145*** | -0.005 | 0.098** | -0.014 |
| Hospital Beds 200-399 | | | 0.253 | -0.483 | 0.128 | -0.774 | -0.018 | -0.966 | 0.253 | -0.344 |
| Hospital Beds 400-599 | | | 0.213 | -0.559 | 0.190 | -0.678 | 0.018 | -0.967 | 0.058 | -0.831 |
| Hospital Beds 600-799 | | | 0.371 | -0.321 | 0.372 | -0.421 | 0.216 | -0.632 | 0.198 | -0.477 |
| Hospital Beds 800-999 | | | 0.266 | -0.480 | 0.304 | -0.512 | 0.152 | -0.738 | 0.204 | -0.469 |
| Hospital Beds 1000-1499 | | | 0.325 | -0.391 | 0.342 | -0.456 | 0.203 | -0.653 | 0.220 | -0.439 |
| Hospital Beds 1500+ | | | -0.026 | -0.953 | 0.091 | -0.852 | 0.010 | -0.984 | -0.418 | -0.257 |
| Ln Care Home Beds | | | | | -0.256*** | 0.000 | -0.230*** | -0.004 | -0.272*** | 0.000 |
| Ln Care Home Price/Week | | | | | -0.141 | -0.667 | 0.001 | -0.997 | -0.018 | -0.944 |
| % of patients aged 60-74 | | | | | | | -0.015 | -0.495 | -0.038*** | -0.002 |
| % of patients older than 75 | | | | | | | 0.019*** | -0.001 | 0.029*** | 0.000 |
| % of male patients | | | | | | | 0.033** | -0.023 | 0.016** | -0.031 |
| % of emergency admissions | | | | | | | 0.002 | -0.715 | 0.004 | -0.250 |
| % standardised readmissions | | | | | | | -0.013 | -0.425 | -0.002 | -0.803 |
| Constant | 8.378*** | 0.000 | 1.569*** | 0.000 | 4.431** | -0.028 | 1.997 | -0.471 | -3.033 | -0.114 |
| Ln alpha | -0.162* | -0.100 | -0.416*** | 0.000 | -0.460*** | 0.000 | -0.492*** | 0.000 | | |
| Ln r | | | | | | | | | 0.892*** | 0.000 |
| Ln s | | | | | | | | | 6.906*** | 0.000 |
| Exposure | | | Ln Beds in Trust | | Ln Beds in Trust | | Ln Beds in Trust | | Ln Beds in Trust | |
| AIC | 11251.8 | | 11079.9 | | 11052.7 | | 11040.6 | | 10692.7 | |
| BIC | 11287.2 | | 11141.7 | | 11123.5 | | 11133.4 | | 10790 | |
| s.e. | Cluster | | Cluster | | Cluster | | Cluster | | OIM | |

Notes: Negative binomial models: (1) to (4) pooled, (5) random effects. Dependent variable: total days of delay in year attributed to NHS. Coefficients are proportionate change in days of delay from one unit increase in explanatory variable. Standardised readmissions are lagged by two years. Exposure term has a coefficient of 1. Ln alpha: log of overdispersion. Ln r and Ln s: shape parameters of the beta (r, s) distribution of random effects. AIC: Akaike Information Criterion. BIC: Bayesian Information Criterion. s.e.: standard errors. Cluster: cluster robust standard errors. OIM: observed information matrix standard errors. Observations: 614 = 208, 203 and 203 for 2011-12, 2012-13 and 2013-14. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

in the study period. All other interactions between Foundation Trust status and Trust type are statistically insignificant at the 5 per cent level.

***Models for all Acute Trusts***

The patients in Mental Health Trusts are very different from those in the three types of Acute Trust in being younger, requiring different types of treatment and having much longer lengths of stay. Mental Health Trusts also have a smaller proportion of their revenue from prospective prices per patient treated, relying more on funding from block contracts negotiated with local health budget holders, and so they may have a smaller financial incentive to discharge patients. Clinical readiness for discharge is also less easy to define than for acute patients with physical conditions.

We therefore re-estimate models 4.4 and 4.5 after excluding Mental Health Trusts. The results are in Table C.2 in Appendix C. We find that the effects associated with being a Foundation Trust and with being located in an area with more care-home beds have even larger negative coefficients than in the models including Mental Health Trusts.

***Relationship between LTC and FT status***

Another potential explanation for the lower rate of delays in Foundation Trusts is that providers of long-term care may be more willing to accept patients discharged from Trusts with FT status. Care homes may believe that FTs provide better care so patients discharged by an FT are healthier and thus less costly to manage. If FT patients have a lower risk of readmission or death, this will also reduce the transaction costs associated with refilling places in the care home. This effect on delays arising from decisions by care homes will be stronger when care homes operate in markets with more than one hospital. We therefore add to model 4.5 an indicator for the hospital being located in a local authority with at least one other hospital and its interaction with FT status. The results are reported in Table C.3 of Appendix C. Neither variable is significant, although the interaction of the competition indicator and FT status is indeed negative.

## 4.5 Discussion

The size of a Trust is a key determinant of bed-days lost due to delayed discharge and Trust type is strongly correlated with size. Specialist Trusts, and to a lesser extent Mental Health Trusts, tend to be smaller than Acute Trusts, and Teaching Trusts tend to be larger. When we do not standardise for beds, Specialist hospitals have about a tenth of the delays of Acute Trusts, and Teaching hospitals have 72 per cent more delays.

We generally do not find evidence of scale economies or of a non-linear relationship between delays and size, as captured by categories of number of beds. Hospitals with a large number of beds tend to have proportionally fewer overall delays (and higher NHS delays) but the differences are not statistically significant.

Hospital Trusts that have Foundation Trust status have 14–28 per cent fewer bed-days lost due to delayed discharge of patients. Our finding that FTs have better performance than Trusts without FT status is in line with other studies. For example, Verzulli et al. (2011) found that FTs have lower hospital infection rates. All NHS hospital Trusts are not-for-profit public sector organisations, but those that have FT status have greater freedom from central control. In particular, they do not have to break even each year, can borrow to finance investment, have fewer limits on the amount of income they can generate from treating private patients, and are not constrained by national agreements on pay and conditions. Their ability to more easily retain financial surpluses implies that they have stronger incentives to contain costs and possibly to compete more aggressively to attract demand. The greater autonomy also implies that if FTs end up with a surplus, they can reinvest it in better systems, including IT systems, for handling discharges (i.e. better management, which can keep costs down) and use it to hire more trained and qualified staff to improve quality. NHS hospital Trusts of all types (Acute, Specialist, Teaching, Mental Health) can apply to become Foundation Trusts but must demonstrate that they meet quality, management and financial requirements[8]. Thus our finding of fewer delays in Foundation Trusts may be because Trusts that are successful in applying for FT status are inherently of higher quality or because their governance structure allows them greater autonomy which permits them to achieve higher quality and thus fewer delays. Because only three hospital Trusts became Foundation Trusts over the period covered by our data, we cannot distinguish between these explanations.

Despite this, policy makers may be able to use Foundation Trusts as examples of good practice, which can be identified by on-site investigations of FTs that have a lower-than-expected number of delays. The fact that the association between FT status and delays was similar across all hospital types suggests that lessons from further investigation of FTs may hold for all types of Trust.

After accounting for size, patient characteristics and long-term care availability, we find that although Mental Health Trusts and Acute Trusts have similar delays attributed to the NHS, Mental Health Trusts incur more delays in total. This suggests that delays in Mental Health Trusts are more likely to be due to non-NHS social care factors. Patients in Mental Health Trusts are more likely to require more complex post-discharge social and community care, which may take longer to organise. An increase in available long-term and community

[8]Requirements for obtaining FT status are set out in (Monitor, 2007; Monitor, 2013).

care resources, appropriate for patients with mental health conditions, may therefore have a bigger impact on delayed discharge for Mental Health Trusts than for other types of Trust.

Specialist hospitals tend to have far fewer delays, after controlling for beds. Differences can be large (about 46 per cent fewer delays after controlling for case mix, readmission rates and long-term care) but are not statistically significant. The lower frequency of delays may be due to the concentration of expertise and experience in the relevant field of medicine, the ability to adopt approaches best suited to the care of a particular patient group, and perhaps better availability of funding and resources.

Teaching Trusts have similar delays to Acute Trusts after controlling for size. Teaching status is generally considered a marker of higher quality. Teaching Trusts also offer a wider range of specialised services, attracting more severe patients. The higher quality may therefore raise demand and a more complex case mix can put an upward pressure on delays. In addition, the responsibilities of training medical students might increase the time it would otherwise have taken to discharge a patient. The higher perceived quality of teaching hospitals may also imply they have better management and more dedicated staff, which in turn may reduce delays.

Increases in the supply of long-term care are associated with fewer delays, as in previous studies (Fernandez and Forder, 2008; Gaughan et al., 2015). As a patient can only be discharged to institutional long-term care when a bed is available, an increased supply of such beds would be expected to reduce delayed discharges from hospital. However, such institutional care might not always be the most appropriate setting for care immediately after discharge. Especially for less severe patients, alternatives such as support in a patient's own home, if available, may be preferred by the patient. Local care homes' prices do not have a statistically significant impact on delays. This may reflect the overriding importance of providing appropriate care in a timely manner rather than searching for the lowest price.

Trusts with a higher percentage of patients aged 75+ have more delays. Older patients are more intensive users of hospital and LTC services, (Bardsley et al., 2012; Forder, 2009) are likely to have more comorbidities and disabilities, (Kasteridis et al., 2015; Meijer et al., 2011) and therefore require a more complex care package. This finding suggests that an ageing population might lead to more delays in the future.

## 4.6 Conclusions

Reducing delays in discharge from hospital is a long-standing policy concern. This study has investigated differences in delays by type of hospital. Hospital types are easily observable to the regulator and policy interventions can easily be targeted at a particular hospital type.

We find that Foundation Trusts have fewer delays. Foundation Trusts might therefore be used as exemplars of good practice in managing delays. Policy makers could investigate how such reductions have been achieved and provide insights to ensure that good practice is spread throughout the NHS. There is particular value in using Foundation Trusts as exemplars as all types of Trust (Acute, Specialist, Teaching, and Mental Health) have become Foundation Trusts.

Mental Health Trusts have more delayed discharges due to non-NHS factors including social care. This may indicate unmet social care needs for mental health patients requiring more sophisticated care packages, which take longer to organise, and suggest that better co-ordination of hospital, community and social care would be particularly beneficial in reducing delayed discharges for mental health patients.

# Chapter 5

# Paying for Efficiency: Incentivising Same-Day Discharges in the English NHS

## 5.1 Introduction

Many healthcare systems reimburse hospitals through prospective payment systems (PPS) in which the price for a defined unit of activity, such as a Diagnosis Related Group (DRG) in the US or a Healthcare Resource Group (HRG) in England, is set in advance and is equal across hospitals (Paris et al., 2010). Economic theory predicts that hospitals will expand activity in areas where price exceeds marginal costs and minimise activity in areas where they stand to make a loss.[1] This form of reimbursement should encourage hospitals to engage in efficient care processes and cost reduction strategies to improve profit margins (Shleifer, 1985; Ellis and McGuire, 1986; Ma, 1994; Hodgkin and McGuire, 1994).

One way to reduce costs is by reducing length of stay, this being an important cost driver. For some patients it may be possible to reduce length of stay to zero, specifically those for whom care can be provided safely[2] within an ambulatory setting in which patients are admitted, treated and discharged on the same day ('same day discharge' (SDD)). Not only may an SDD be less costly, it might be to the patient's benefit. The British Association of Day Surgery (BADS) has recommended SDD for nearly 180 types of planned surgery

[1](Semi-)altruistic providers may be willing to treat patients for which marginal costs exceed price as long as the financial losses are offset by sufficient patient benefit. The extent to which this is possible depends on the potential for cross-subsidisation within the organisation, and whether they face a soft budget constraint (Brekke et al., 2015).

[2]As early as 1985, the Royal College of Surgeons of England noted that " *[...] it should be clear to all concerned, the surgeon, the nursing staff, and in particular the patient, that day-surgery is in no way inferior to conventional admission for those procedures for which it is appropriate, indeed it is better.*" (Royal College of Surgeons of England, 1985).

(BADS, 2006) and the British Association for Ambulatory Emergency Care (BAAEC) has identified a range of conditions that require urgent care but where a subsequent overnight stay for observation is generally considered unnecessary (British Association of Ambulatory Emergency Care, 2014). Implementing these recommendations makes financial sense in the English National Health Service (NHS): for patients allocated to the same HRG, hospitals are paid the same amount for SDD treatment as for treating those who have an overnight hospital stay, despite the cost of providing SDD care being substantially lower (Street et al., 2007).[3] This should give hospitals a financial incentive to treat patients on an SDD basis whenever clinically appropriate.

Despite these recommendations and financial incentives, SDD rates are lower than is clinically recommended for a wide range of treatments (DH, 2010) (see also Figure 5.1). The reasons for low rates may relate to reluctance by doctors or to features of the hospital that constrain the ability to offer care on an SDD basis. One way to encourage doctors and hospitals to address these reasons is by increasing the SDD price, and this has been the approach taken in England. A payment reform known as the SDD *Best Practice Tariff* (BPT) involves paying a higher price for SDD than for care that involves an overnight or longer stay in hospital and has been applied to 32 different conditions.[4] The SDD payment policy is unusual in that it pays more for the less costly treatment, making it distinct from the usual form of PPS in which prices are set at average cost (Shleifer, 1985).

We investigate whether hospitals responded to the SDD incentive scheme and, in so doing, we contribute to two related strands of literature. First, we contribute to studies that focus on the effect of price changes on treatment choices. These find that physicians are willing to change their care patterns in response to financial incentives (see Chandra et al. (2011) for a recent review of this literature). For example, a growing body of literature has shown that obstetricians respond to changes in the profitability of caesarean section compared to vaginal birth by amending their treatment thresholds for the invasive surgical procedure (e.g. Gruber et al., 1999; Allin et al., 2015; Foo et al., 2017). For planned hip replacement, Papanicolas and McGuire (2015) found that more generous reimbursement for un-cemented relative to cemented implants in the English NHS led to greater provision of the former, despite a clinical recommendation in favour of the latter. Finally, Farrar et al. (2009) evaluated the introduction of PPS in England and found that it led to 0.4-0.8% more planned surgery being performed as SDD as well as an overall reduction in length of stay.

Our work also contributes to a second strand of literature evaluating pay-for-performance

[3]For example, in 2013/14 the average cost of planned surgery carried out as a day case in the English NHS was £698 compared to the average cost of £3,375 for overnight stays. (`https://www.kingsfund.org.uk/blog/2015/07/day-case-surgery-good-news-story-nhs`).

[4]Formally, planned and emergency SDD care is incentivised through two different BPTs. However, the design of both BPTs is identical and we therefore refer to both as one BPT.

(P4P) programmes. A review of 34 hospital sector P4P schemes in the US and other OECD countries finds the effects to be generally modest in size, short lived and sometimes associated with unintended consequences (Milstein and Schreyögg, 2016). The authors argue that the effectiveness of a P4P scheme is associated with the size of the incentive and that they are most appropriate for emergency care, where hospitals have less opportunity to select patients. Most P4P schemes focus on incentivising quality, either through rewarding health outcomes or process measures of quality. But the P4P policy we examine is distinct in that it incentivises efficiency so may be better termed a pay-for-*efficiency* (P4E) programme.

We offer several novelties to the existing literature. First, we analyse an unusual payment policy in which English hospitals are paid a bonus BPT for treating patients on an SDD basis. This policy explicitly and intentionally overpays hospitals for the cheapest care pathway, the objective being to stimulate take-up and improve efficiency. Our study extends a previous study by Allen et al. (2016) which evaluates the short-term effects of this P4E policy for cholecystectomy patients in England. That study used a difference-in-difference approach with a control group of all non-incentivised procedures recommended for SDD and found an increase in SDD rates of 5.8 percentage points (pp) in the first 12 months following the policy introduction. We extend that study in two ways. Firstly, instead of just one condition, we examine 32 conditions to which a similar bonus policy applied. This allows us to assess the generalisability of the policy by, in effect, conducting 32 separate experiments. Secondly, we examine longer-term effects, up to five years after the introduction of the bonus payment policy, which allows us to examine temporal responses.

Second, a distinctive feature is that the SDD incentive scheme was high-powered. The size of the bonus was economically significant, varying from 8% to 66% more than for an overnight hospital stay. This price differential compounds the cost advantage, which varied from 23% to 71% lower for SDD than for an overnight hospital stay in the pre-policy period. These incentives are much larger than those associated with most other P4P schemes, which are often around 5% (Cashin et al., 2014). The analysis can therefore shed light on whether limited responsiveness to P4P schemes as documented in literature is simply due to the small size of the bonus.

Third, we apply and compare three different econometric strategies, namely interrupted time series (ITS) analysis, difference-in-difference (DiD) methods, and synthetic control (SC) methods pioneered by Abadie and Gardeazabal (2003) and Abadie et al. (2010). While DID methods are commonly applied in health policy evaluations, SC methods are a fairly recent addition to our analytical armoury but are receiving increasing attention in the wider economic literature (e.g. Billmeier and Nannicini, 2013; Bharadwaj et al., 2014; Green et al., 2014; Kreif et al., 2016; Acemoglu et al., 2017). Sometimes it is not possible to apply DID or SC methods because of the need to identify appropriate control groups. In this study, because we examine the same type of policy applied to 32 different conditions, we have subsets of conditions to which either all three or just a subset of the methods can be applied. Consequently we are able to compare results from different methods for subsets of conditions we analyse, according to which underpinning methodological assumptions are satisfied for each condition. This serves as a robustness check for our findings.

Our results can be summarised as follows: Reassuringly, we find similar results to Allen et al. (2016) for cholecystectomy but, disappointingly from a policy perspective, it turns out that the bonus has the largest effect for this condition and its impact cannot be generalised. The BPT policy led to a statistically significant increase in SDD rates of 4-10pp for four out of 13 planned conditions. Results for emergency conditions are more mixed with four positive and three negative statistically significant effects. Furthermore, the magnitudes of effects for emergency conditions are generally smaller, ranging from +6pp to -6pp where statistically significant. The median elasticity of SDD rates to price is 0.24 for planned conditions and 0.01 for emergency conditions (overall median = 0.09). Elasticities are larger for conditions with larger post-policy price differences between SDD and overnight care, and, for planned conditions only, with bigger profit margins. We find no clear temporal pattern of policy response across conditions, again making it difficult to draw general policy conclusions. Findings are broadly robust to the use of different analytical approaches.

The paper is organised as follows. Section 5.2 provides the institutional background and the SDD pricing policy. Section 5.3 describes the data. Section 5.4 outlines the empirical methods. Section 5.5 describes the results. Section 5.6 is devoted to discussion and concluding remarks.

## 5.2 Institutional background and theoretical predictions

The English NHS is funded by general taxation and patients face no charges for hospital care. Residents have to be registered with a general practitioner, who act as gatekeepers and can refer patients for planned inpatient care to any licenced hospital in England. Patients can be admitted for emergency care via a hospital's Accident & Emergency department or by direct referral from their general practitioner. Most hospitals are publicly owned, although a small number of private hospitals also provide care to NHS patients. All NHS hospital doctors are salaried and do not share in hospitals' profits or losses.

The NHS adopted a PPS for hospital reimbursement in 2003. Hospitals are paid a pre-determined tariff for treating NHS-funded patients, differentiated by HRGs (the English equivalent of DRGs). Patients are assigned to a HRG based on diagnoses, procedures and, in some cases, other characteristics such as age (DH, 2002; Grašič et al., 2015).[5] Initially limited to a small number of planned conditions, PPS has been extended progressively over time and now covers most hospital activity.

We start by describing the construction of prices in the pre-policy period prior to the introduction of the SDD policy. We denote the pre-policy period with $\alpha = 0$ and the post-policy period as $\alpha = 1$. While the SDD policy was introduced for different patient groups at different times, we analyse each group individually.

The tariff for a HRG ($g$) in year ($k$) in the pre-policy period ($P_{0,k,g}$) is proportional to the average cost of care reported across all English NHS hospitals for patients (admitted as planned or emergency) who were treated three years before, $\bar{C}_{k-3,g}$.[6] More formally, $\bar{C}_{k-3,g} = (\sum_{j=1}^{J}(C_{k-3,j,g} \times N_{k-3,j,g})/\sum_{j=1}^{J} N_{k-3,j,g})$, where $j = 1,\dots,J$ denotes the hospital, $N_{k-3,j,g}$ is the number of patients for a given hospital $j$, and $C_{k-3,g}$ is the average cost of patients in hospital $j$. Reimbursement is further adjusted to account for inflation ($I$) and expected efficiency improvement ($E$) factors.[7] Therefore, the pre-policy price $P_{0,k,g} = \bar{C}_{k-3,g} \times I_k \times E_k$, with $I_k > 1$ and $E_k < 1$.

For most planned treatment, patients admitted and discharged on the same day ($SDD$) attract the same payment as overnight stays ($ON$). Therefore, $P_{0,k,g} = P^{SDD}_{0,k,g} = P^{ON}_{0,k,g}$ if treatment is planned. However, a short-stay adjustment is applied to patients admitted as an emergency and discharged on the same day. The adjustment takes the form of a factor $0 < \lambda \leq 1$ which takes the value 1 if the national average length of stay for the HRG is less or equal to two nights and increasingly smaller values as average length of stay increases. The short-stay adjustment is aimed at reducing the incentive to admit less severe patients for observation rather than intervention. Therefore, emergency care including at least one overnight stay has a price constructed equivalently to planned care $P^{ON}_{0,k,g} = P_{0,k,g}$ while $P^{SDD}_{0,k,g} = \lambda P_{0,k,g}$.

The BADS and BAAEC both produce directories listing 191 clinical conditions (i.e. specific diagnoses or surgical treatments) that are deemed suitable for SDD and a recommended rate (RR) of SDD that is considered safe and appropriate (BADS, 2006; British Association of Ambulatory Emergency Care, 2014). The directories represent a clinical consensus about the appropriate level of SDD. From 2010, the English Department of Health has gradually introduced explicit financial incentives (SDD BPTs) for specific conditions from these direc-

[5] The policy was originally known as *'Payment by Results'* and has since been renamed as *'National Tariff Payment System'*.

[6] All NHS hospitals provide detailed reference cost information to the Department of Health on an annual basis. These data are collated in the reference cost schedule and provide information on the average cost of production across hospitals, further broken down by admission type.

[7] The base price is further adjusted for hospital-specific factors such as local cost of capital and labour and specialist hospital status. As the policy evaluated is national and applies equally to all hospitals, these hospital-specific adjustments do not affect the incentives created.

tories.[8] These incentives apply to all providers of NHS-funded care. The selection and design of SDDs was informed by discussions with clinical stakeholders and varies across clinical areas (DH, 2007b). New conditions to be incentivised are announced six months in advance of introduction. The general criteria for potential selection are volume (>5,000 patients/year)[9], the national SDD rate being below the RR for this condition, and evidence of variation in the SDD rate across hospitals (DH, 2010). Not all clinical conditions meeting these general criteria have an SDD incentive but by April 2014, 13 planned and 19 emergency conditions were covered by SDD incentives (Monitor and NHS England, 2014).

A condition incentivised by an SDD BPT has two prices such that $P^{SDD}_{1,k,g} > P^{ON}_{1,k,g}$ for both planned and emergency care. For example, under this scheme in 2010, hospitals are paid approximately £329 (or 24%) more for a same day discharge than an overnight stay for planned cholecystectomy (gall bladder removal) (DH, 2010). This structure is common to all 32 SDD BPTs. However, the absolute and relative size of the differential varies considerably and range from 8% to 66% of the overnight admission price. After their introduction bonuses were approximately stable over time.[10] For planned care, a higher price is only paid if the patient was scheduled to be treated as a day case in advance of admission. Therefore, the price for a patient discharged on the same day but not admitted as a day case is the same as an overnight stay.

Table 5.1 provides an overview of the incentivised SDD conditions, the financial year in which the incentive was introduced[11], the hospital reimbursement with and without the SDD incentive, the average cost of care reported by NHS hospitals in the year prior to the policy, as well as the SDD rate and the number of patients eligible in the twelve months prior to announcement of the incentive for that group.

### 5.2.1 Hospital incentives

In this section we compare the financial incentives that hospitals faced before and after the policy. To keep the presentation simple, we suppress the HRG notation $g$ and year variability $k$ therefore focusing on changes before and after the policy. Moreover, we assume that (i) each hospital has a total volume of patients treated (either as SDD or overnight) equal to N and this is constant over time, (ii) each hospital has identical costs, therefore suppressing h,

[8] In some cases, additional exclusion criteria are applied to limit the scope of the SDD BPT to non-complex patients. In these cases, the group of patients with incentivised tariffs attached is a subset of those given in relevant directories and recommended rates can be considered a lower bound of what is clinically appropriate.

[9] One noteworthy exception is 'simple mastectomy' which has been incentivised since 2011 despite an annual volume of about 4,000 patients.

[10] The bonus as a percentage of base price changed by more than 5% from introduction to the financial year 2014/15 for six out of 32 SDD BPT conditions. This variation arises due to changes to the base price that reflects year-on-year variation in the reported cost data used for price setting rather than because of purposeful policy refinement.

[11] Financial years run from 1st April to 31st March of the following calendar year.

Table 5.1: Overview of incentivised conditions

| # | Condition | Year of introduction | Recommended rate (RR)(%) | Number of patients eligible (pre-policy) | SDD rate (pre-policy) (%) | Price | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Pre-policy | | | Post-policy | | | Production cost (pre-policy) | | |
| | | | | | | SDD | ON | Δ | SDD | ON | Δ | SDD | ON | Δ |
| **Planned care** | | | | | | | | | | | | | | |
| 1 | Cholecystectomy | 2010 | 60 | 11,004 | 16 | 1,365 | 1,365 | 0 | 1,694 | 1,369 | 325 | 1,365 | 2,145 | -780 |
| 2 | Simple mastectomy | 2011 | 15 | 4,048 | 7 | 2,123 | 2,123 | 0 | 2,385 | 2,085 | 300 | 1,480 | 2,682 | -1,202 |
| 3 | Sentinel node mapping | 2011 | 80 | 13,971 | 31 | 2,073 | 2,073 | 0 | 1,376 | 1,076 | 300 | 1,423 | 2,574 | -1,151 |
| 4 | Operations to manage female incontinence | 2011 | 80 | 13,658 | 25 | 1,222 | 1,222 | 0 | 995 | 695 | 300 | 1,021 | 1,574 | -553 |
| 5 | Endoscopic prostate resection | 2011 | 15 | 6,395 | 1 | 1,959 | 1,959 | 0 | 1,947 | 1,797 | 150 | 1,274 | 2,321 | -1,047 |
| 6 | Laser prostate resection | 2011 | 90 | 16,000 | 3 | 1,890 | 1,890 | 0 | 1,863 | 1,563 | 300 | 1,240 | 2,236 | -996 |
| 7 | Hernia repair | 2011 | 85 | 90,575 | 57 | 1,233 | 1,233 | 0 | 1,124 | 824 | 300 | 1,287 | 1,913 | -626 |
| 8 | Shoulder decompression | 2011 | 80 | 26,836 | 49 | 2,172 | 2,172 | 0 | 2,253 | 2,053 | 200 | 1,319 | 2,047 | -729 |
| 9 | Bunion operation | 2011 | 85 | 16,148 | 50 | 1,063 | 1,063 | 0 | 1,170 | 970 | 200 | 1,123 | 1,972 | -848 |
| 10 | Fasciectomy | 2011 | 95 | 9,211 | 74 | 2,735 | 2,735 | 0 | 2,297 | 2,097 | 200 | 1,499 | 2,286 | -787 |
| 11 | Tonsillectomy | 2012 | 80 | 15,243 | 37 | 1,074 | 1,074 | 0 | 1,071 | 771 | 300 | 1,130 | 1,468 | -337 |
| 12 | Septoplasty | 2012 | 80 | 18,830 | 48 | 1,164 | 1,164 | 0 | 1,204 | 1,004 | 200 | 1,219 | 1,622 | -403 |
| 13 | Tympanoplasty | 2013 | 80 | 7,577 | 48 | 2,008 | 2,008 | 0 | 2,182 | 1,882 | 300 | 2,038 | 2,947 | -909 |
| **Emergency care** | | | | | | | | | | | | | | |
| 14 | Epilepsy | 2012 | 90 | 42,601 | 27 | 445 | 1,781 | -1,336 | 1,157 | 946 | 211 | 435 | 1,713 | -1,278 |
| 15 | Acute headache | 2012 | 60 | 55,826 | 34 | 511 | 730 | -219 | 748 | 537 | 211 | 424 | 1,151 | -727 |
| 16 | Asthma | 2012 | 30 | 27,986 | 23 | 606 | 1,173 | -568 | 1,081 | 891 | 190 | 404 | 1,190 | -785 |
| 17 | Respiratory | 2012 | 60 | 9,794 | 40 | 489 | 1,086 | -597 | 776 | 585 | 191 | 412 | 1,137 | -725 |
| 18 | Pulmonary embolism | 2012 | 90 | 11,235 | 14 | 512 | 2,049 | -1,536 | 1,658 | 1,468 | 190 | 476 | 1,697 | -1,221 |
| 19 | Chest pain | 2012 | 60 | 232,317 | 41 | 561 | 802 | -241 | 748 | 543 | 205 | 433 | 1,216 | -783 |
| 20 | Appendicular fractures | 2012 | 60 | 39,931 | 30 | 298 | 1,111 | -813 | 832 | 599 | 233 | 554 | 2,262 | -1,708 |
| 21 | Cellulitis | 2012 | 90 | 28,965 | 25 | 568 | 1,477 | -909 | 1,147 | 924 | 222 | 433 | 1,546 | -1,113 |
| 22 | Renal/ureteric stones | 2012 | 60 | 28,241 | 33 | 642 | 876 | -234 | 821 | 606 | 215 | 459 | 1,273 | -814 |
| 23 | Deep vein thrombosis | 2012 | 90 | 18,121 | 56 | 612 | 1,360 | -748 | 785 | 558 | 227 | 463 | 1,718 | -1,255 |
| 24 | Deliberate self-harm | 2012 | 90 | 95,973 | 46 | 414 | 532 | -119 | 535 | 326 | 209 | 372 | 899 | -527 |
| 25 | Falls | 2012 | 90 | 62,230 | 32 | 443 | 985 | -542 | 751 | 546 | 205 | 401 | 994 | -593 |
| 26 | Pneumonia | 2013 | 30 | 11,121 | 19 | 609 | 1,353 | -744 | 1,136 | 936 | 200 | 447 | 1,374 | -927 |
| 27 | Fibrillation | 2013 | 60 | 96,203 | 26 | 682 | 1,588 | -906 | 1,242 | 1,026 | 216 | 465 | 1,373 | -908 |
| 28 | Head injury | 2013 | 60 | 13,976 | 53 | 477 | 546 | -69 | 698 | 453 | 245 | 424 | 1,074 | -649 |
| 29 | Pelvis fracture | 2013 | 90 | 6,935 | 8 | 344 | 1,374 | -1,030 | 1,711 | 1,466 | 245 | 971 | 3,861 | -2,890 |
| 30 | Bladder outflow | 2013 | 60 | 11,133 | 23 | 632 | 1,121 | -489 | 1,009 | 798 | 211 | 423 | 1,373 | -950 |
| 31 | Anaemia | 2013 | 90 | 13,315 | 16 | 635 | 2,249 | -1,614 | 1,908 | 1,662 | 246 | 525 | 1,440 | -915 |
| 32 | Abdominal pain | 2013 | 60 | 199,320 | 31 | 441 | 441 | 0 | 918 | 693 | 225 | 452 | 452 | 0 |

Notes: SDD = Same day discharge; ON = Overnight
*If* incentive applied to more than one HRG within a condition, the price and cost information shown are weighted averages according to volume.
Pre- and post-policy refer to the 12 months before or after the policy start, respectively. The pre-policy SDD rate is calculated in the 12 months prior to the policy announcement and therefore not affected by anticipatory effects.

but average costs can vary over time before and after the policy (for example as a result in the change in case-mix arising from a change in the proportion of patient treated as overnight admission).

The aim of the SDD pricing policy was to increase the rate of SDD towards the recommended rate by introducing a financial incentive for hospitals. We illustrate this incentive for *planned* day case surgery first. The profit function, denoted with $\pi$ in the pre-policy and the post-policy period is given respectively by

$$\pi_0 = N_0^{SDD}(P_0 - C_0^{SDD}) + (N - N_0^{SDD})(P_0 - C_0^{ON}) \tag{5.1}$$

$$\pi_1 = N_1^{SDD}(P_1^{SDD} - C_1^{SDD}) + (N - N_1^{SDD})(P_1^{ON} - C_1^{ON}) \tag{5.2}$$

The difference in profit before and after the policy is:

$$\begin{aligned} \Delta\pi = \pi_1 - \pi_0 = {} & (P_1^{SDD} - P_1^{ON})N_1^{SDD} - N(P_0 - P_1^{ON}) \\ & + (N_1^{SDD} - N_0^{SDD})(C_0^{ON} - C_0^{SDD}) \\ & - [N_1^{SDD}(C_1^{SDD} - C_0^{SDD}) + (N - N_1^{SDD})(C_1^{ON} - C_0^{ON})] \end{aligned} \tag{5.3}$$

Under the assumptions outlined above, the first term is positive and gives the additional revenues for every treatment which is provided as SDD. The second term is negative and is given by the reduction in revenues due to a reduction in the overnight tariff. The third term is positive if the SDD price induces an increase in the SDD rate, which are less costly (evaluated at pre-policy costs). The fourth and last term, in square brackets, relates to changes in the average costs, which can be due to patient composition or external factors, the sign being generally indeterminate. We could argue, for example, that patients who are treated as SDD after the policy are at the margin more severe, so that this will translate into an increase in the average cost of SDD and a reduction in the average cost of an overnight stay (see Siciliani, 2006; Hafsteinsdottir and Siciliani, 2010, for more formal theoretical models.). We assume that the increase in average costs for SDD is relatively small, so that an increase in SDD rates leads to a reduction in overall costs (i.e. the sum of the third and fourth term is positive).

The analysis highlights that the SDD pricing policy generates a financial incentive for hospitals, equal to $(P_1^{SDD} - P_1^{ON}) > P_0^{SDD} - P_0^{ON} > 0$, to increase planned day case treatments, but the overall effect on profits also depends on the reduction in the base tariff. A similar analysis holds for emergency care where the only difference is that pre-policy the tariff was higher for overnight treatments, i.e. $(P_1^{SDD} - P_1^{ON}) > P_0^{SDD} - P_0^{ON} < 0$.

Notice that, under the assumption that the cost of SDD is always lower than the cost with an overnight stay for a given patient, hospitals already had an incentive in the pre-policy period to treat planned patients up to the RR as SDD. But as shown below in Section 5.3, hospitals had very low planned SDD rates in the pre-policy period, and always well below the recommended one. This could be due to the motivations of the doctor providing treatment or the constraining features of the hospital in which the doctor works.

As regards motivation, slow uptake of SDD may reflect poor dissemination about best practice. Doctors may not be aware of or may doubt the evidence that SDD is as safe as traditional practice involving overnight admission. They may also struggle to identify the patient population that is suitable for SDD, particularly if it is not recommended for all patients, i.e. RR<100%. Greater uptake of SDD may also require some re-training (e.g. in laparoscopic surgical techniques) that carries monetary and time costs for doctors.

Moreover, the hospital in which the doctor works may be constrained in its ability to extend SDD to more patients. While many SDD treatments can be performed in a normal hospital setting, making SDD standard practice may require building new facilities or repurposing existing hospital units that are devoted to SDD care. If so, expanding the volume of SDDs may require a long-term capital investment. Some English hospitals may not undertake this investment, particularly those that face greater borrowing constraints that restrict their access to capital funds (Marini et al., 2008; Thompson and McKee, 2011).

### 5.2.2 Welfare

We conclude this section by discussing welfare implications. We discuss welfare under two perspectives. First, we define welfare as the difference in patient benefits minus provider costs. It has been argued that an increase in SDD rate will not harm patients as long as it remains below the RR. Under this assumption, the introduction of the SDD price incentive will have no effect on patient benefits if SDD rates increase, so that the effect of welfare is driven by its effect on costs. As argued above, an increase in SDD will reduce costs under minimal regularity conditions. We can therefore conclude that the SDD pricing policy is welfare improving, and that the size of the welfare gain increases with the number of SDDs (up to the RR).

Second, we take the purchaser perspective, and define welfare more narrowly as the difference between patient benefit and the transfer to the provider. Since patient benefit does not differ between SDD and ON, the effect of the SDD price on purchaser welfare is, as shown above, given by its effect on the overall transfer, and equal to $(P_1^{SDD} - P_1^{SDD})N_1^{SDD} - N(P_0 - P_1^{ON})$. This suggests that the purchaser is always better off when the SDD price is introduced as long as it sufficiently reduces the ON tariff to compensate for the increase in the transfer to the provider due to the increase in SDD price.

## 5.3 Data

We use data from Hospital Episode Statistics (HES) on all NHS-funded patients aged 19 or older admitted to English hospitals between April 2006 and March 2015 for care which could be delivered as SDD according to the BADS / BAAEC directories (157 planned and 34 emergency conditions). HES is an admission-level dataset that contains detailed information on clinical and socio-demographic characteristics, the admission pathway and its timings, and whether care was scheduled as SDD in advance (planned admissions only). The outcome of interest is constructed as a binary variable that takes the value of 1 if the patient is admitted and discharged on the same calendar day, and zero otherwise.

Figure 5.1 shows the SDD rate and the RR for each of the 32 incentivised conditions in the year 2009, prior to the start of the SDD pricing policy. Observed rates for planned conditions are highlighted in light grey, and those for emergency conditions in dark grey. There is marked heterogeneity both in the observed rate of SDD and the gap between SDD rate and RR, i.e. the potential for growth.

In our empirical analyses we control for potential changes in patient complexity over time that may explain observed changes in SDD rates. We construct a set of risk-adjustment variables from the HES dataset including age (coded as a categorical variable in 10-year bands with separate categories for 19-24 and $\geq$85), gender (male = 1), number of Elixhauser comorbidities (coded as 0, 1, 2-3, 4-6 and $\geq$7)(Elixhauser et al., 1998) and whether the patient had any past emergency admissions within 365 days (yes = 1). As a measure of socio-economic status, we use the income deprivation score of the English Indices of Deprivation 2010 (McLennan et al., 2011) for the patients' lower layer super output area of residence.

Hospitals are consulted on any changes to the payment system — including the introduction of new BPTs — approximately six months prior to the change. This gives them time and opportunity to adapt to the new policy before the actual implementation, which may bias observed pre-policy outcomes. We therefore exclude data for all patients treated in the six months prior to the condition being incentivised. Also, for some conditions eligibility criteria were refined over time to restrict the incentive to a more tightly defined patient population. In these instances, we apply the criteria that were valid when the financial incentive first applied to this condition to ensure consistency throughout the study period.

The overall sample includes 11,336,138 patients with incentivised conditions and 21,121,500 patients with non-incentivised conditions. Descriptive statistics for case-mix variables by condition are available in Table D in the Appendix.

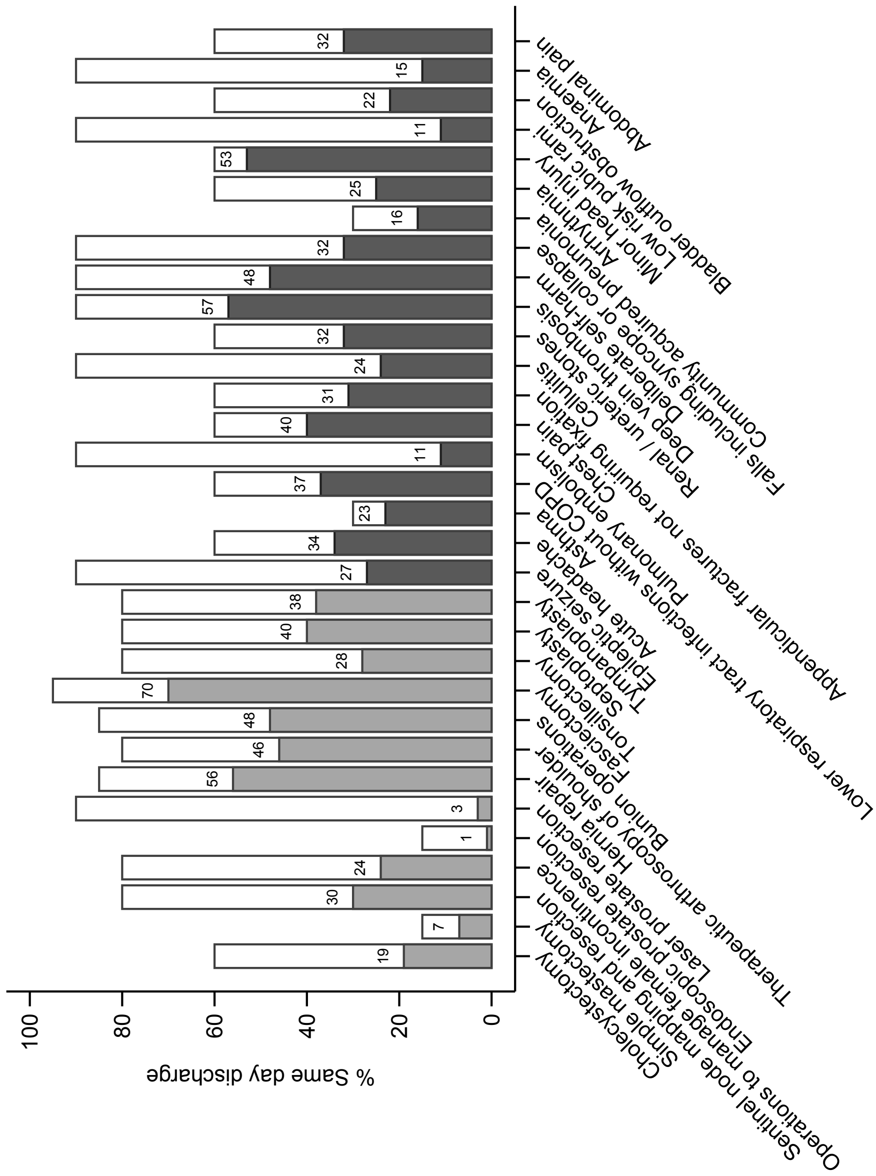



Figure 5.1: Observed SDD rate (grey bar) and recommended rate (white bar) for incentivised conditions in 2009

## 5.4 Methods

Our empirical analysis seeks to estimate the impact of the SDD pricing policy on the probability of a patient being discharged on the same day as admission.[12] Separate models are estimated for each of the 32 incentivised conditions.

We follow the potential outcome framework developed by Rubin and commonly applied in the policy evaluation literature (Rubin, 1974; Abadie and Imbens, 2006). For every patient, we define two potential outcomes: $Y_{it}^1$ is the outcome that a patient $i$ would realise in month $t$ if the SDD incentive was in effect (potential outcome under treatment) and $Y_{it}^0$ is the potential outcome that the same patient would realise without the SDD incentive (potential outcome under control). For patients who received care for one of the 32 incentivised conditions, their observed outcomes before the introduction of the SDD policy ($t < t^{BPT}$) correspond to their potential outcome under control, where $t^{BPT}$ is defined as the month when the SDD BPT was introduced. After the introduction of the SDD BPT, their observed outcomes correspond to their potential outcomes under treatment. By contrast, for patients who received care for non-incentivised conditions (used as control groups in Sections 5.4.2 and 5.4.3), observed outcomes correspond to potential outcomes under control throughout the entire study period.

Policy interest is in the average treatment effect on the treated (ATT), i.e. the patients who were treated as an SDD for incentivised conditions after the introduction of the policy, defined as $E[Y_{it}^1 - Y_{it}^0 | t \geq t^{BPT}]$. While $Y_{it}^1$ is observed for these patients, the potential counterfactual outcome under control $Y_{it}^0$ is unobserved. We employ three different analytical approaches to estimate the expected counterfactual outcome $E[Y_{it}^0]$.

### 5.4.1 Interrupted time series analysis

Our first analytical approach employs *interrupted time series* (ITS) analysis. The identifying assumption of the ITS design is that a linear pre-policy trend in the proportion of SDD would have continued uninterrupted in the absence of the SDD BPT policy. Therefore, the trend in the observed values of $Y_{it}$ for $t < t^{BPT}$ can be used to construct the counterfactual outcome $Y_{it}^0$ for $t \geq t^{BPT}$.

ITS analysis uses segmented regression techniques to test for structural breaks in the linear time trend when the SDD policy is introduced. The ITS specification commonly used in empirical policy evaluations allows for a single break, which may manifest as an immediate

[12]Our analysis focuses on the intensive margin. Hospitals may also respond to the financial incentive by increasing the volume of incentivised activity. However, we do not observe faster annual growths in volume of activity after the introduction of the SDD BPT (pre: 6.5% vs. post: 2.3%, p = 0.264). Furthermore, the growth in non-incentivised conditions over the 9 year period (mean = 13.3% per year) exceeds that of the incentivised conditions (mean = 5.4%). Appendix Table D.2 shows annual volumes of activity for the incentivised conditions.

shift in the proportion of SDD and/or a homogeneous change in its trend. We extend this base specification to allow for heterogeneous effects in each of the $k = 1, \ldots, K$ post-policy years following the introduction of the SDD policy and specify the regression model as

$$\begin{aligned} Y_{ijt} = \alpha_0 + \alpha_1 M_t + \sum_{k=1}^{K} [\gamma_k D_k + \delta_k (D_k \times M_t)] + \sum_{1}^{4} \nu_s Q_s \\ + \sum_{j=1}^{J} \theta_j H_j + (\boldsymbol{X_i} \times \boldsymbol{Z_t})' \boldsymbol{\xi} + \varepsilon_{ijt} \end{aligned} \tag{5.4}$$

where $Y_{ijt}$ is a dummy variable taking the value of 1 if patient $i = 1, \ldots, I$ treated in hospital $j = 1, \ldots, J$ in month $t = 1, \ldots, T$ was admitted and discharged on the same day and the value of 0 if the patient was admitted and stayed at least one night in hospital. The variable $M_t$ is a continuous measure of time in months.

$D_k$ are dummy variables which take the value of 1 in each of the $k = 1, \ldots, K$ post-policy years and zero otherwise. The coefficients $\gamma_k$ and $\delta_k$ measure shifts and changes in trend in the proportion of SDD in each of the post-SDD years, respectively. Our model thus allows for a delayed impact of the SDD policy which may be because clinical processes take time to be reorganised. Alternatively, positive policy effects may fade over time due to increasing marginal costs of further increasing the proportion of patients treated on an SDD basis.

$Q_s$ is a vector of seasonal (quarter) dummies, e.g. to allow for winter effects. $H_j$ is a vector of hospital dummies, which capture unobserved time-invariant differences amongst hospitals (e.g. management quality, local demand) in the propensity to discharge patients the same day.

The adoption of SDD practice is likely to differ according to patient characteristics, with more severely ill patients less likely to be suitable for discharge on the same day that they receive treatment. Failure to account for patient case-mix may lead to biased estimates of the policy parameters if there are case-mix changes over time or if hospitals respond differently to the incentive for different patient groups. We address this concern by inter-acting a vector of patient characteristics $\boldsymbol{X_i}$ with $\boldsymbol{Z_t} = [M_t, (D_k \times M_t)]$. As a result, trends in SDD rates can vary with patient severity and, therefore, the policy parameters also can vary across patient groups. $\varepsilon_{ijt}$ is an idiosyncratic error term.

The ATT of the SDD BPT in year $k$ for the baseline patient (when all elements of $\boldsymbol{X_i}$ equal zero), defined as $\tau_k$, is calculated at the mid-point of each year $k$ and given by:

$$\tau_k = \gamma_k + \frac{1}{2}\delta_k \tag{5.5}$$

where $\gamma_k$ denotes the level change in the SDD rate in the year $k$ relative to the level implied by the pre-policy trend and $\delta_k$ is the change in its average monthly growth rate in the same years (relative to the counterfactual growth rate $\alpha_1$). We calculate separate estimates of $\tau_k$ for each patient group defined by $X_i$ and then average over the distribution of patients treated in each year $k$.

The key focus of this study is the ATT calculated over the entire post-policy period, which we define as $\bar{\tau}$, and is given by:

$$\bar{\tau} = \frac{1}{N} \sum_{k=1}^{K} \tau_k N_k \tag{5.6}$$

where $N_k$ is the number of patients in year $k$ and $N = \sum_{k=1}^{K} N_k$.

All models are estimated as linear probability models with Huber-White robust standard errors of the model coefficients. The corresponding standard errors of policy parameters of interest are calculated using the delta method.

### 5.4.2 Difference-in-difference analysis

A key assumption of the ITS model is that the pre-policy trend is an unbiased estimate of the counterfactual $Y_{it}^0$ for the post-policy period. In other words, the trend in the proportion of SDD observed before the policy change would have continued afterwards if the intervention had not come into effect. This assumption may not hold if other concurrent events in the post-policy period affect the trend in SDD rates.

We relax this assumption by employing a *difference-in-difference* (DID) strategy. We construct $Y_{it}^0$ based on the observed outcomes of a control group that is not affected by the SDD policy but is subject to the same external influences and would respond similarly to them. These requirements imply that both the intervention and the control show parallel trends in the average $Y_{it}$ prior to the policy introduction. After accounting for differences between intervention and control groups in levels of expected outcomes prior to the policy introduction, any further difference in levels after the policy introduction can be interpreted as average effects of the SDD policy.

We estimate the following specification

$$\begin{aligned} Y_{ijt} = \beta_0 + \beta_1 BPT_i + \sum_{k=1}^{K} [\gamma_k D_k + \mu_k (D_k \times BPT_i)] + \sum_{1}^{4} [\nu_s Q_s + \varphi (Q_s \times BPT_i)] \\ + \sum_{j=1}^{J} [\theta_j H_j + \omega_j (H_j \times BPT_i)] + (\boldsymbol{X_i} \times \boldsymbol{V_i})' \boldsymbol{\xi} + \varepsilon_{ijt} \end{aligned} \tag{5.7}$$

where $BPT_i$ is a dummy variable that takes the value of 1 for patients in the intervention group and 0 for patients in the control group. All other variables are defined as in Section 5.4.1, except for $V_i$ which is a matrix composed of $BPT_i$, $D_k$ and $D_k * BPT_i$. This is analogous to $(\boldsymbol{X_i} \times \boldsymbol{Z_t})$ in the ITS analysis and is, again, designed to capture changes in case-mix over time. We allow for hospital fixed effects to vary between the intervention and the control group to account for any differences in a hospital's relative propensity to discharge patients with different clinical conditions on the same day.[13]

The effect of the SDD policy in year $k$ for the baseline patient is now given by $\tau_k = \mu_k$ and the calculation of the policy parameters proceeds as outlined before.

We select a separate control group for each incentivised condition. We consider as potential control groups all non-incentivised conditions from the clinical directories that follow the same admission pathway (planned or emergency), have a RR±15% of the intervention group (see also Allen et al., 2016) and have at least, on average, 100 admissions per calendar month over the pre-policy period. Furthermore, to meet the assumptions of the DID approach, we only consider control groups that show a similar trend in the proportion of SDDs prior to the introduction of the pricing policy, defined as $(\alpha_1^{BPT})/(\alpha_1^{Control}) = [0.9, 1.1]$ with estimates of $\alpha_1$ obtained from separate ITS regressions. Where multiple control groups meet these criteria, we use the control group with the most similar pre-policy level, i.e. $min|\alpha_0^{BPT} - \alpha_0^{Control}|$.

### 5.4.3 Synthetic control analysis

DID models are commonly applied using a single control group. In our study, we consider 32 incentivised conditions. For some of these there might be more than one potential control group that satisfies the selection criteria. For other incentivised conditions we might find no controls. We therefore also apply the *synthetic control* (SC) method. In short, the SC method allows for the evaluation of the effect of a policy on a single treated unit (e.g. a country, region or, as in our case, an incentivised condition) by employing an algorithm to select a weighted combination of potential control units. Weights are chosen to minimise the route mean squared error between the observed outcome of the intervention unit and the predicted outcome from the synthetic unit over the pre-policy period. Under a number of assumptions, including a linear relationship between the covariates and the outcome variable and a sufficiently long pre-policy time period relative to the variance of the error term, the post-policy outcomes of the SC group can be interpreted as the counterfactual outcome of the intervention group. The difference between observed and counterfactual outcomes provides an estimate of the ATT.

As regards our study, there are two advantages of the SC method over the DID method. First, SC considers all potential control conditions, thereby making best use of available data without the need to select just one particular condition as the control group. Second, it

[13]For example, a hospital may be 5pp more likely than the average hospital to discharge patients in the intervention group on the same day and 12pp more likely to do so for patients in the control group. In this case, forcing a common hospital fixed effect for both groups would be inappropriate.

does not require any single control group to exhibit a parallel trend with the intervention group; rather, by construction, the control group matches the intervention group in *levels* of pre-policy outcomes.

The SC method requires a panel data structure with the same units of observation being followed over time. We therefore follow Abadie et al. (2010) and aggregate the patient level data to monthly proportions of same-day discharge at the level of the intervention group, i.e. one observation per month for each condition. We apply indirect standardisation to adjust for changes in case-mix over time. We estimate the relationship between patient characteristics and the probability of SDD in the financial year 2006 and then calculate an adjusted proportion of SDD for all months $t$:

$$\widehat{Y}_t = \frac{\sum_{i=1}^{N_t} Y_{it}}{\sum_{i=1}^{N_t} \widehat{Y}_{it}} \times \bar{Y}_t \tag{5.8}$$

where $\widehat{Y}_{it}$ is the predicted probability of SDD for a patient in period $t$ given the estimated relationship:

$$Y_{i,2006} = \alpha + \boldsymbol{X'_{i,2006}\theta} + \varepsilon_i \tag{5.9}$$

which we estimate as a linear probability model. This process is conducted separately for each condition. This approach assumes the relationship between patient characteristics and outcome is constant over time. Any deviations in adjusted predicted outcome between the intervention group and the control group can therefore be interpreted as improvements in the probability of SDD. Note that, as long as the same case-mix model is used for all periods, the choice of base year is arbitrary. Also, as our primary concern is changes over time, we do not include hospital fixed effects in predicting the proportion of SDD.

The pool of potential control units includes all non-incentivised conditions meeting the criteria of similar RR, admission pathway and minimum number of observations set out in Section 5.4.2. We specify the SC algorithm to maximise similarity of the intervention and SC groups in terms of outcomes and average pre-policy patient characteristics. We then test if this is a reasonable control group from which to draw inferences by graphical assessment of how well the pre-policy outcomes of the intervention group are predicted by the control group, but also by constructing explicit tests. First, as recommended by Abadie et al. (2010), we assess goodness of fit in the pre-policy period by calculating the root mean square error (RMSE) of the predictions of the SDD rates of the control group compared to the intervention group for each pre-policy month. We reject the control group if the average RMSE exceeds 20% of the pre-policy SDD rate; similar to the ±10% rule used for the selection of DID groups based on pre-trend. Second, good control groups should not consistently over- or under-predict the outcomes of the intervention group in the pre-policy period. We therefore construct a test statistic based on the number of times the monthly trend lines cross in the pre-policy period and reject control groups that cross less than 20% of the time. While these cut-offs are somewhat arbitrary, this procedure in effect operationalises the graphical analysis of the goodness of pre-treatment trajectories of the SC outcome.

The effect of the SDD BPT in year $k$ is now given by:

$$\tau_k = \frac{1}{12} \sum_{t=t^{BPT}+12(k-1)}^{t^{BPT}+12k} E[\widehat{Y}_t^1 - \widehat{Y}_t^0] \tag{5.10}$$

The average ATT over the post-policy period is computed as outlined in Section 5.4.1.

As an SC model has a single treatment unit for each point in time, it is not appropriate to construct traditional standard errors. We therefore adopt the approach of placebo tests originally proposed by Abadie et al. (2010). We estimate a set of SC models, as described above, but treating each potential control unit as if it was the treated unit in turn and including the original treatment unit as a control condition. From this process we acquire as many placebo tests as there are potential control units. The original model is also included We then apply the tests described above and drop any placebo results that do not meet the criteria.

For each iteration, we calculate the RMSE in the pre- and post-intervention periods. P-values are constructed as the proportion of RMSE ratios that are at least as large as that of the original model for the incentivised condition[14]. We convert these placebo p-values to standard errors through a normal approximation. The quality of this inference framework relies on the number of potential control conditions; for example, with only 19 potential controls, the smallest p-value that could be calculated is $1/(1 + 19) = 0.05$. Note that no standard errors can be computed if $p = 1$.

All computations are performed using the user-written `synth` command in Stata 14.

## 5.5 Results

We conduct ITS analysis for all 32 incentivised conditions. DID and SC analyses are conducted for 18 of these conditions for which appropriate control groups are identified: 13 conditions are analysed using both DID and SC, 3 using just DID and 2 using just SC. We, therefore, discuss the ITS results and compare them with those supported by DID or SC analyses, where applicable. Time-series graphs of the proportion of patients being admitted and discharged on the same day with superimposed trend lines are presented in Appendix E.

[14]Because the main estimate is also compared against itself, the numerator of this ratio is always $\geq 1$ and the denominator is $V + 1$, where $V$ is the number of potential controls.

### 5.5.1 Average effect over the post-policy period

Our main focus is on the average effect of the SDD BPT policy, represented by the parameter estimate $\bar{\tau}$ (i.e. the ATT in the average year over the full post-policy period) for each of the 32 conditions. Figures 5.2 and 5.3 present the estimated effects with 95% confidence intervals for incentivised planned and emergency conditions, respectively.

The results for the *planned* conditions generally support a (weakly) positive effect for 11 of the 13 conditions, with a weakly negative effect for two conditions (#9-10). However, the ITS effect is statistically significant for only four out of the 13 conditions (#1-4). The largest effects are for #1 cholecystectomy and #3 sentinel node mapping (>10pp/year), but are smaller (<5pp/year) for #2 simple mastectomy and #4 female incontinence management. The results from applying the DID methods generally concur with ITS, with three exceptions that show positive and statistically significant effects (#5,7,13) under DID but not ITS (with >5pp/year for the latter two conditions). SC indicates ATT values which are generally similar to those of ITS and DID and indicates a positive and significnat effect for BPT #10. However, the strength of inference from SC analysis is limited by the relatively small number of control units, especially for BPT #1.

The results for the *emergency* conditions in Figure 5.3 are more mixed, but tend to be of smaller magnitude than for the planned conditions. Of the 19 emergency conditions, ITS analysis indicates a non-significant effect for 12 conditions, while four have a significantly positive effect (#18-19,21,31) and three have a significantly negative effect (#14,20,24). The size of the effect ranges from -6pp/year to +6pp/year. For the 8 (out of 19) conditions for which a DID control group can be identified, the results from DID analysis generally concur with ITS, though now #15 acute headache appears significantly positive, #23 deep vein thrombosis appears significantly negative and #14 epilepsy is non-significant. For the 3 (out of 19) conditions for which a SC analysis is conducted, the effect is always very close to zero, including for two conditions estimated to have a significantly positive effect (#21, 31) and one estimated to have a significantly negative effect (#14) when applying alternative methods. The low number of SC analyses that satisfy our quality criteria is due to the limited pool of potential controls.

Taken together, these results indicate that the SDD pricing policy had a positive effect on planned conditions with a positive statistically significant effect for 4/13 conditions under ITS and 4/10 under DiD. The results are rather mixed for emergency conditions, with positive effects for 4/19 under ITS and 1/6 under DID and negative effects for 3/19 under ITS and 2/6 under DiD. There is no general pattern to either the size of the mean effects or the relative widths of the confidence intervals when comparing the ITS and DID results. The SC results

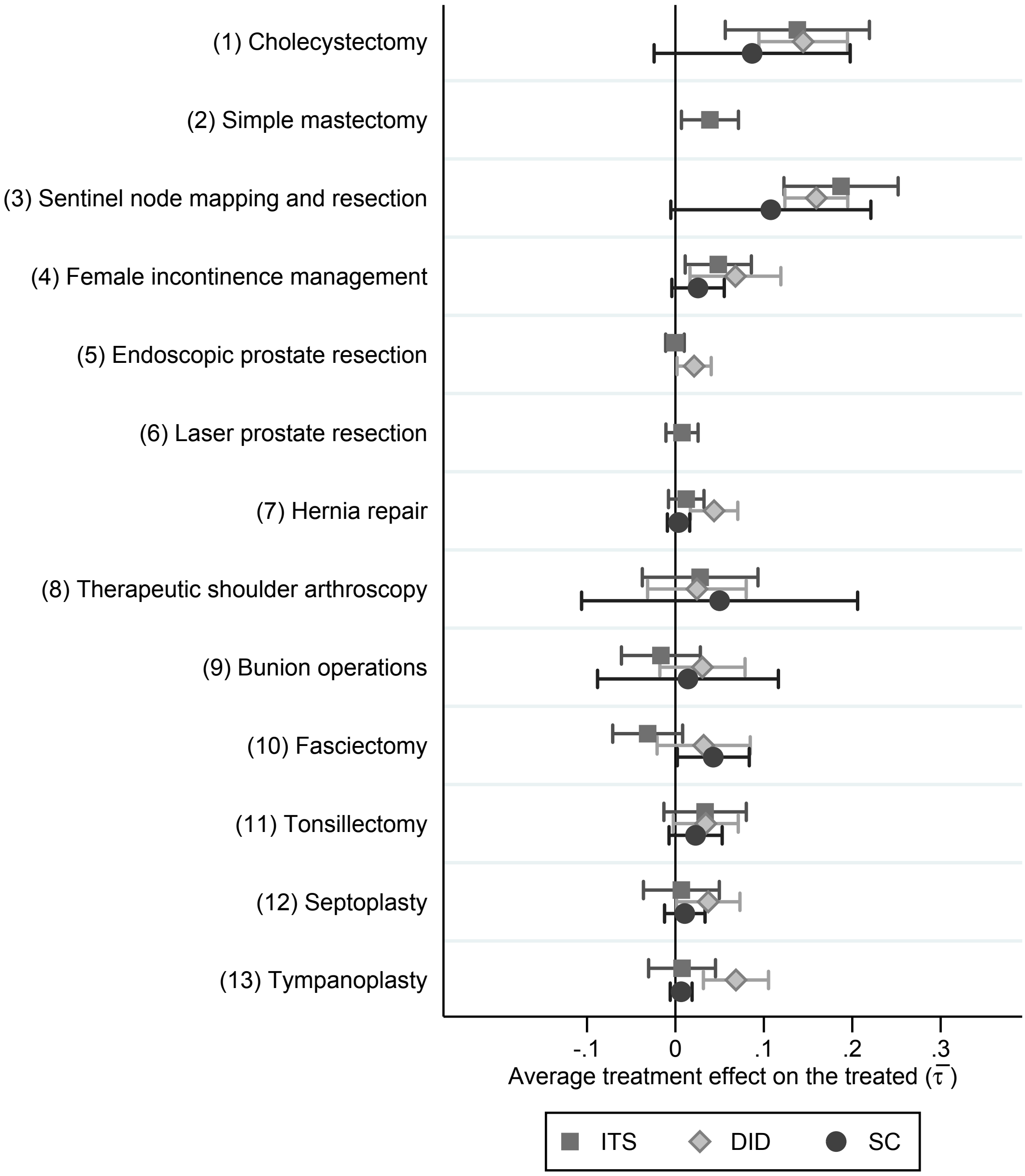



Figure 5.2: Average change in SDD rate over post-policy - planned conditions

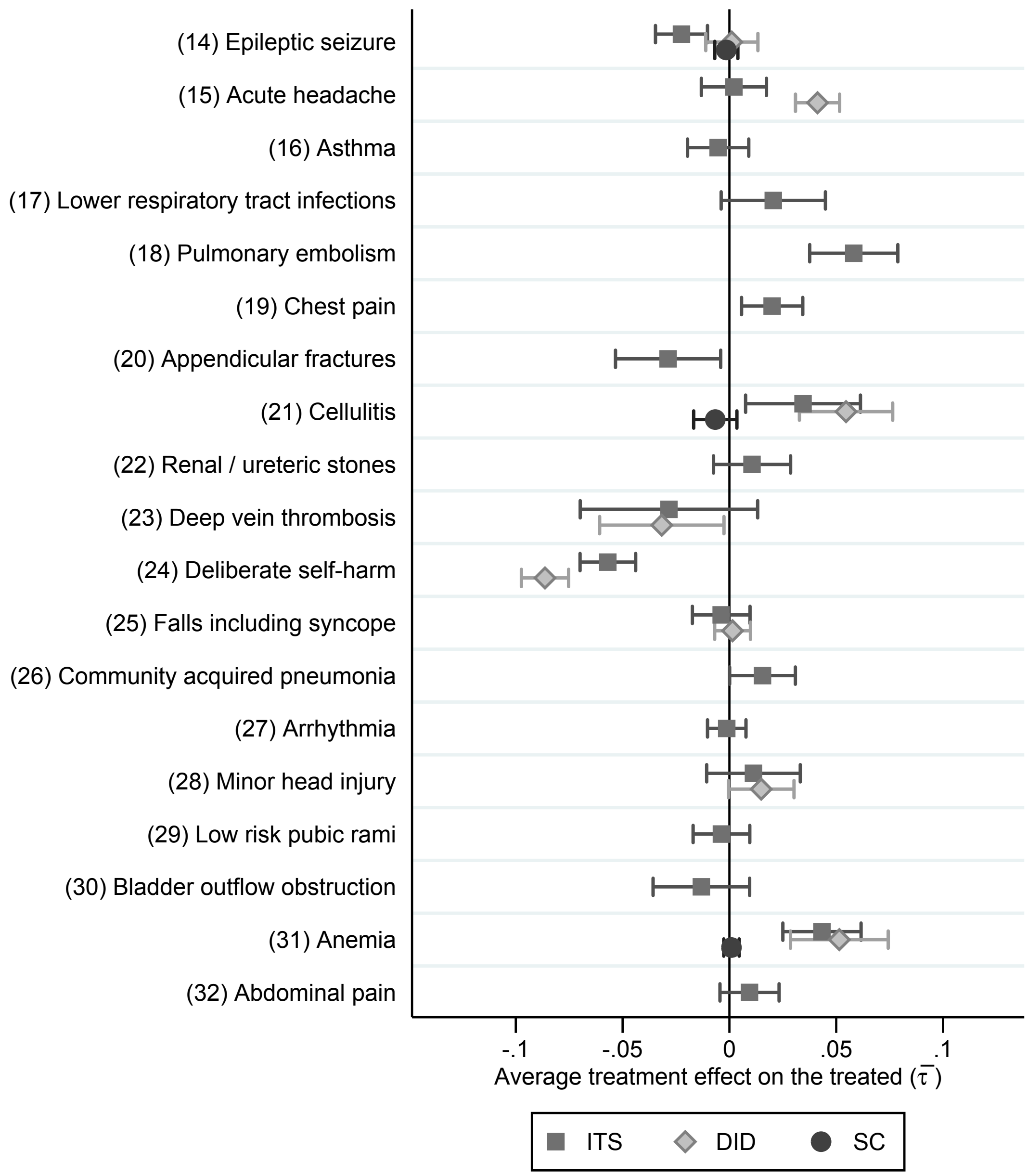



Figure 5.3: Average change in SDD rate over post-policy - emergency conditions

appear to be more pessimistic compared to the other two methods.

The significant ITS results translate into approximately 6,500 more patients admitted, treated and discharged on the same day in a year across all incentivised conditions[15]. As Figure 5.4 shows, these overall effects are driven by large positive effects for cholecystectomy (#1), sentinel node mapping (#3) and chest pain (#19), but these are offset by a large negative effect for self-harm (#24).

### 5.5.2 Time-varying effects

Our models allow for policy effects to vary over time and effects for each year after policy introduction are reported for each type of analysis in Tables 5.2-5.4. Focussing on the ITS results, as these are available for all 32 conditions, we find that 22 indicate at least one significant year effect. The patterns over time are non-linear and almost every possible combination of year-on-year effects is observed. We find conditions with initially positive and then strengthening effects (#1,3-4,18-19,21,31) or weakening effects (#7-8); and conditions with initially negative effects which grow more pronounced (#10,14,24) or less pronounced (#15-17,22-23,25,32). The results exhibit a similar variety of year-on-year patterns when we conduct DID (Table 5.3) or SC analysis (Table 5.4). The results suggest that there is no common behavioural response to the introduction of the SDD BPT over time.

### 5.5.3 Association with incentive design features

We now investigate if the response to policy is associated with features of the design of SDD incentives. The 32 conditions incentivised by the policy vary in the size of the price differential $P_1^{SDD} - P_1^{ON}$ relative to the base price $P_1^{ON}$. To compare the estimated ITS effect across conditions we, therefore, compute the elasticities of the proportion of SDD with respect to price as:

$$\epsilon = \frac{\bar{\tau}/\bar{Y}_{Pre}}{(P_1^{SDD} - P_1^{ON})/P_1^{ON}} \tag{5.11}$$

where $\bar{Y}_{Pre}$ is the observed outcome for the incentivised condition in the year before the announcement period. The median elasticity across the 13 planned and 19 emergency conditions is 0.24 and 0.01, respectively. Five conditions show an elasticity above 1.

Hospitals may respond more strongly for conditions offering relatively higher financial returns, keeping other factors constant. Figures 5.5a and 5.5b plot the elasticities as a function of the post-policy SDD price $P_1^{SDD}$ and as a function of the price difference $P_1^{SDD} - P_1^{ON}$.

[15]The additional patients treated as SDD across all incentivised conditions in a given year is $\sum_{c=1}^{32} \bar{\tau} N_c$ where $N_c$ is the number of patients within the scope of each incentivised condition $c$ in the average post-policy year. Where the estimate for $\bar{\tau}$ is insignificant, we assume the value of this parameter is zero. Where the estimated effect is significant, we use the point estimate.

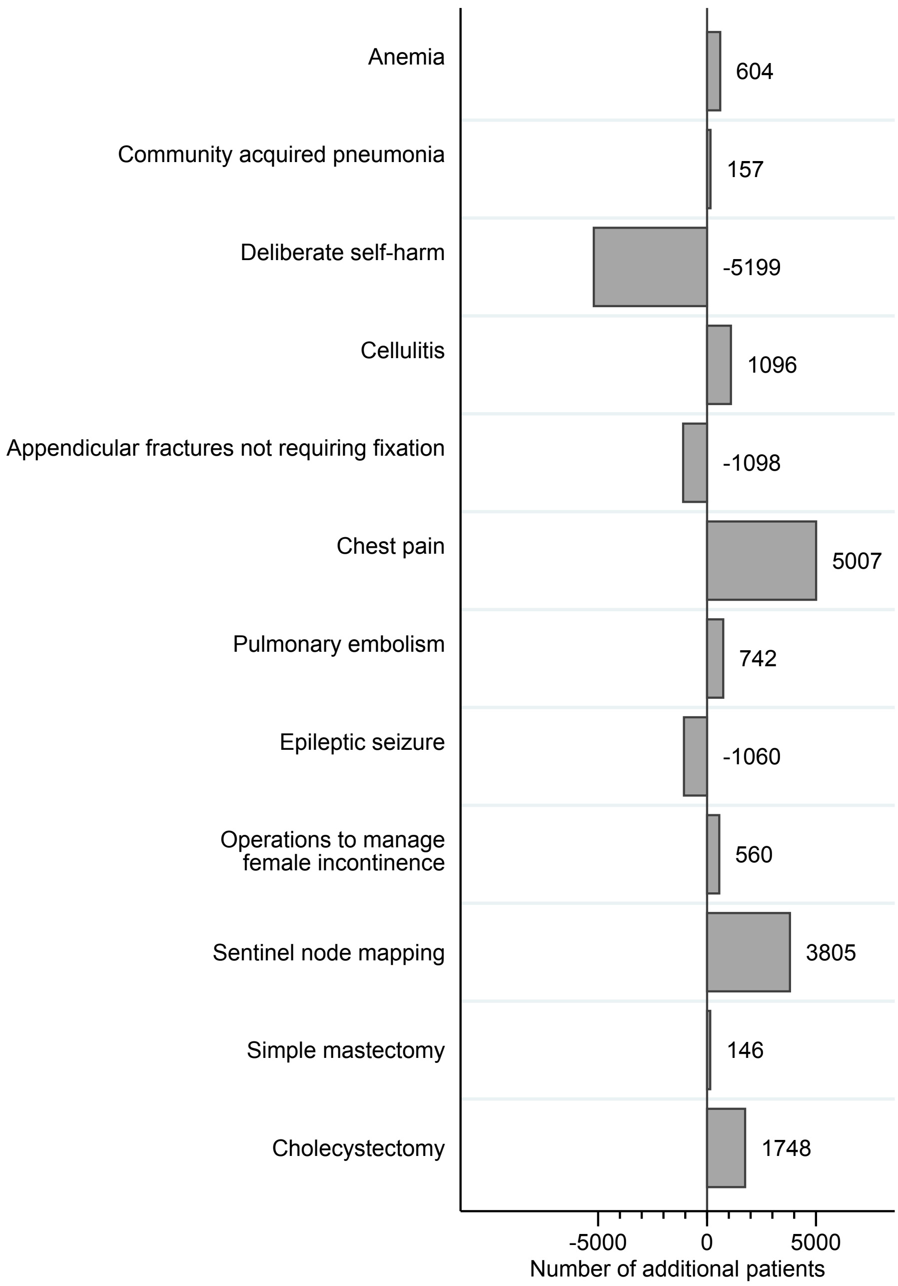



Figure 5.4: Additional SDD patients per year based on ITS estimates

Table 5.2: Average treatment effect on the treated - ITS analyses

| # | Condition | Average ($\bar{\tau}$) Est | SE | Year 1 ($\tau_{k=1}$) Est | SE | Year 2 ($\tau_{k=2}$) Est | SE | Year 3 ($\tau_{k=3}$) Est | SE | Year 4 ($\tau_{k=4}$) Est | SE | Year 5 ($\tau_{k=5}$) Est | SE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Cholecystectomy | 0.138 | 0.042*** | 0.088 | 0.022*** | 0.121 | 0.033*** | 0.137 | 0.043** | 0.161 | 0.054** | 0.179 | 0.066** |
| 2 | Simple mastectomy | 0.039 | 0.016* | 0.017 | 0.009* | 0.048 | 0.019* | 0.048 | 0.020* | 0.043 | 0.022 | | |
| 3 | Sentinel node mapping | 0.187 | 0.033*** | 0.108 | 0.023*** | 0.164 | 0.030*** | 0.222 | 0.037*** | 0.234 | 0.043*** | | |
| 4 | Operations to manage female incontinence | 0.048 | 0.019* | 0.031 | 0.015* | 0.059 | 0.020** | 0.053 | 0.022* | 0.054 | 0.027* | | |
| 5 | Endoscopic prostate resection | -0.001 | 0.005 | 0.006 | 0.005 | 0.005 | 0.006 | 0.009 | 0.006 | -0.025 | 0.008** | | |
| 6 | Laser prostate resection | 0.007 | 0.009 | 0.000 | 0.007 | 0.006 | 0.009 | 0.009 | 0.011 | 0.016 | 0.013 | | |
| 7 | Hernia repair | 0.012 | 0.010 | 0.023 | 0.007** | 0.029 | 0.009** | 0.000 | 0.013 | -0.003 | 0.014 | | |
| 8 | Shoulder decompression | 0.028 | 0.033 | 0.050 | 0.020* | 0.062 | 0.029* | 0.010 | 0.040 | -0.006 | 0.048 | | |
| 9 | Bunion operation | -0.016 | 0.023 | 0.000 | 0.014 | 0.009 | 0.023 | -0.035 | 0.028 | -0.042 | 0.032 | | |
| 10 | Fasciectomy | -0.031 | 0.020 | 0.009 | 0.015 | -0.002 | 0.018 | -0.051 | 0.024* | -0.086 | 0.029** | | |
| 11 | Tonsillectomy | 0.034 | 0.024 | 0.023 | 0.019 | 0.032 | 0.025 | 0.045 | 0.030 | | | | |
| 12 | Septoplasty | 0.007 | 0.022 | 0.012 | 0.017 | 0.019 | 0.023 | -0.011 | 0.028 | | | | |
| 13 | Tympanoplasty | 0.007 | 0.019 | 0.009 | 0.017 | 0.006 | 0.023 | | | | | | |
| 14 | Epilepsy | -0.022 | 0.006*** | -0.016 | 0.005** | -0.029 | 0.007*** | -0.022 | 0.008** | | | | |
| 15 | Acute headache | 0.002 | 0.008 | -0.016 | 0.006* | 0.000 | 0.009 | 0.021 | 0.010* | | | | |
| 16 | Asthma | -0.005 | 0.007 | -0.017 | 0.007* | -0.003 | 0.008 | 0.004 | 0.009 | | | | |
| 17 | Respiratory | 0.021 | 0.012 | -0.004 | 0.012 | 0.023 | 0.014 | 0.044 | 0.016** | | | | |
| 18 | Pulmonary embolism | 0.058 | 0.011*** | 0.025 | 0.009** | 0.056 | 0.011*** | 0.093 | 0.014*** | | | | |
| 19 | Chest pain | 0.020 | 0.007** | 0.001 | 0.006 | 0.016 | 0.008 | 0.044 | 0.010*** | | | | |
| 20 | Appendicular fractures | -0.029 | 0.013* | -0.028 | 0.011* | -0.032 | 0.014* | -0.026 | 0.014 | | | | |
| 21 | Cellulitis | 0.034 | 0.014* | 0.004 | 0.011 | 0.031 | 0.015* | 0.066 | 0.020*** | | | | |
| 22 | Renal/ureteric stones | 0.011 | 0.009 | -0.002 | 0.008 | 0.006 | 0.010 | 0.028 | 0.013* | | | | |
| 23 | Deep vein thrombosis | -0.028 | 0.021 | -0.064 | 0.017*** | -0.034 | 0.023 | 0.011 | 0.027 | | | | |
| 24 | Deliberate self-harm | -0.057 | 0.007*** | -0.047 | 0.005*** | -0.061 | 0.007*** | -0.063 | 0.009*** | | | | |
| 25 | Falls | -0.004 | 0.007 | -0.017 | 0.006** | -0.006 | 0.008 | 0.013 | 0.010 | | | | |
| 26 | Pneumonia | 0.015 | 0.008* | 0.006 | 0.008 | 0.024 | 0.009* | | | | | | |
| 27 | Fibrillation | -0.001 | 0.005 | -0.008 | 0.004 | 0.005 | 0.006 | | | | | | |
| 28 | Head injury | 0.011 | 0.011 | 0.006 | 0.011 | 0.017 | 0.013 | | | | | | |
| 29 | Pelvis fracture | -0.004 | 0.007 | -0.004 | 0.007 | -0.004 | 0.008 | | | | | | |
| 30 | Bladder outflow | -0.013 | 0.012 | -0.016 | 0.011 | -0.010 | 0.015 | | | | | | |
| 31 | Anaemia | 0.043 | 0.009*** | 0.022 | 0.009* | 0.064 | 0.011*** | | | | | | |
| 32 | Abdominal pain | 0.009 | 0.007 | -0.004 | 0.006 | 0.023 | 0.008** | | | | | | |

Notes: *** $p < 0.001$; ** $p<0.01$; * $p<0.05$
Standard errors (SEs) are clustered at hospital level.

Table 5.3: Average treatment effect on the treated - DID analyses

| | | Average ($\bar{\tau}$) | | Year 1 ($\tau_{k=1}$) | | Year 2 ($\tau_{k=2}$) | | Year 3 ($\tau_{k=3}$) | | Year 4 ($\tau_{k=4}$) | | Year 5 ($\tau_{k=5}$) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| # | Condition | Est | SE | Est | SE | Est | SE | Est | SE | Est | SE | Est | SE |
| 1 | Cholecystectomy | 0.145 | 0.026*** | 0.085 | 0.024*** | 0.120 | 0.028*** | 0.133 | 0.031*** | 0.177 | 0.028*** | 0.205 | 0.001 |
| 3 | Sentinel node mapping | 0.159 | 0.018*** | 0.084 | 0.019*** | 0.139 | 0.019*** | 0.196 | 0.020*** | 0.198 | 0.023*** | | |
| 4 | Operations to manage female incontinence | 0.068 | 0.026** | 0.038 | 0.024 | 0.072 | 0.027** | 0.094 | 0.030** | 0.071 | 0.031* | | |
| 5 | Endoscopic prostate resection | 0.021 | 0.010* | 0.021 | 0.010* | 0.014 | 0.012 | 0.023 | 0.011* | 0.027 | 0.012* | | |
| 7 | Hernia repair | 0.044 | 0.014** | 0.031 | 0.015* | 0.055 | 0.015*** | 0.033 | 0.019 | 0.056 | 0.019** | | |
| 8 | Shoulder decompression | 0.024 | 0.028 | -0.001 | 0.027 | 0.017 | 0.033 | 0.028 | 0.036 | 0.049 | 0.032 | | |
| 9 | Bunion operation | 0.031 | 0.025 | 0.001 | 0.024 | 0.018 | 0.029 | 0.038 | 0.031 | 0.070 | 0.029* | | |
| 10 | Fasciectomy | 0.032 | 0.027 | 0.025 | 0.026 | 0.022 | 0.031 | 0.038 | 0.033 | 0.044 | 0.031 | | |
| 11 | Tonsillectomy | 0.034 | 0.019 | 0.031 | 0.020 | 0.023 | 0.022 | 0.049 | 0.021* | | | | |
| 12 | Septoplasty | 0.037 | 0.018* | 0.006 | 0.018 | 0.048 | 0.021* | 0.056 | 0.021** | | | | |
| 13 | Tympanoplasty | 0.068 | 0.019*** | 0.054 | 0.020** | 0.084 | 0.022*** | | | | | | |
| 14 | Epilepsy | 0.001 | 0.006 | 0.009 | 0.009 | 0.002 | 0.008 | -0.008 | 0.009 | | | | |
| 15 | Acute headache | 0.041 | 0.005*** | -0.017 | 0.005** | 0.148 | 0.007*** | -0.010 | 0.006 | | | | |
| 21 | Cellulitis | 0.055 | 0.011*** | 0.027 | 0.012* | 0.060 | 0.014*** | 0.075 | 0.015*** | | | | |
| 23 | Deep vein thrombosis | -0.032 | 0.015* | -0.056 | 0.015*** | -0.041 | 0.017* | 0.000 | 0.018 | | | | |
| 24 | Deliberate self-harm | -0.086 | 0.006*** | -0.072 | 0.006*** | -0.088 | 0.006*** | -0.100 | 0.007*** | | | | |
| 25 | Falls | 0.001 | 0.004 | -0.009 | 0.005 | 0.006 | 0.005 | 0.008 | 0.005 | | | | |
| 28 | Head injury | 0.015 | 0.008 | 0.017 | 0.009* | 0.012 | 0.009 | | | | | | |
| 31 | Anaemia | 0.051 | 0.012*** | 0.040 | 0.012*** | 0.062 | 0.014*** | | | | | | |

Notes: *** p< 0.001; ** p<0.01; * p<0.05
Standard errors (SEs) are clustered at hospital level.

Table 5.4: Average treatment effect on the treated - SC analyses

| # | Condition | Average ($\bar{\tau}$) | | Year 1 ($\tau_{k=1}$) | | Year 2 ($\tau_{k=2}$) | | Year 3 ($\tau_{k=3}$) | | Year 4 ($\tau_{k=4}$) | | Year 5 ($\tau_{k=5}$) | | Number of placebo tests |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Est | SE | Est | SE | Est | SE | Est | SE | Est | SE | Est | SE | |
| 1 | Cholecystectomy | 0.087 | 0.057 | 0.077 | 0.050 | 0.107 | 0.070 | 0.135 | 0.088 | 0.173 | 0.113 | 0.190 | 0.124 | 16 |
| 3 | Sentinel node mapping | 0.108 | 0.058 | 0.091 | 0.051 | 0.144 | 0.077 | 0.203 | 0.109 | 0.194 | 0.109 | | | 65 |
| 4 | Operations to manage female incontinence | 0.026 | 0.015 | 0.020 | 0.018 | 0.065 | 0.035 | 0.070 | 0.039 | 0.084 | 0.047 | | | 66 |
| 7 | Hernia repair | 0.004 | 0.006 | 0.003 | 0.023 | 0.008 | 0.008 | 0.007 | 0.015 | 0.012 | 0.018 | | | 84 |
| 8 | Shoulder decompression | 0.050 | 0.080 | 0.058 | 0.069 | 0.085 | 0.075 | 0.058 | 0.123 | 0.066 | 0.146 | | | 66 |
| 9 | Bunion operation | 0.014 | 0.052 | 0.027 | 0.080 | 0.052 | 0.052 | 0.016 | 0.081 | 0.020 | 0.222 | | | 84 |
| 10 | Fasciectomy | 0.043 | 0.021* | 0.078 | 0.031* | 0.114 | 0.046* | 0.107 | 0.058 | 0.110 | 0.059 | | | 77 |
| 11 | Tonsillectomy | 0.023 | 0.015 | 0.054 | 0.036 | 0.059 | 0.055 | 0.078 | 0.048 | | | | | 66 |
| 12 | Septoplasty | 0.011 | 0.012 | 0.028 | 0.023 | 0.036 | 0.035 | 0.027 | 0.055 | | | | | 66 |
| 13 | Tympanoplasty | 0.006 | 0.006 | 0.028 | 0.030 | 0.040 | 0.036 | | | | | | | 66 |
| 14 | Epilepsy | -0.001 | 0.003 | 0.005 | 0.006 | -0.003 | 0.005 | -0.014 | 0.011 | | | | | 5 |
| 21 | Cellulitis | -0.007 | 0.005 | -0.029 | 0.023 | -0.032 | 0.025 | 0.003 | 0.004 | | | | | 5 |
| 31 | Anaemia | 0.001 | 0.002 | -0.008 | † | 0.015 | 0.017 | | | | | | | 5 |

Notes: *** p< 0.001; ** p<0.01; * p<0.05
Standard errors (SEs) are obtained through p-value inversion, where p-values are calculated using the placebo test proposed by Abadie et al. (2010).
† All placebo tests generate $|\bar{\tau}^{Placebo}| > |\bar{tau}|$ so that no SE can be calculated.

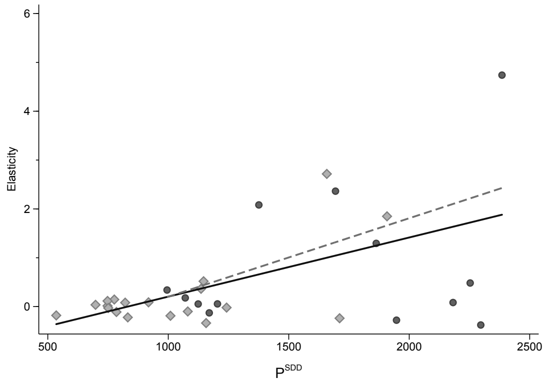
Figure 5.5c shows the association between the policy response and the total incentive, capturing both price and cost differences between SDD and ON, the latter being approximated by information on average costs in the year prior to the policy introduction. There is suggestive evidence that larger elasticities are concentrated in conditions with higher SDD prices and larger price differences. Moreover, elasticities appear to increase in the size of the total incentive $\Delta(P - AC) = (P_1^{SDD} - AC_0^{SDD}) - (P_1^{ON} - AC_0^{ON})$ and this association is more pronounced across planned SDD conditions.

We also explore whether responses appear to be driven by clinical reasons. We hypothesise that responses to the BPT are more pronounced if SDD pre-policy rates are lower and the gap to the RR is higher, therefore giving more scope for improvement. Figure 5.5d provides some support that larger elasticities occur for conditions with lower pre-policy SDD rates, but Figure 5.5e does not suggest a relationship between the elasticities and the gap between existing practice (i.e. pre-policy SDD rate) and the RR.

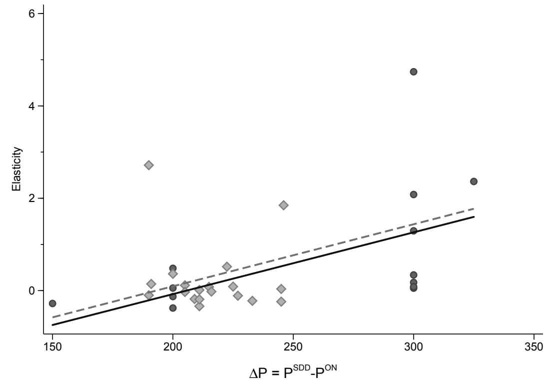
## 5.6 Conclusions

We have assessed the long-term impact of a generous pricing policy designed to encourage hospitals to treat patients as a 'same day discharge', involving admission, treatment and discharge on the same calendar day. Despite being considered clinically appropriate and having lower costs, English policy makers have been frustrated by the low rates of SDD for many conditions. Consequently, in order to encourage behavioural change by doctors and hospitals, policy makers have set prices for SDD that are well above costs and are also higher than the price for otherwise identical hospital care that involves an overnight stay. This P4E policy is, therefore, unusual both in having different objectives to most P4P schemes and also in offering high-powered incentives.

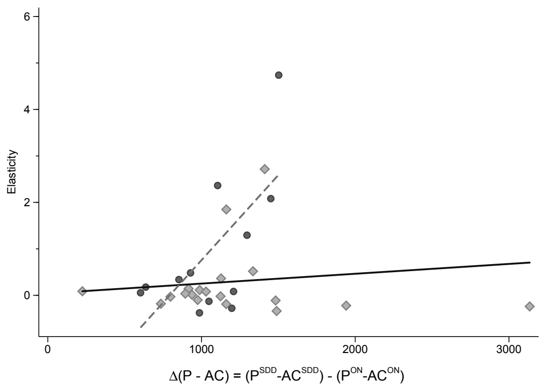
Economic theory predicts that a significant price differential would result in greater provision of treatment on an SDD basis. An early study into the policy impact for one condition, cholecystectomy, suggested that the SDD pricing policy met short-term policy objectives (Allen et al., 2016). This supported the roll-out of the policy to 31 more conditions. Our study set out to assess how far the original findings are generalisable and would also be observed for these other conditions, whether short-term impacts would hold over the longer-term and what design features of the policy might explain the magnitude of any response. Evaluating across all 32 conditions, we do find a positive response, translating into approximately 6,500 more patients treated on an SDD basis per year. However, perhaps surprisingly, we do not find a consistent positive response across all incentivised conditions. Indeed, for some conditions the response is negative: despite the enhanced price advantage, fewer SDD



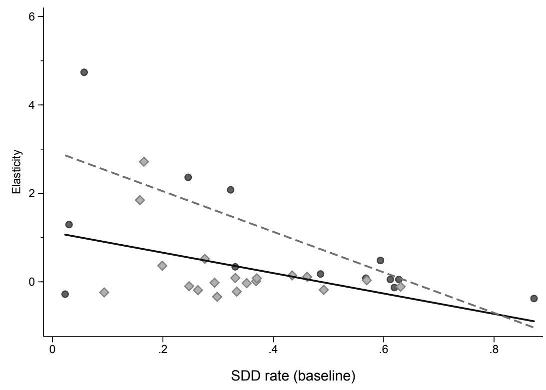

(a) SDD price



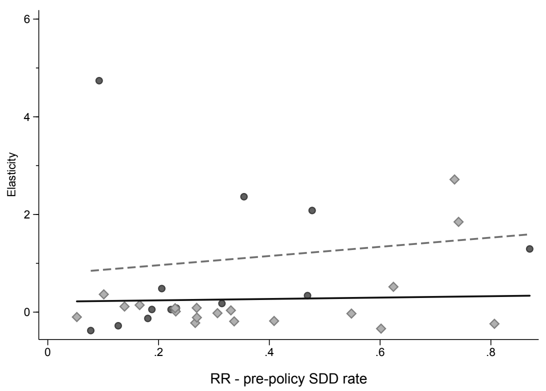

(b) % price difference SDD vs. ON




(c) Cost and price incentive




(d) Baseline SDD rate




(e) Gap between RR and baseline SDD rate

*Notes: Solid line shows fitted relationship for all incentivised conditions. Dashed line shows relationship for planned conditions only.*

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Figure 5.5: Association between price elasticity of SDD care and tariff design factors

treatments are provided post-policy than predicted. For others there is no apparent response. Nor are we able to identify any general temporal pattern in the policy response, with both rapid and delayed uptake of SDD practices being observed. These mixed results mirror those of the literature on P4P, which provides inconclusive evidence for the effectiveness of using financial incentives to drive quality (Milstein and Schreyögg, 2016).

This lack of generalisability cautions against drawing firm conclusions from a single analysis. Indeed, cholecystectomy turns out to be the condition exhibiting the greatest positive response among the 32 conditions. Moreover, while Milstein and Schreyögg (2016) suggested that P4P arrangements are most appropriate for emergency care, where hospitals have less opportunity to select patients, we find that the SDD pricing policy was more effective for planned care (median elasticity = 0.24) than emergency care (median = 0.01). This may be because clinicians may have ethical concerns about discharging patients in urgent need of care without a period of observation, whereas such concerns are less prominent when care is scheduled in advance. Also, emergency admissions occur at unpredictable points in the day, making it difficult to achieve SDD for some patients such as those admitted late in the evening. This may limit the scope for rapid increases in SDD rates in emergency conditions compared to planned conditions that permit efficient scheduling.

It has been argued that the limited impact of P4P schemes is due to incentives being too small and the incentivised behaviour lacking clinical buy-in. In this study, for all conditions, the price incentive was more high-powered than that typically associated with P4P schemes. But there was significant variation across the conditions in terms of the relative size of the incentive, and we exploit this to investigate the association of incentive size and the estimated clinical response across 32 conditions; in effect evaluating 32 separate experiments. There is suggestive evidence that the response to the incentive was greater for conditions with higher SDD prices post policy and with lower SDD rates pre policy. There does not appear to be an association between the size of the price differential, i.e. the marginal reimbursement that hospitals attract from adopting SDD care, and the size of the response but there is a positive association, especially for planned conditions, when both price and cost advantages of SDD care are taken into consideration.

In conclusion, we find some evidence that hospitals respond to price signals and that payers, therefore, can use pricing instruments to improve supply-side efficiency. However, there appears to be substantial variation in hospitals' reactions even among similar types of financial incentives that is not explained by the size of the financial incentive or the clinical setting in which it is applied. It has been said that a randomised control trial demonstrates only that something works for one group of patients in one particular context but may not be generalisable (Rothwell, 2005). Similarly, a pricing policy that appears to work as intended in one area may not be effective when applied elsewhere, hence the need for continued experimentation and evaluation.

# Chapter 6

# Conclusions

This thesis considers two areas of hospital care where an improvement in efficiency might be achieved. The first is the interface between hospital and long-term care (LTC). An externality problem can arise between these sectors because they treat the same patients but are managed and financed separately. The second area relates to the provision of same-day discharge (SDD) within hospitals instead of overnight care. When SDD is clinically appropriate, it provides similar health outcomes to patients at a lower cost to providers. A range of administrative data sources are used at the patient, hospital and local government levels in a series of empirical analyses. The evidence presented sheds light on the impact of relationships between sectors structures and incentives created by policy interventions to assist policy makers.

Chapters 2-4 investigate the interface between hospital and LTC. Chapter 2 evaluates the impact of LTC supply on the discharge destination and length of stay (LOS) of patients admitted with hip fracture or stroke. Results indicate hip fracture patients discharged to a care home have shorter hospital stays by up to 30% when local care home bed supply is relatively high. In contrast, the LOS of stroke patients and discharge destination are unaffected by care home bed supply. Chapter 3 models delayed discharges in different local government areas (Local Authorities, LAs in England). It is found that 10% higher local care home beds supply is associated with 6-9% fewer delayed discharges. Further, more people aged 65+ and fewer care home beds in other LAs are associated with more delayed discharges in the local LA. Chapter 4 investigates the relationship between hospital type and delayed discharges. In common with Chapter 3, results suggest an inverse relationship between care home bed supply and delayed discharges. Of hospital types, Foundation Trusts (FTs) incur fewer delays than Trusts without this status by 14-28%. More delays occur in Mental Health Trusts than Acute Trust, but delays attributed to the NHS are similar for Acute and Mental Health Trusts.

The evidence provided in Chapters 2-4 of this thesis has several policy implications. All three chapters indicate that patients have shorter hospital stays if living in an area where care home bed supply is relatively high. Further, Chapters 3 and 4 indicate hospital stays are shorter because there are fewer delayed discharges. This finding has three main implications.

First, an expansion of care home beds would reduce hospital LOS. This benefits patients through a direct preference for shorter stays and a reduced risk of negative outcomes from prolonged stays, such as hospital acquired infection. Second, expanding LTC supply is efficient. Patients who might be cared for in hospital or LTC can be cared for at lower cost in a LTC setting and receive similar health benefits. Delayed discharges occur once a hospital patient is ready to be discharged from hospital. Therefore, delays represent the use of a more costly form of care than is necessary. Third, the finding lends support to closer integration of the hospital and LTC sectors. These sectors are managed independently, respectively by Hospital Trusts and LAs. Where delayed discharges are due to insufficient supply of LTC, additional costs fall on the hospital sector due to conditions in the LTC sector. This is an externality problem. Closer integration of the sectors would incentivise an optimal level of LTC supply for providing hospital as well as LTC. In addition, the incentive to optimise LTC supply would persist over time. Integration could take many forms, including managing budgets jointly or giving responsibility for health and LTC to a single sector.

Two findings suggest expanding LTC for specific patient groups might be most beneficial. First, Chapter 2 indicates supply of care home beds effects the LOS of hip fracture but not stroke patients. This finding supports expansion of LTC in areas with low supply relative to the number of hip fracture patients. Similarly, Chapter 4 suggests unmet need for LTC is higher among patients with mental health conditions. Delayed discharges are more frequent from Mental Health Hospitals than Acute Hospitals, while the delays attributed to the NHS are similar. This finding supports expanding LTC with a mental health focus or where LTC supply is low relative to the rate of mental health conditions.

A further implication from Chapter 3 is that a national approach to an expansion of LTC may be most effective. Evidence of spillovers between LAs is found in Chapter 3. This suggests externalities could arise between authorities, as the supply of LTC in one area effects delays in another area. Applying a national policy based on needs which may cross LA boundaries would avoid this problem.

Finally, findings from Chapter 4 indicate FTs are good exemplars of minimising delayed discharges. An advantage of using FTs as exemplars is that it is a status available to all types of hospital. Further, investigations would be needed to understand the reasons behind the lower delayed discharge rates in FTs.

These analyses indicate implications for patients of LTC supply. The appropriateness of any policy to change LTC supply also depends on the costs of implementing such change.

Costs include investment costs of increasing capacity and repeated costs such as paying for additional staff. These costs might predominantly be paid by specific parts of the public sector, for example by increasing the supply of care homes run by the acute sector. Alternatively, incentives might be introduced for the private sector to expand supply where needed through reduced tax liabilities. Policy decisions therefore depend on the magnitude of costs compared to benefits and which sectors bear the costs.

The main limitation of Chapters 3 and 4 is that these analyses are performed at an aggregated (LA and Trust) level. Chapter 2 is an analysis at the patient level. However, as only LOS is observed, it is unknown if longer hospital stays necessarily represent delayed discharges. An analysis of delayed discharges at the patient level would overcome both of these limitations and provide additional insights. First, it would identify the impact of care home bed supply on delayed discharges after accounting for patient characteristics which might also drive delays. Finding an independent effect of care home bed supply on delays would improve the evidence base for an expansion in care home bed supply and integration of the acute and LTC sectors. Second, such an analysis could identify which patient characteristics lead to a greater propensity to be delayed. A better understanding of these characteristics could be used to identify where any expansion in LTC might be most beneficial to patients.

As noted above, a limitation of Chapter 2 is that LOS instead of delayed discharges are observed. Hospitals face pressure to admit patients promptly, in response to high demand for emergency admissions or to reduce waiting times for elective care. It is therefore possible that hospitals in areas with higher supply of LTC may discharge patients more quickly than is optimal. Past research has considered a similar potential effect from reimbursing hospitals at the same level for treating patients in shorter time periods, sometimes referred to as 'quicker and sicker'. This possibility could be evaluated by modelling the rate of emergency readmissions or death within 30 days on the supply of care home beds and hospital LOS. A finding that patients with shorter LOS are not readmitted more frequently, would lend support to the hypothesis that increase in LOS represent delayed discharges.

A further limitation of Chapters 2-4 is that they provide a partial picture of a broader patient pathway. That is, only hospital inpatients are considered and other patient groups might also benefit from an increase in care home bed supply. For example, an additional benefit of expanding LTC supply might be to admit patients to hospital more promptly. In the same way that some patients are unable to leave hospital if no care home bed is available, admission of other patients is likely to be delayed by no hospital inpatient bed being available.

Delayed admissions might be evaluated by modelling the impact of LTC on the time spent by patients in Accident and Emergency (A&E) departments. A finding that A&E waits are longer in areas with lower LTC supply would suggest bed-blocking is present and increasing

LTC supply would reduce A&E waits. Further, the complexity of admitted patients and cost of care might be affected by delayed admissions, as delays can lead to clinical complications. A finding that admitted patients in areas with lower LTC supply have more comorbidities or are more costly to treat would lend support to this hypothesis and support expanding LTC supply.

Chapter 5 of this thesis evaluates a policy aiming to increase the SDD rate from hospital where clinically appropriate. The findings indicate the policy has been generally positive for planned conditions, leading to an increase in SDD rates following introduction. Results for emergency conditions are mixed, with some significantly positive and negative effects. The magnitude of any response to the policy varies substantially across conditions. There is suggestive evidence that responses are larger for planned conditions when the combined cost saving and revenue increase of SDD is larger.

The findings in Chapter 5 have three main policy implications. First, the impact of the policy, especially for planned conditions, has been broadly positive. A significant increase in SDD rates is observed for eight conditions compared to three negative effects. Further, all negative effects have been limited to emergency conditions. These findings lend support to continuing the policy as it can be effective in meeting its primary objective.

Second, the finding that responses vary substantially between conditions suggests the policy could be refined to increase the benefits generated. A simple approach would be to maintain the policy for conditions where a positive effect is observed and discontinuing it where a negative effect is observed. However, it is not guaranteed that a successful policy in a given year would continue to lead to faster SDD growth in subsequent years, as highlighted by variation in policy effects over time found in Chapter 5. For example, hospitals might reach a ceiling about what is clinically possible.

Third, there is suggestive evidence of stronger responses for planned conditions with larger combined reduced cost and increased revenue from switching to SDD care. This finding suggests introducing a similar policy for planned conditions with large cost differentials in shifting from overnight to SDD might be most effective and be achieved with relatively small differentials of reimbursement. However, the observed wide heterogeneity in policy responses implies caution is needed in any expansion.

One limitation of Chapter 5 is the potential to investigate drivers of heterogeneity in hospital response to the financial incentives introduced. While the same incentive is offered to all hospitals treating each condition, their response might vary due to (i) different costs of treating patients as an SDD or overnight stay (ii) the influence of senior clinicians in adapting SDD treatments. Further, hospital characteristics may affect the strength or speed of response to the policy, for example access to specific day-case facilities. These characteristics can be investigated by determining the size of response for each condition and hospital combination, then modelling the response on hospital characteristics.

The introduction of BPT policies could also be used as a natural experiment for the impact of incentives on technology adoption. Switching from treating patients with an overnight stay to SDD might be considered a change in the production of healthcare. Achieving a higher SDD rate is likely to require the adoption of specific clinical approaches, such as the maximum use of minimally invasive surgery and employing day case units. Therefore, changes in rates could be used as a signal of adoption. As the SDD rate of individual senior doctors can be observed in HES data, peer effect models could be used to investigate patterns of dissemination. These are similar in structure to spatial econometric models but are generally applied to individuals instead of geographic areas.

# Appendix A

# Data Appendix for Chapter 2

A patient is admitted from home if their admission code is “usual place of residence, including no fixed abode” or “temporary place of residence when usually resident elsewhere, for example, hotels and residential educational establishments” (admisorc = 19, 29). Care homes are not considered usual residence and are therefore excluded (see more below). Each HES record covers a single finished consultant episode (FCE) during which the patient is continuously under the care of a single consultant (senior hospital doctor).

We link FCEs into continuous inpatient stays (CIPS) to allow for changes of consultant, including transfers to other hospitals.We combine FCEs into CIPS using the methodology in Castelli et al. (2008) and Cookson and Laudicella (2011). We include patients whose CIPS finish in the financial year 1 April 2008–31 March 2009 and start between 1 April 2007 and 31 March 2009.

Patients are coded as being discharged to their home if their HES discharge destination field indicates usual or temporary residence (disdest 19, 29), to a long-term care facility if their destination is an NHS-run nursing home, a residential home or group home (disdest 54), a local authority care home (disdest 69) or non-NHS (other than local authority) residential care home (disdest 85).

Hip fracture patients have a primary diagnosis ICD10 code of S72.0 (fracture of neck of femur or unspecified femur fracture), S72.1 (pertrochanteric fracture) or S72.2 (subtrochanteric fracture) (Jarman et al., 2004). Stroke patients have primary ICD10 code I60-2 (intracerebral haemorrhage), I63 (cerebral infarction), I64 (unspecified stroke), I66 or I67.2, I69.8 or R47.0 (other form of stroke).

There are 33,082 hip fracture and 59,316 stroke emergency admissions in our study period. We exclude 11,113 hip fracture and 26,211 stroke patients from the analysis because: the patient dies in-hospital (4,253 for hip fracture and 15,501 for stroke), the hospital spell is incomplete (2,080 for hip fracture and 2,518 for stroke), the patient is discharged elsewhere than to usual residence or care home (1,595 for hip fracture and 3,211 for stroke), is admitted from elsewhere than usual residence where "usual residence" excludes a care home (1,910 for hip fracture and 2,437 for stroke), has a repeat emergency admission (376 for hip fracture and 1,194 for stroke), is treated in a hospital with 10 or fewer cases in 2008/2009 (46 for hip fracture and 60 for stroke).We exclude cases with very long length of stay, and the logarithm of the length of stay is more than three standard deviations above the mean (205 for hip fracture), and cases with missing data (658 for hip fracture and 1294 for stroke).

HES records the patient's Lower Super Output Area (LSOA) of residence. There are 32,482 LSOAs in England with an average population of 1,500 in 2001. We compute the number of beds in care homes within 10km of the centroid of the patient's LSOA of residence. For each provider, we have the minimum and maximum price by type of room (single, shared) and type of care (nursing, non-nursing).We compute the average price for care homes within 10km of each LSOA centroid. 1,682 care homes (14%) do not report any price and we impute the price of these from the average price for providers in the same quintile of beds supply. We measure the average quality of care homes within 10km by assigning numerical values 1–4 to the CQC quality ratings (poor, adequate, good, and excellent). We use the same strategy as for missing price data to impute quality rating for 1,953 providers without information (16.5%).

Appendix B

# Chapter 3 Appendices

Table B.1: Delayed discharges (all)

| | Patients Delayed | | | | Days of Delay | | | |
|---|---|---|---|---|---|---|---|---|
| | RE | | SLX | | RE | | SLX | |
| | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.436*** | 0.001 | -0.357** | 0.013 | -0.396*** | 0.006 | -0.321** | 0.044 |
| Care-homes price | 0.149 | 0.504 | 0.017 | 0.951 | 0.094 | 0.688 | -0.010 | 0.972 |
| Pop 65+ | 1.498*** | 0.000 | 1.401*** | 0.000 | 1.496*** | 0.000 | 1.395*** | 0.000 |
| 2010 | -0.038 | 0.167 | -0.078** | 0.014 | -0.107*** | 0.000 | -0.156*** | 0.000 |
| 2011 | -0.099** | 0.031 | -0.100** | 0.043 | -0.088* | 0.059 | -0.095* | 0.054 |
| 2012 | -0.161*** | 0.002 | -0.108 | 0.105 | -0.093* | 0.071 | -0.044 | 0.500 |
| 2013 | -0.184*** | 0.002 | -0.194** | 0.010 | -0.103* | 0.082 | -0.129* | 0.089 |
| Beds spatial lag | | | -1.724*** | 0.004 | | | -1.956*** | 0.003 |
| Pop 65+ spatial lag | | | 2.768*** | 0.003 | | | 3.254*** | 0.002 |
| Constant | -10.68*** | 0.000 | -26.15*** | 0.000 | -7.364*** | 0.000 | -26.39*** | 0.000 |
| $R^2$ | 0.662 | | 0.675 | | 0.653 | | 0.670 | |
| Mundlak Test | 4.360 | 0.225 | 3.118 | 0.682 | 7.393 | 0.060 | 7.057 | 0.216 |
| Hausman Test | 5.509 | 0.598 | 3.877 | 0.919 | 8.954 | 0.256 | 7.794 | 0.555 |

Notes: Dependent variable and continuous explanatories are in logs. All models are estimated with random effects and cluster robust standard errors.
Spatial models: SLX (Spatially Lagged Xs). Observations: 735 = 5x147. *p<0.1, **p<0.05, ***p<0.01.

Table B.2: Patients delayed and days of delay (all). IV and augmented models

| | IV models | | | | Augmented models | | | |
|---|---|---|---|---|---|---|---|---|
| | Patients delayed | | Days of delay | | Patients delayed | | Days of delay | |
| | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.499** | 0.010 | -0.421** | 0.032 | -0.419*** | 0.006 | -0.386** | 0.022 |
| Care-homes price | -0.022 | 0.947 | 0.063 | 0.865 | 0.334 | 0.289 | 0.328 | 0.332 |
| Pop 65+ | 1.549*** | 0.000 | 1.496*** | 0.000 | 1.031*** | 0.001 | 1.074*** | 0.003 |
| 2010 | -0.0783* | 0.068 | -0.160*** | 0.000 | -0.094*** | 0.002 | -0.173*** | 0.000 |
| 2011 | -0.098* | 0.061 | -0.104* | 0.057 | -0.101* | 0.088 | -0.010 | 0.104 |
| 2012 | -0.104 | 0.155 | -0.057 | 0.465 | -0.108 | 0.200 | -0.048 | 0.579 |
| 2013 | -0.191** | 0.019 | -0.147* | 0.093 | -0.194* | 0.056 | -0.137 | 0.197 |
| SD Care-homes price | | | | | 0.036 | 0.533 | 0.034 | 0.630 |
| % care-homes rated excellent | | | | | -0.002 | 0.534 | -0.003 | 0.448 |
| % 65+ on income benefit | | | | | 0.192 | 0.113 | 0.302** | 0.015 |
| Price*(% 65+ on income benefit) | | | | | -0.028 | 0.146 | -0.045** | 0.020 |
| Deaths in pop 65+ | | | | | 0.506 | 0.177 | 0.458 | 0.257 |
| Beds spatial lag | -1.654** | 0.018 | -1.863** | 0.010 | -1.650*** | 0.005 | -1.889*** | 0.003 |
| Pop 65+ spatial lag | 2.748** | 0.010 | 3.258*** | 0.003 | 2.867*** | 0.001 | 3.331*** | 0.000 |
| Constant | -26.74*** | 0.000 | -27.90*** | 0.000 | -33.32*** | 0.000 | -35.78*** | 0.000 |
| $R^2$ | 0.675 | | 0.671 | | 0.710 | | 0.705 | |
| F Test (Beds) | 107.5 | 0.000 | 98.68 | 0.000 | | | | |
| F Test (Price) | 135.6 | 0.000 | 123.6 | 0.000 | | | | |
| F Test (Beds spatial lag) | 1438 | 0.000 | 1311 | 0.000 | | | | |
| Hausman Test | 2.429 | 0.983 | 4.927 | 0.841 | | | | |
| Mundlak Test | | | | | 9.856 | 0.275 | 14.73 | 0.065 |

Notes: Dependent variable and continuous explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. .F tests are for the joint significance of the instruments in each first stage model. The instruments are one year lag of care-homes beds, one year lag of care-homes price, and one year spatially lagged care-homes beds. % 65+ on income benefit is the proportion of the population aged 65 and over who are receiving income support in 2010.Observations: 735 = 5x147. *p<0.1, **p<0.05, ***p<0.01.

Table B.3: Delayed discharges (social care). Alternative spatial models

| | Patients Delayed | | | | | | Days of Delay | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SDEM | | SAR | | SDM | | SDEM | | SAR | | SDM | |
| | coef | p | coef | p | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.581*** | 0.007 | -0.645*** | 0.001 | -0.567*** | 0.009 | -0.784*** | 0.006 | -0.875*** | 0.001 | -0.770*** | 0.007 |
| Care-homes price | 0.541 | 0.207 | 0.634** | 0.046 | 0.542 | 0.203 | 0.791 | 0.127 | 0.873** | 0.026 | 0.787 | 0.128 |
| Pop 65+ | 1.603*** | 0.000 | 1.684*** | 0.000 | 1.583*** | 0.000 | 2.022*** | 0.000 | 2.145*** | 0.000 | 2.000*** | 0.000 |
| 2010 | -0.160** | 0.011 | -0.066* | 0.097 | -0.131*** | 0.009 | -0.319*** | 0.001 | -0.133** | 0.043 | -0.263*** | 0.004 |
| 2011 | -0.189** | 0.049 | -0.119* | 0.057 | -0.148** | 0.046 | -0.206* | 0.087 | -0.129 | 0.120 | -0.176* | 0.069 |
| 2012 | -0.243* | 0.051 | -0.195** | 0.012 | -0.179* | 0.088 | -0.223 | 0.119 | -0.212** | 0.032 | -0.182 | 0.147 |
| 2013 | -0.467*** | 0.001 | -0.277*** | 0.002 | -0.361*** | 0.004 | -0.480*** | 0.004 | -0.289*** | 0.008 | -0.409*** | 0.008 |
| Beds spatial lag | -2.975*** | 0.002 | | | -2.311** | 0.015 | -4.375*** | 0.004 | | | -3.640** | 0.022 |
| Pop 65+ spatial lag | 5.045*** | 0.001 | | | 3.861** | 0.011 | 7.466*** | 0.002 | | | 6.199** | 0.015 |
| Constant | -45.53*** | 0.000 | -15.92*** | 0.000 | -38.48*** | 0.000 | -62.33*** | 0.000 | -18.98*** | 0.000 | -55.57*** | 0.001 |
| Error spatial lag | 0.342*** | 0.006 | | | | | 0.282* | 0.052 | | | | |
| Dep spatial lag | | | 0.504*** | 0.000 | 0.330*** | 0.005 | | | 0.489*** | 0.000 | 0.267* | 0.055 |
| R2 | 0.524 | | 0.504 | | 0.523 | | 0.484 | | 0.458 | | 0.484 | |
| Mundlak Test | 4.298 | 0.507 | 3.745 | 0.290 | 3.970 | 0.554 | 3.282 | 0.657 | 2.413 | 0.491 | 2.871 | 0.720 |
| Hausman Test | 5.619 | 0.777 | 6.858 | 0.444 | 5.359 | 0.802 | 4.496 | 0.876 | 6.121 | 0.526 | 4.216 | 0.897 |

Notes: Dependent variable and continuous explanatories are in logs. Dep spatial lag is spatial lag of dependent variable. All models are estimated with random effects and cluster robust standard errors. SDEM: Spatial Durbin Error Model, SAR: Spatial Autoregressive Model, SDM: Spatial Durbin Model. Observations: 735 = 5x147. *p<0.1, **p<0.05, ***p<0.01

Table B.4: Delayed discharges (all). Alternative spatial models

| | Patients Delayed | | | | | | Days of Delay | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SDEM | | SAR | | SDM | | SDEM | | SAR | | SDM | |
| | coef | p | coef | p | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.348** | 0.016 | -0.442*** | 0.001 | -0.338** | 0.019 | -0.308* | 0.053 | -0.412*** | 0.005 | -0.297* | 0.063 |
| Care-homes price | -0.006 | 0.981 | 0.240 | 0.278 | -0.018 | 0.946 | -0.032 | 0.910 | 0.222 | 0.331 | -0.057 | 0.843 |
| Pop 65+ | 1.392*** | 0.000 | 1.468*** | 0.000 | 1.377*** | 0.000 | 1.382*** | 0.000 | 1.466*** | 0.000 | 1.365*** | 0.000 |
| 2010 | -0.056 | 0.488 | -0.030 | 0.273 | -0.044 | 0.176 | -0.105 | 0.306 | -0.044 | 0.139 | -0.062* | 0.082 |
| 2011 | -0.099 | 0.437 | -0.068 | 0.145 | -0.044 | 0.384 | -0.052 | 0.737 | -0.049 | 0.287 | -0.024 | 0.636 |
| 2012 | -0.108 | 0.452 | -0.105** | 0.050 | -0.028 | 0.682 | -0.015 | 0.931 | -0.069 | 0.173 | 0.018 | 0.785 |
| 2013 | -0.196 | 0.202 | -0.143** | 0.017 | -0.093 | 0.233 | -0.113 | 0.531 | -0.108* | 0.061 | -0.053 | 0.481 |
| Beds spatial lag | -1.840*** | 0.003 | | | -1.227** | 0.050 | -2.079*** | 0.002 | | | -1.406** | 0.033 |
| Pop 65+ spatial lag | 2.922*** | 0.002 | | | 1.513 | 0.129 | 3.418*** | 0.001 | | | 1.758* | 0.095 |
| Constant | -26.77*** | 0.000 | -12.65*** | 0.000 | -17.89*** | 0.006 | -27.07*** | 0.000 | -11.97*** | 0.000 | -18.35*** | 0.007 |
| Error spatial lag | 0.674*** | 0.000 | | | | | 0.732*** | 0.000 | | | | |
| Dep spatial lag | | | 0.602*** | 0.000 | 0.590*** | 0.000 | | | 0.686*** | 0.000 | 0.682*** | 0.000 |
| R2 | 0.674 | | 0.665 | | 0.674 | | 0.669 | | 0.657 | | 0.668 | |
| Mundlak Test | 3.552 | 0.616 | 5.861 | 0.119 | 3.039 | 0.694 | 7.001 | 0.221 | 10.08 | 0.018 | 6.518 | 0.259 |
| Hausman Test | 4.572 | 0.870 | 2.736 | 0.908 | 1.543 | 0.997 | 8.525 | 0.482 | 10.09 | 0.184 | 6.188 | 0.721 |

Notes: Dependent variable and continuous explanatories are in logs. Dep spatial lag is spatial lag of dependent variable. All models are estimated with random effects and cluster robust standard errors. SDEM: Spatial Durbin Error Model, SAR: Spatial Autoregressive Model, SDM: Spatial Durbin Model. Observations: 735 = 5x147. *p<0.1, **p<0.05, ***p<0.01

Table B.5: Patients delayed and days of delay. IV models with 2 year lag instruments

| | Patients delayed | | | | Days of delay | | | |
|---|---|---|---|---|---|---|---|---|
| | Attributed to social care | | All delays | | Attributed to social care | | All delays | |
| | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.718*** | 0.000 | -0.452*** | 0.000 | -1.067*** | 0.000 | -0.452** | 0.012 |
| Care-homes price | 1.061*** | 0.001 | 0.271 | 0.241 | 1.684*** | 0.003 | 0.650* | 0.081 |
| Pop 65+ | 1.719*** | 0.000 | 1.482*** | 0.000 | 2.262*** | 0.000 | 1.504*** | 0.000 |
| 2011 | -0.059 | 0.536 | -0.044 | 0.462 | 0.054 | 0.581 | 0.010 | 0.843 |
| 2012 | -0.154 | 0.134 | -0.081 | 0.238 | -0.036 | 0.788 | -0.004 | 0.957 |
| 2013 | -0.393*** | 0.000 | -0.161** | 0.016 | -0.311** | 0.012 | -0.087 | 0.249 |
| Beds spatial lag | -2.390*** | 0.000 | -1.137*** | 0.007 | -3.181*** | 0.004 | -0.835 | 0.180 |
| Pop 65+ spatial lag | 4.660*** | 0.000 | 2.106*** | 0.001 | 6.584*** | 0.000 | 2.134** | 0.015 |
| Constant | -49.34*** | 0.000 | -25.25*** | 0.000 | -68.05*** | 0.000 | -27.16*** | 0.000 |
| R2 | 0.516 | | 0.669 | | 0.476 | | 0.661 | |
| F Test (Beds) | 674.1 | 0.000 | 556.5 | 0.000 | 202.1 | 0.000 | 128.7 | 0.000 |
| F Test (Price) | 589.6 | 0.000 | 509.5 | 0.000 | 220.3 | 0.000 | 147.0 | 0.000 |
| F Test (Beds spatial lag) | 6847 | 0.000 | 5976 | 0.000 | 2736 | 0.000 | 1859 | 0.000 |
| Hausman Test | 0.328 | 0.999 | 0.595 | 0.996 | 2.517 | 0.867 | 2.918 | 0.819 |

Notes: Dependent variable and continuous explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. Observations: 735 = 5x147. *p<0.1, **p<0.05, ***p<0.01. F tests are for the joint significance of the instruments in each first stage model. The instruments are two year lag of care-homes beds, two year lag of care-homes price, and two year spatially lagged care-homes beds.

Table B.6: Patients delayed and days of delay. IV models with 1 year lag instruments

| | Patients Delayed | | | | Days of Delay | | | |
|---|---|---|---|---|---|---|---|---|
| | Attributed to social care | | All delays | | Attributed to social care | | All delays | |
| | coef | p | coef | p | coef | p | coef | p |
| Care-homes beds | -0.847*** | 0.007 | -0.583*** | 0.001 | -1.017** | 0.019 | -0.496*** | 0.007 |
| Care-homes price | 0.934** | 0.016 | 0.093 | 0.698 | 1.317** | 0.013 | 0.117 | 0.647 |
| Pop 65+ | 1.941*** | 0.000 | 1.658*** | 0.000 | 2.345*** | 0.000 | 1.608*** | 0.000 |
| 2010 | -0.099* | 0.075 | -0.038 | 0.332 | -0.224*** | 0.004 | -0.110*** | 0.008 |
| 2011 | -0.190*** | 0.003 | -0.094** | 0.033 | -0.208** | 0.013 | -0.089* | 0.052 |
| 2012 | -0.326*** | 0.000 | -0.148*** | 0.004 | -0.347*** | 0.001 | -0.090* | 0.077 |
| 2013 | -0.449*** | 0.000 | -0.172*** | 0.002 | -0.446*** | 0.000 | -0.103* | 0.066 |
| Constant | -17.86*** | 0.000 | -10.96*** | 0.000 | -20.16*** | 0.000 | -7.957*** | 0.000 |
| R2 | 0.489 | | 0.662 | | 0.442 | | 0.655 | |
| F Test (Beds) | 162.2 | 0.000 | 184.1 | 0.000 | 156.9 | 0.000 | 166.4 | 0.000 |
| F Test (Price) | 337.5 | 0.000 | 380.5 | 0.000 | 326.9 | 0.000 | 345.8 | 0.000 |
| Hausman Test | 2.241 | 0.945 | 2.100 | 0.954 | 1.585 | 0.979 | 4.555 | 0.714 |

Notes: Dependent variable and continuous explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. Observations: 735 = 5x147. *p<0.1, **p<0.05, ***p<0.01. F tests are for the joint significance of the instruments in each first stage model. The instruments are one year lag of care-homes beds and one year lag of care-homes price.

# Appendix C

# Chapter 4 Appendices

Table C.1: Days of delay with interaction of FT status and Trust type

| | Days of delay | | | | Days of delay attributed to NHS | | | |
|---|---|---|---|---|---|---|---|---|
| | Pooled mode | | Random hospital effects | | Pooled model | | Random hospital effects | |
| | Coef | p | Coef | p | Coef | p | Coef | p |
| Acute Specialist Trust | –0.685 | 0.144 | 0.137 | 0.816 | –2.833*** | 0.000 | –2.815*** | 0.007 |
| Acute Teaching Trust | 0.193 | 0.420 | 0.061 | 0.738 | 0.108 | 0.657 | 0.114 | 0.566 |
| Mental Health Trust | 0.501** | 0.028 | 0.193 | 0.361 | –0.222 | 0.453 | –0.400* | 0.095 |
| Foundation Trust | –0.120 | 0.228 | –0.276*** | 0.003 | –0.163 | 0.155 | –0.460*** | 0.000 |
| Interaction of Teaching Trust and FT | –0.111 | 0.683 | –0.366* | 0.090 | –0.061 | 0.832 | –0.318 | 0.181 |
| Interaction of Specialist Trust and FT | 0.061 | 0.846 | –0.130 | 0.823 | 2.241*** | 0.000 | 2.972*** | 0.004 |
| Interaction of Mental Health Trust and FT | –0.066 | 0.701 | –0.001 | 0.995 | –0.163 | 0.412 | 0.269 | 0.204 |
| Ln care-home beds | –0.263*** | 0.000 | –0.287*** | 0.000 | –0.239*** | 0.004 | –0.258*** | 0.000 |
| Ln care-home price/week | 0.221 | 0.433 | 0.418* | 0.081 | 0.034 | 0.923 | –0.0206 | 0.935 |
| Ln alpha | –0.807*** | 0.000 | | | –0.511*** | 0.000 | | |
| Ln r | | | 1.147*** | 0.000 | | | 0.866*** | 0.000 |
| Ln s | | | 7.393*** | 0.000 | | | 6.831*** | 0.000 |
| Exposure | Ln beds in Trust | | Ln beds in Trust | | Ln beds in Trust | | Ln beds in Trust | |
| AIC | 11,492 | | 11,187 | | 11,031 | | 10,676 | |
| BIC | 11,593 | | 11,297 | | 11,133 | | 10,787 | |
| Standard errors | Cluster | | OIM | | Cluster | | OIM | |

Notes: Negative binomial models. 'Days of delay' is total days of delay in year. 'Days of delay attributed to NHS' is total days of delay in year attributed to NHS. Coefficients are proportionate changes in days of delay from a one-unit increase in the explanatory variable. These coefficients are also conditional on year dummies, hospital beds, age, gender, emergency and readmission variables, as in models 4 and 5 in Tables 3 and 4. Exposure term has a coefficient of 1. Ln alpha is the log of overdispersion. Ln r and ln s are shape parameters of the beta(r,s) distribution of random effects. AIC is the Akaike Information Criterion. BIC is the Bayesian Information Criterion. 'Cluster' indicates robust standard errors clustered at Trust level. 'OIM' indicates observed information matrix standard errors. Observations: 614 (208, 203 and 203 for 2011–12, 2012–13 and 2013–14 respectively). $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.2: Days of delay without Mental Health Trusts

| | Days of delay | | | | Days of delay attributed to NHS | | | |
|---|---|---|---|---|---|---|---|---|
| | Pooled mode | | Random hospital effects | | Pooled model | | Random hospital effects | |
| | Coef | p | Coef | p | Coef | p | Coef | p |
| Acute Specialist Trust | –0.796 | 0.256 | –0.674 | 0.232 | –1.318 | 0.106 | –0.359 | 0.536 |
| Acute Teaching Trust | 0.146 | 0.367 | –0.068 | 0.744 | 0.100 | 0.603 | 0.144 | 0.510 |
| Foundation Trust | –0.185* | 0.063 | –0.393*** | 0.000 | –0.191* | 0.091 | –0.457*** | 0.000 |
| Ln care-home beds | –0.382*** | 0.000 | –0.455*** | 0.000 | –0.337*** | 0.002 | –0.455*** | 0.000 |
| Ln care-home price/week | –0.250 | 0.554 | 0.344 | 0.305 | –0.223 | 0.653 | –0.172 | 0.631 |
| Ln alpha | –0.768*** | 0.000 | | | –0.456*** | 0.000 | | |
| Ln r | | | 1.021*** | 0.000 | | | 0.781*** | 0.000 |
| Ln s | | | 7.123*** | 0.000 | | | 6.720*** | 0.000 |
| Exposure | Ln beds in Trust | | Ln beds in Trust | | Ln beds in Trust | | Ln beds in Trust | |
| AIC | 8,636 | | 8,380 | | 8,421 | | 8,111 | |
| BIC | 8,719 | | 8,467 | | 8,504 | | 8,197 | |
| Standard errors | Cluster | | OIM | | Cluster | | OIM | |

Notes: Negative binomial models. 'Days of delay' is total days of delay in year. 'Days of delay attributed to NHS' is total days of delay in year attributed to NHS. Coefficients are proportionate changes in days of delay from a one-unit increase in the explanatory variable. These coefficients are also conditional on year dummies, hospital beds, age, gender, emergency and readmission variables, as in models 4 and 5 in Tables 3 and 4. Exposure term has a coefficient of 1. Ln alpha is the log of overdispersion. Ln r and ln s are shape parameters of the beta(r,s) distribution of random effects. AIC is the Akaike Information Criterion. BIC is the Bayesian Information Criterion. 'Cluster' indicates robust standard errors clustered at Trust level. 'OIM' indicates observed information matrix standard errors. Observations: 463 (157, 153 and 153 for 2011–12, 2012–13 and 2013–14 respectively). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.3: Model 4.5 with competing Trusts indicator

| | Days of delay | | Days of delay attributed to NHS | |
|---|---|---|---|---|
| | Coef | p | Coef | p |
| Acute Specialist Trust | 0.071 | 0.798 | –0.132 | 0.688 |
| Acute Teaching Trust | –0.137 | 0.363 | –0.034 | 0.809 |
| Mental Health Trust | 0.208 | 0.220 | –0.215 | 0.283 |
| Foundation Trust | –0.211* | 0.084 | –0.271** | 0.042 |
| Ln care-home beds | –0.296*** | 0.000 | –0.274*** | 0.000 |
| Ln care-home price/week | 0.448* | 0.062 | 0.010 | 0.970 |
| Other Trusts in the same local authority | 0.091 | 0.469 | 0.128 | 0.352 |
| Interaction of FT and Other Trusts in local authority | –0.186 | 0.223 | –0.193 | 0.352 |
| Ln r | 1.174*** | 0.000 | 0.910*** | 0.000 |
| Ln s | 7.442*** | 0.000 | 6.934*** | 0.000 |
| Exposure | Ln beds in Trust | | Ln beds in Trust | |
| AIC | 11,186 | | 10,695 | |
| BIC | 11,292 | | 10,802 | |
| Standard errors | OIM | | OIM | |

Notes: Negative binomial models with hospital-level random effects. 'Days of delay' is total days of delay in year. 'Days of delay attributed to NHS' is total days of delay in year attributed to NHS. Coefficients are proportionate changes in days of delay from a oneunit increase in the explanatory variable. These coefficients are also conditional on year dummies, hospital beds, age, gender, emergency and readmission variables, as in model 5 in Tables 3 and 4. Exposure term has a coefficient of 1. Ln r and ln s are shape parameters of the beta(r,s) distribution of random effects. AIC is the Akaike Information Criterion. BIC is the Bayesian Information Criterion. 'OIM' indicates observed information matrix standard errors. Observations: 614 (208, 203 and 203 for 2011–12, 2012–13 and 2013–14 respectively). *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

# Appendix D

# Chapter 5 Appendix Tables

Table D.1: Means of patient characteristics

| # | BPT | Age | Male | Deprivation score | Elixhauser score | Past emergency admission |
|---|---|---|---|---|---|---|
| 1 | Cholecystectomy | 49.9 | 0.22 | 0.16 | 0.97 | 0.43 |
| 2 | Simple mastectomy | 50.9 | 0.17 | 0.13 | 0.54 | 0.09 |
| 3 | Sentinel node mapping | 59.0 | 0.10 | 0.13 | 0.99 | 0.08 |
| 4 | Operations to manage female incontinence | 53.3 | 0.00 | 0.14 | 0.73 | 0.07 |
| 5 | Endoscopic prostate resection | 72.1 | 1.00 | 0.13 | 1.78 | 0.38 |
| 6 | Laser prostate resection | 71.4 | 1.00 | 0.13 | 1.56 | 0.37 |
| 7 | Hernia repair | 58.3 | 0.85 | 0.14 | 0.86 | 0.11 |
| 8 | Shoulder decompression | 56.1 | 0.50 | 0.14 | 0.95 | 0.07 |
| 9 | Bunion operation | 56.4 | 0.16 | 0.14 | 0.72 | 0.05 |
| 10 | Fasciectomy | 64.6 | 0.78 | 0.13 | 0.81 | 0.06 |
| 11 | Tonsillectomy | 32.0 | 0.37 | 0.16 | 0.37 | 0.17 |
| 12 | Septoplasty | 41.2 | 0.69 | 0.15 | 0.42 | 0.06 |
| 13 | Tympanoplasty | 42.4 | 0.50 | 0.16 | 0.15 | 0.06 |
| 14 | Epilepsy | 53.5 | 0.54 | 0.18 | 3.57 | 0.59 |
| 15 | Acute headache | 45.9 | 0.35 | 0.17 | 1.22 | 0.30 |
| 16 | Asthma | 47.1 | 0.30 | 0.19 | 2.55 | 0.40 |
| 17 | Respiratory | 51.7 | 0.44 | 0.17 | 0.70 | 0.26 |
| 18 | Pulmonary embolism | 62.3 | 0.47 | 0.14 | 3.03 | 0.36 |
| 19 | Chest pain | 59.3 | 0.53 | 0.17 | 2.22 | 0.37 |
| 20 | Appendicular fractures | 63.4 | 0.41 | 0.16 | 1.61 | 0.26 |
| 21 | Cellulitis | 57.0 | 0.56 | 0.16 | 1.66 | 0.31 |
| 22 | Renal/ureteric stones | 45.8 | 0.69 | 0.17 | 0.74 | 0.27 |
| 23 | Deep vein thrombosis | 61.8 | 0.50 | 0.16 | 2.03 | 0.43 |
| 24 | Deliberate self-harm | 39.1 | 0.43 | 0.20 | 2.19 | 0.44 |
| 25 | Falls | 67.6 | 0.52 | 0.16 | 2.46 | 0.37 |
| 26 | Pneumonia | 51.8 | 0.50 | 0.16 | 0.63 | 0.22 |
| 27 | Fibrillation | 68.1 | 0.48 | 0.14 | 3.42 | 0.39 |

Table D.1: (continued)

| # | BPT | Age | Male | Deprivation score | Elixhauser score | Past emergency admission |
|---|---|---|---|---|---|---|
| 28 | Head injury | 54.9 | 0.56 | 0.18 | 1.63 | 0.33 |
| 29 | Pelvis fracture | 81.3 | 0.15 | 0.14 | 2.43 | 0.37 |
| 30 | Bladder outflow | 68.5 | 0.81 | 0.15 | 2.15 | 0.39 |
| 31 | Anemia | 69.7 | 0.36 | 0.17 | 3.94 | 0.38 |
| 32 | Abdominal pain | 47.7 | 0.35 | 0.17 | 1.51 | 0.39 |

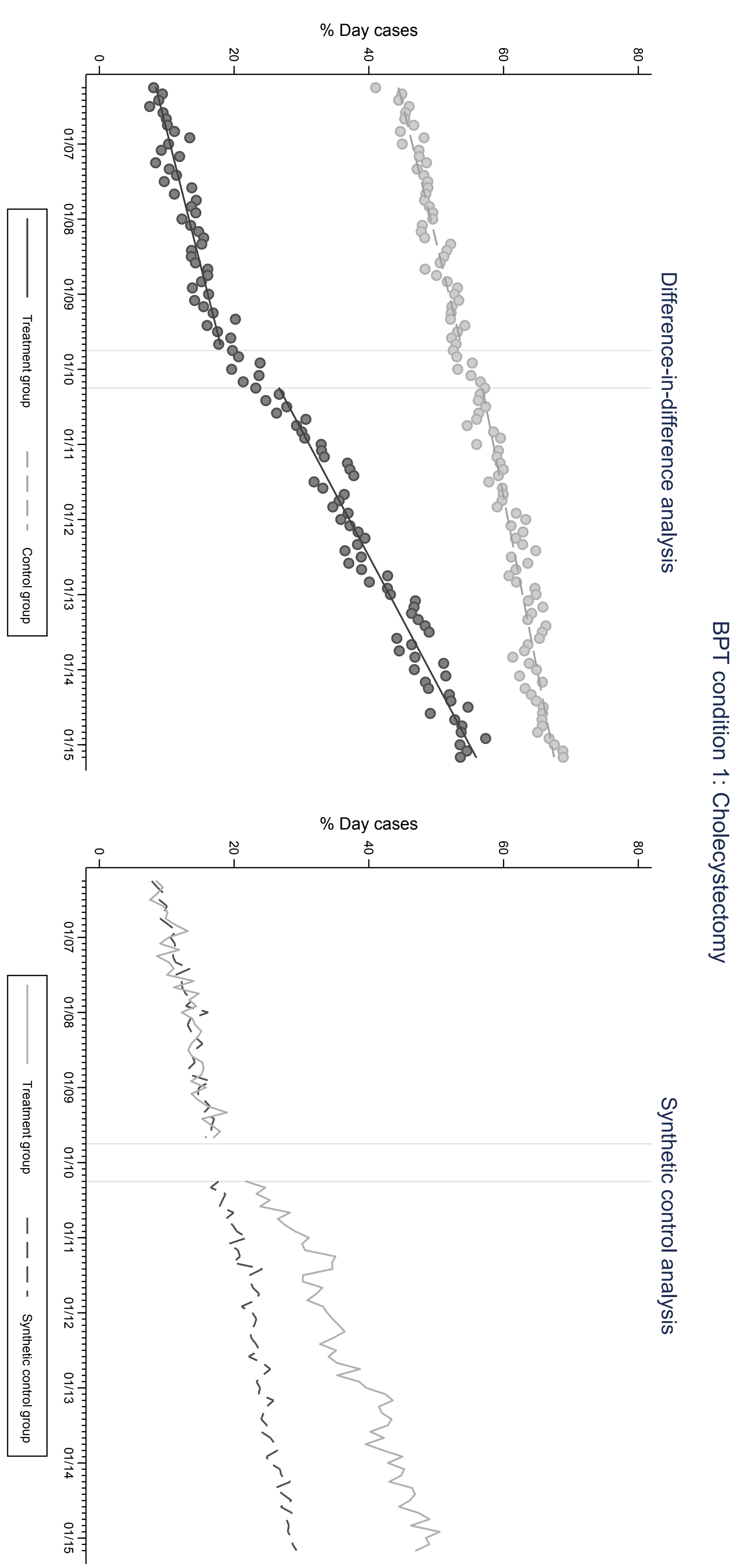
Notes: See Section 5.3 for variable definitions.

Table D.2: Volume of incentivised activity and % growth over time

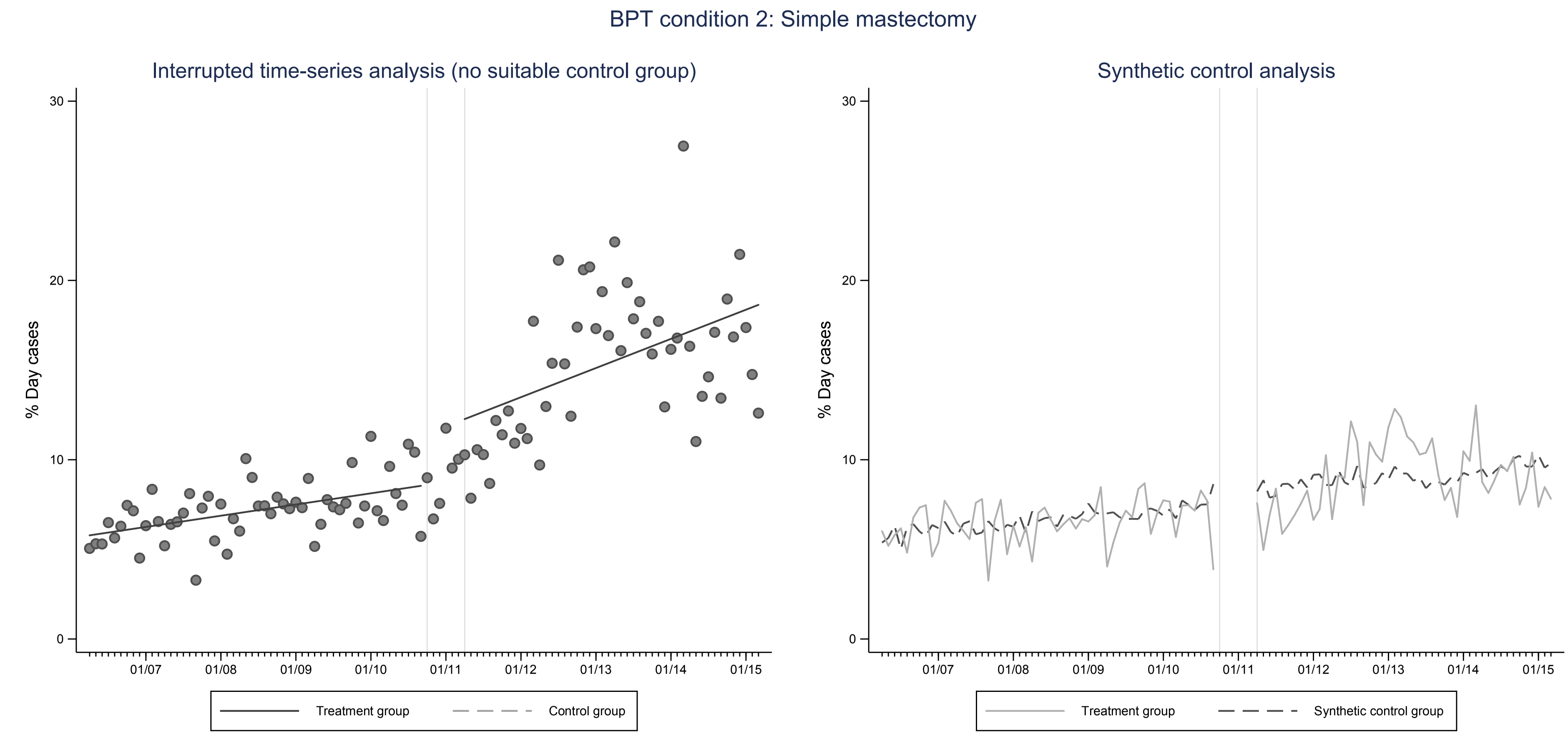
| | | Volume of activity | | | | | | | | | Average growth per annum | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| # | BPT | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | Pre-policy | Post-policy | Total |
| 1 | Cholecystectomy | 9,751 | 9,997 | 10,253 | 12,087 | 12,244 | 12,842 | 12,327 | 13,064 | 12,914 | 4.8% | 1.1% | 4.1% |
| 2 | Simple mastectomy | 4,417 | 4,393 | 4,437 | 4,430 | 3,949 | 3,713 | 3,667 | 3,821 | 3,801 | -1.8% | 0.6% | -1.7% |
| 3 | Sentinel node mapping | 4,982 | 6,048 | 9,513 | 11,842 | 15,190 | 17,224 | 19,504 | 21,408 | 23,131 | 34.1% | 8.6% | 45.5% |
| 4 | Operations to manage female incontinence | 8,623 | 13,751 | 14,138 | 13,803 | 13,380 | 12,891 | 11,935 | 11,853 | 9,586 | 9.2% | -6.4% | 1.4% |
| 5 | Endoscopic prostate resection | 6,654 | 6,288 | 5,856 | 6,312 | 6,111 | 6,146 | 6,102 | 5,934 | 5,458 | -1.4% | -2.8% | -2.2% |
| 6 | Laser prostate resection | 15,563 | 17,051 | 17,381 | 16,453 | 15,531 | 15,453 | 15,032 | 15,505 | 14,867 | 0.0% | -0.9% | -0.6% |
| 7 | Hernia repair | 89,900 | 94,914 | 92,737 | 89,731 | 90,208 | 94,571 | 92,502 | 97,968 | 98,148 | 0.1% | 0.9% | 1.1% |
| 8 | Shoulder decompression | 3,542 | 2,780 | 1,572 | 22,223 | 29,176 | 33,607 | 33,411 | 35,526 | 36,886 | 120.6% | 2.4% | 117.7% |
| 9 | Bunion operation | 10,741 | 12,882 | 13,985 | 14,757 | 16,811 | 16,848 | 14,753 | 14,850 | 14,771 | 9.4% | -3.1% | 4.7% |
| 10 | Fasciectomy | 11,813 | 10,551 | 9,631 | 9,128 | 9,174 | 8,865 | 8,526 | 8,360 | 7,950 | -3.7% | -2.6% | -4.1% |
| 11 | Tonsillectomy | 16,456 | 16,693 | 16,123 | 16,148 | 15,301 | 15,138 | 15,830 | 17,066 | 17,000 | -1.1% | 2.5% | 0.4% |
| 12 | Septoplasty | 19,158 | 19,511 | 19,375 | 19,039 | 19,542 | 19,391 | 18,580 | 19,527 | 19,078 | 0.2% | 0.9% | -0.1% |
| 13 | Tympanoplasty | 9,624 | 10,284 | 9,728 | 9,428 | 8,910 | 7,677 | 7,204 | 7,104 | 6,899 | -3.1% | -1.4% | -3.5% |
| 14 | Epilepsy | 41,716 | 42,427 | 45,337 | 47,181 | 35,170 | 47,479 | 47,477 | 47,477 | 46,671 | 2.0% | -0.6% | 1.5% |
| 15 | Acute headache | 40,674 | 43,194 | 49,439 | 54,866 | 55,835 | 56,501 | 58,532 | 62,290 | 63,113 | 5.6% | 2.6% | 6.9% |
| 16 | Asthma | 32,030 | 30,236 | 33,114 | 30,523 | 30,132 | 26,555 | 29,690 | 27,871 | 31,879 | -2.4% | 2.5% | -0.1% |
| 17 | Respiratory | 15,168 | 14,128 | 14,023 | 10,411 | 10,235 | 8,867 | 10,281 | 8,689 | 9,873 | -5.9% | -1.3% | -4.4% |
| 18 | Pulmonary embolism | 9,170 | 10,033 | 10,849 | 11,689 | 11,014 | 11,394 | 12,638 | 12,801 | 12,826 | 3.5% | 0.5% | 5.0% |
| 19 | Chest pain | 248,882 | 243,410 | 258,997 | 264,983 | 198,080 | 259,147 | 253,091 | 254,538 | 243,264 | 0.6% | -1.3% | -0.3% |
| 20 | Appendicular fractures | 35,950 | 38,678 | 40,348 | 43,422 | 40,252 | 38,783 | 37,659 | 38,221 | 38,857 | 1.1% | 1.1% | 1.0% |
| 21 | Cellulitis | 33,305 | 32,478 | 32,906 | 32,893 | 24,675 | 31,633 | 30,479 | 31,713 | 33,229 | -0.7% | 3.0% | 0.0% |
| 22 | Renal/ureteric stones | 26,553 | 25,805 | 26,889 | 29,182 | 28,817 | 27,891 | 26,667 | 27,627 | 28,137 | 0.7% | 1.8% | 0.7% |
| 23 | Deep vein thrombosis | 20,314 | 20,763 | 22,313 | 22,233 | 19,842 | 17,060 | 16,686 | 17,135 | 17,770 | -2.3% | 2.2% | -1.6% |
| 24 | Deliberate self-harm | 85,936 | 88,754 | 91,402 | 93,432 | 96,790 | 97,304 | 91,016 | 94,837 | 88,189 | 1.9% | -1.0% | 0.3% |
| 25 | Falls | 61,251 | 60,699 | 66,399 | 66,905 | 65,019 | 60,617 | 55,991 | 54,337 | 51,485 | -0.1% | -2.7% | -2.0% |
| 26 | Pneumonia | 13,717 | 13,161 | 13,160 | 11,998 | 12,514 | 10,483 | 11,326 | 9,377 | 10,914 | -2.2% | 8.2% | -2.6% |
| 27 | Fibrillation | 87,039 | 89,842 | 91,941 | 97,052 | 93,371 | 94,086 | 95,232 | 97,292 | 97,223 | 1.2% | 0.0% | 1.5% |
| 28 | Head injury | 21,092 | 19,196 | 18,336 | 18,700 | 15,914 | 14,914 | 13,003 | 13,115 | 12,416 | -4.8% | -2.7% | -5.1% |
| 29 | Pelvis fracture | 5,374 | 5,799 | 5,945 | 6,521 | 6,414 | 6,712 | 7,230 | 7,645 | 7,853 | 4.3% | 1.4% | 5.8% |
| 30 | Bladder outflow | 13,584 | 13,610 | 13,567 | 13,472 | 11,898 | 11,529 | 10,446 | 9,467 | 8,674 | -2.9% | -4.2% | -4.5% |
| 31 | Anaemia | 9,387 | 10,839 | 11,731 | 13,100 | 11,435 | 12,241 | 13,088 | 13,711 | 14,189 | 4.9% | 1.7% | 6.4% |
| 32 | Abdominal pain | 174,494 | 173,899 | 185,860 | 197,229 | 199,249 | 197,419 | 196,163 | 199,559 | 198,755 | 1.6% | -0.2% | 1.7% |

## Appendix E

# Chapter 5 Appendix Figures

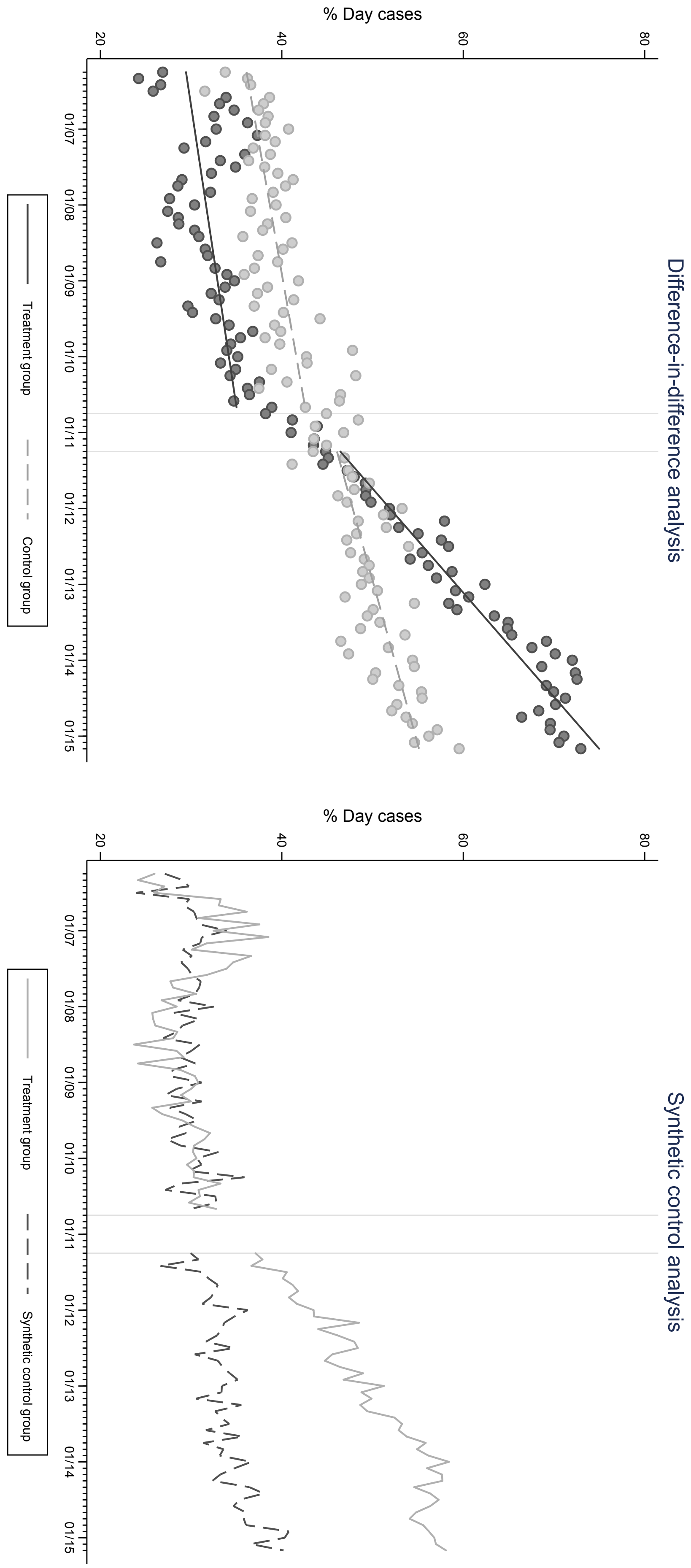



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*



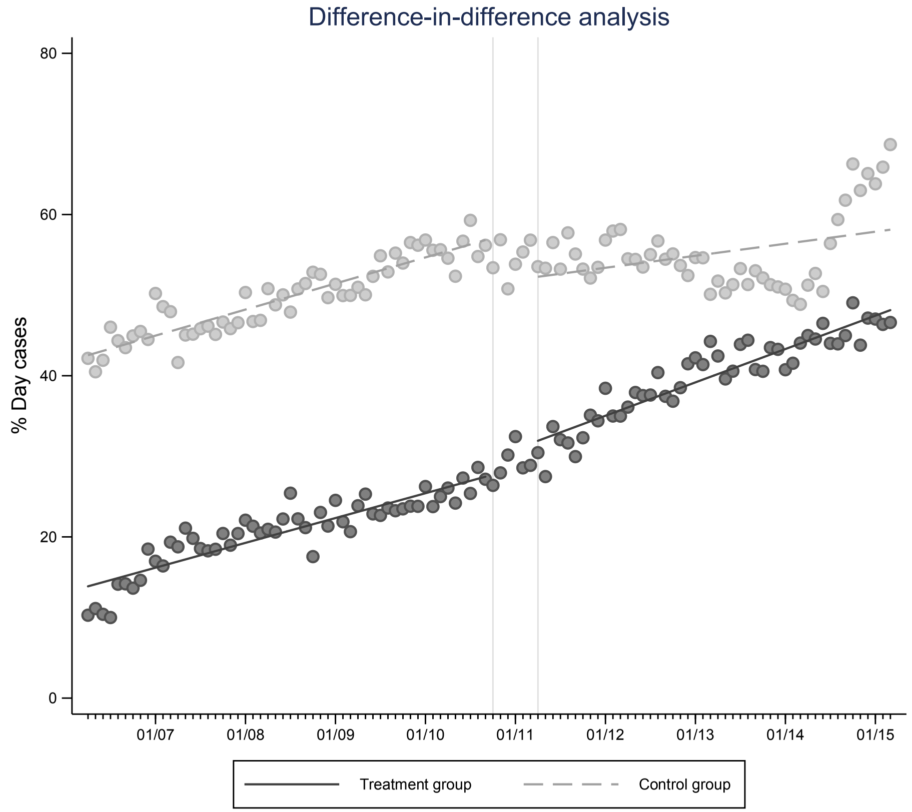

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

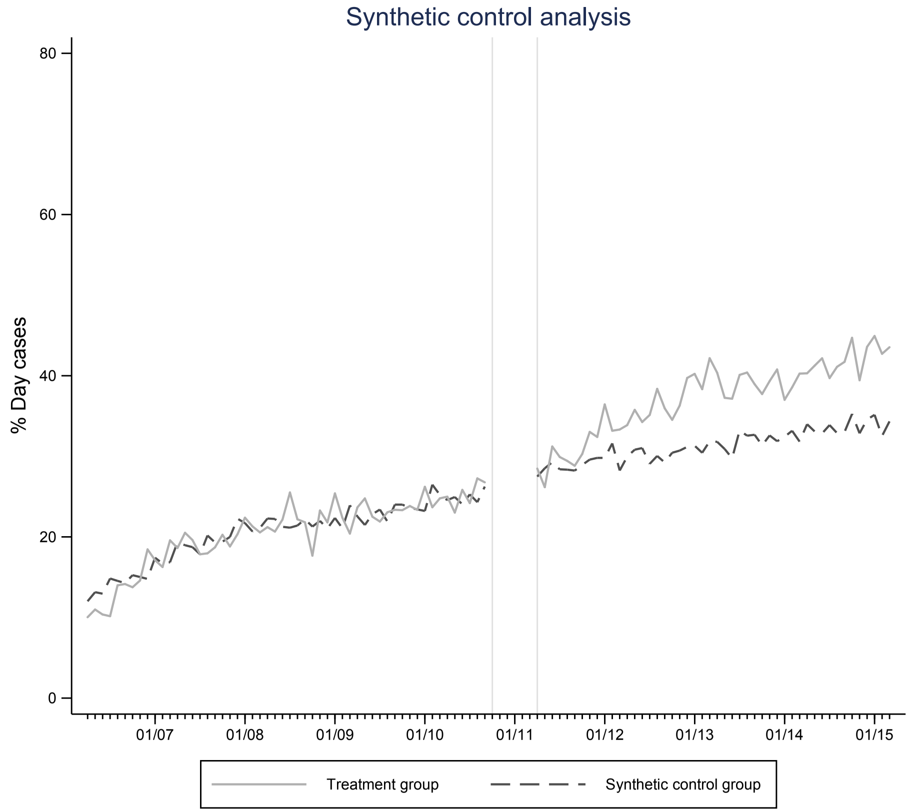
BPT condition 3: Sentinel node mapping



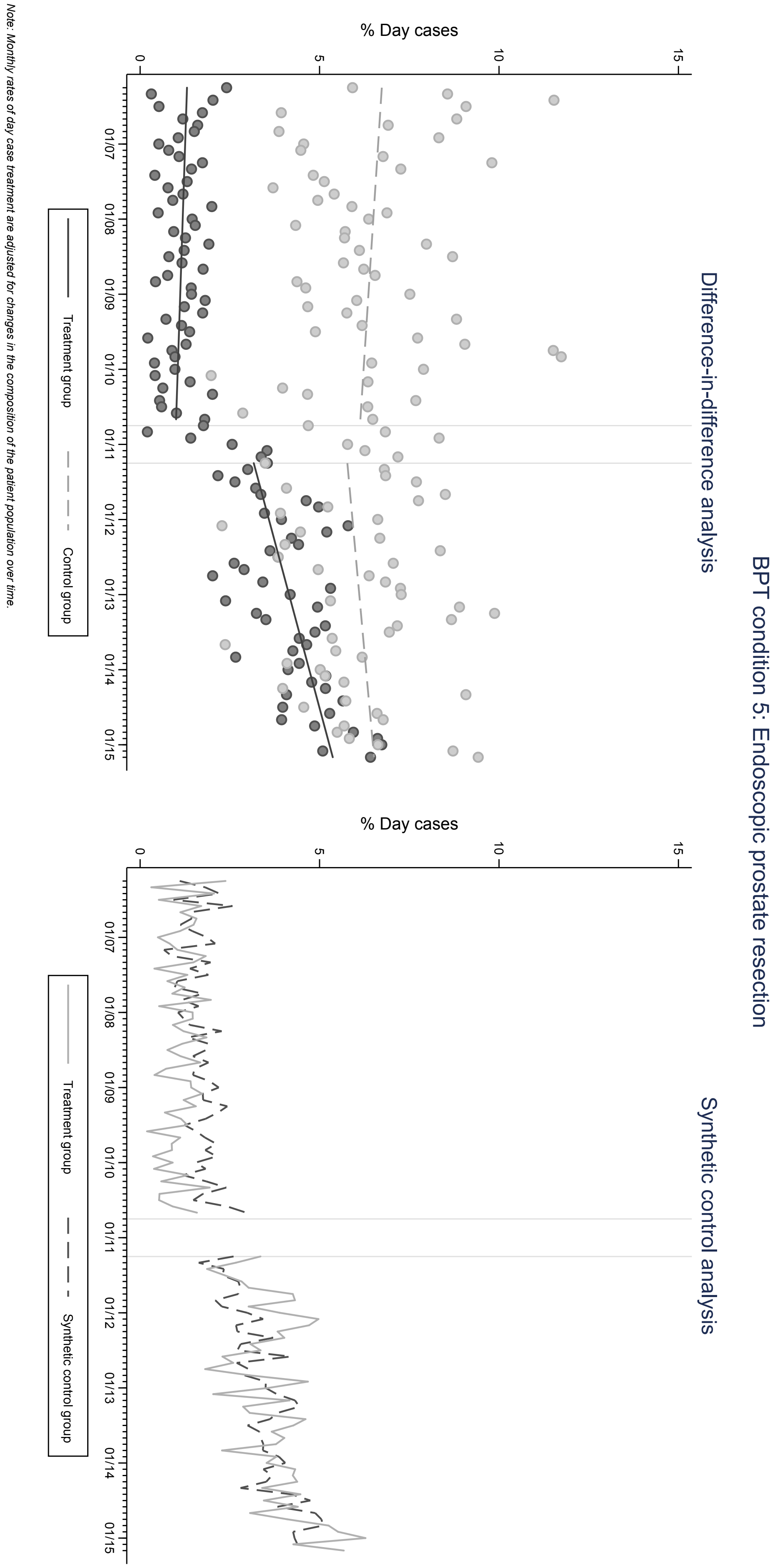

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

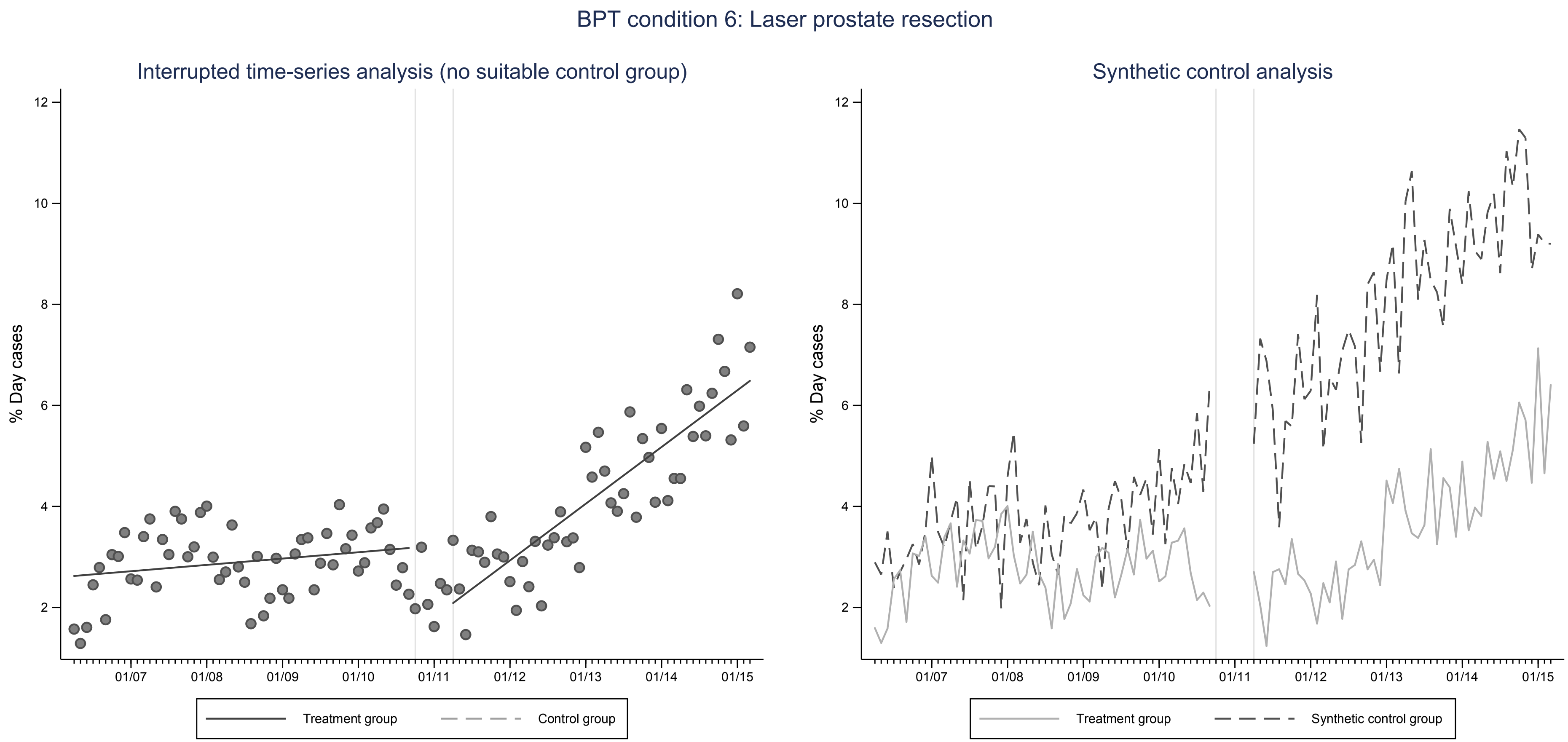
BPT condition 4: Operations to manage female incontinence



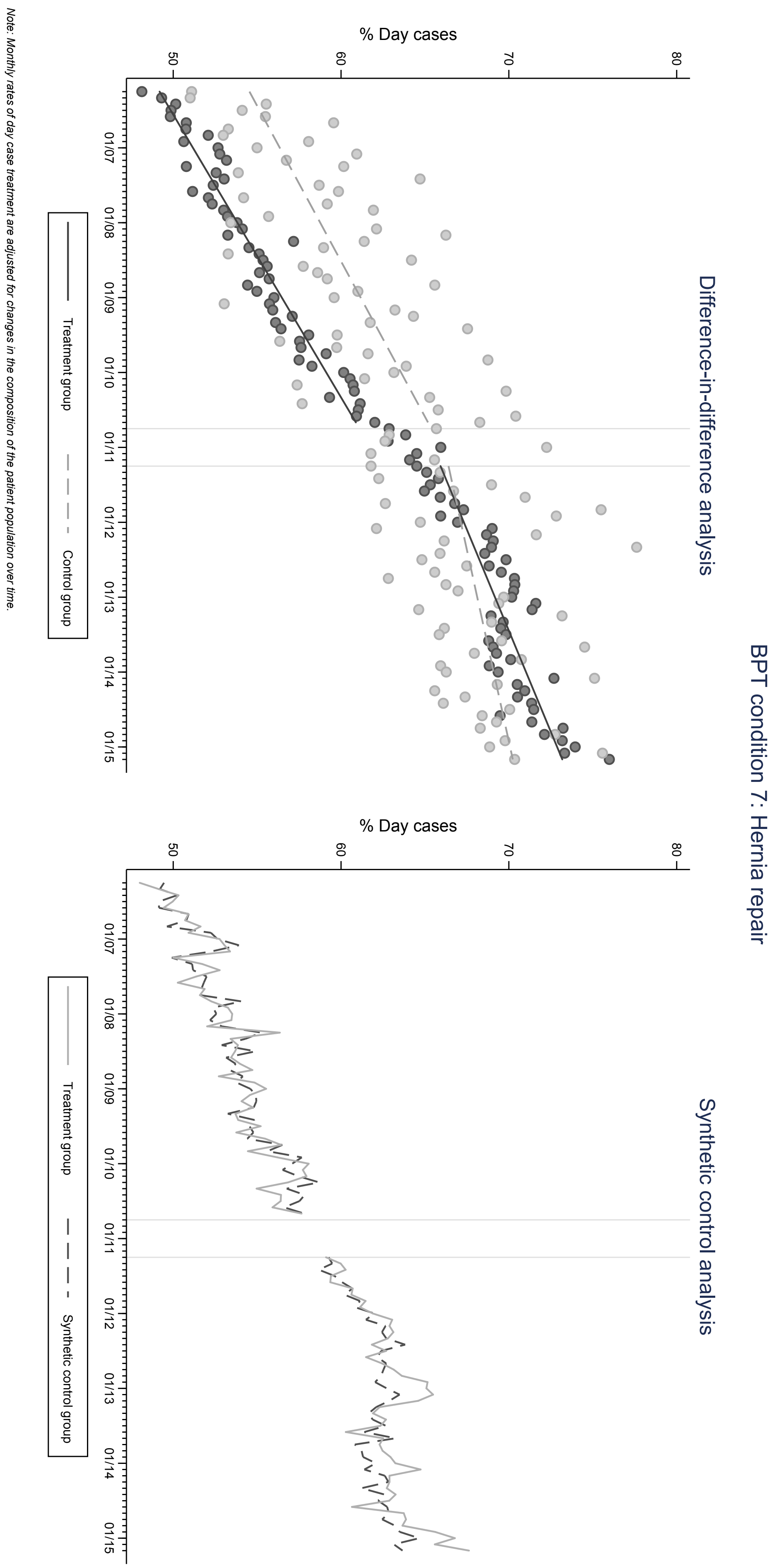




*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

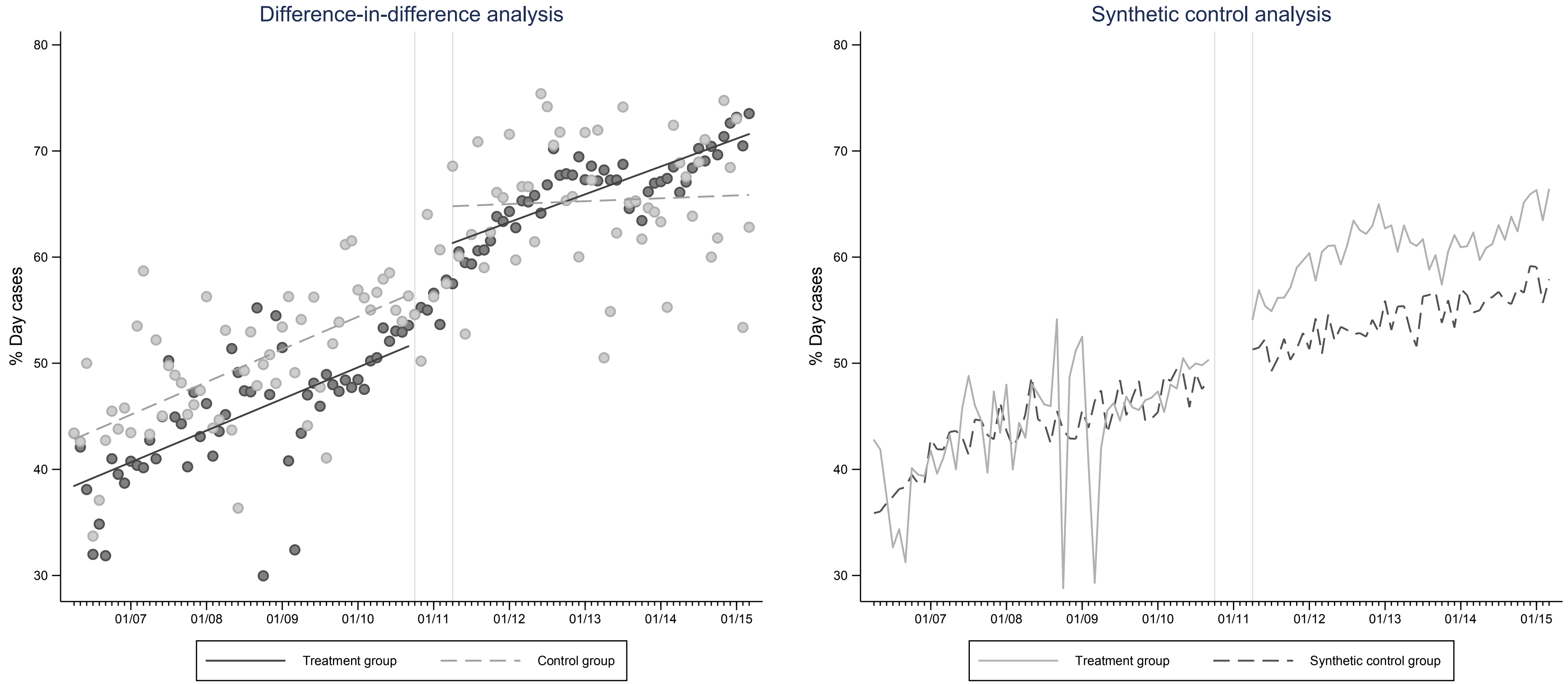

BPT condition 5: Endoscopic prostate resection
Difference-in-difference analysis
% Day cases
0
5
10
15
01/07
01/08
01/09
01/10
01/11
01/12
01/13
01/14
01/15
Treatment group
Control group
Synthetic control analysis
% Day cases
0
5
10
15
01/07
01/08
01/09
01/10
01/11
01/12
01/13
01/14
01/15
Treatment group
Synthetic control group
Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.



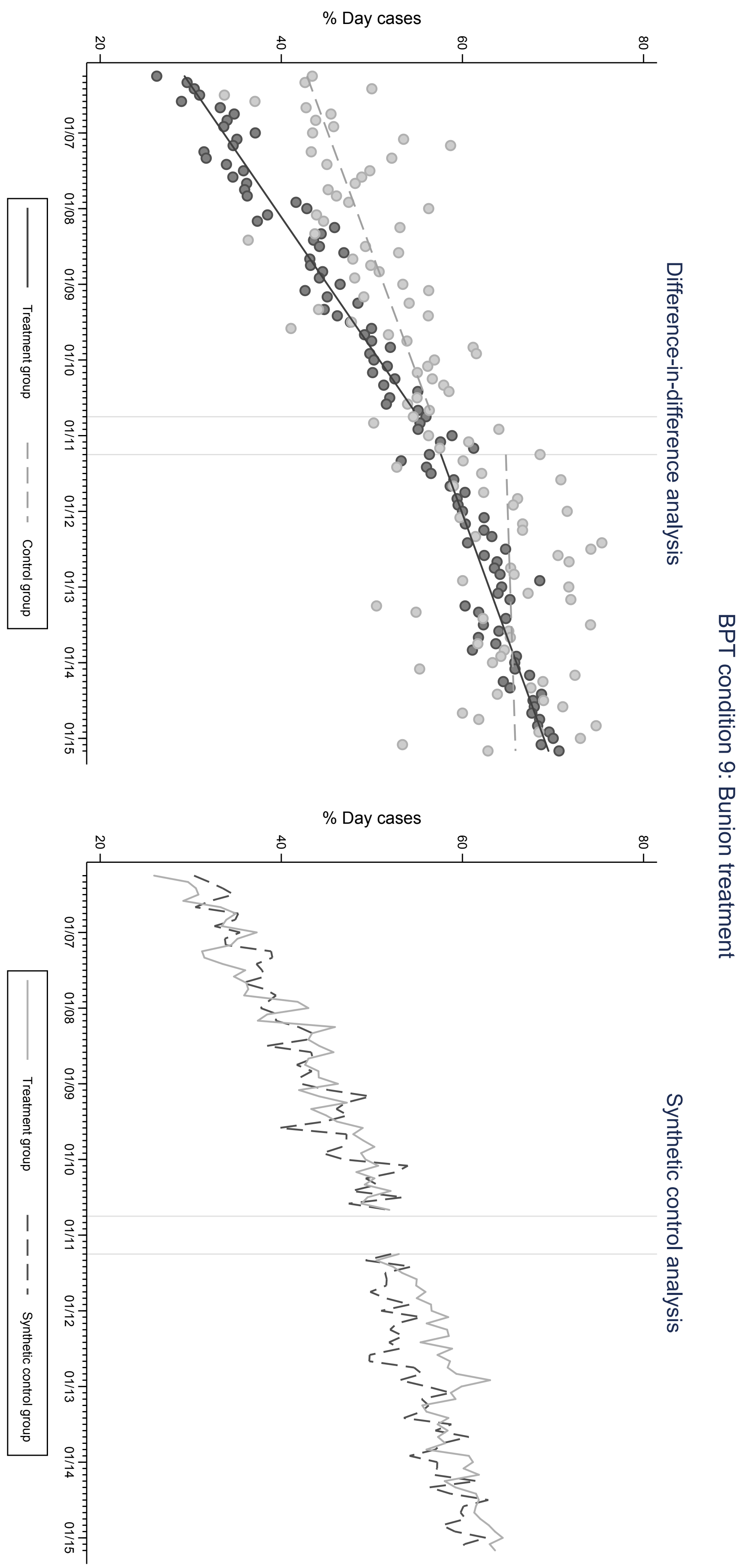

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*


BPT condition 7: Hernia repair
Difference-in-difference analysis
% Day cases
50
60
70
80
01/07
01/08
01/09
01/10
01/11
01/12
01/13
01/14
01/15
Treatment group
Control group
Synthetic control analysis
% Day cases
Treatment group
Synthetic control group
Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.

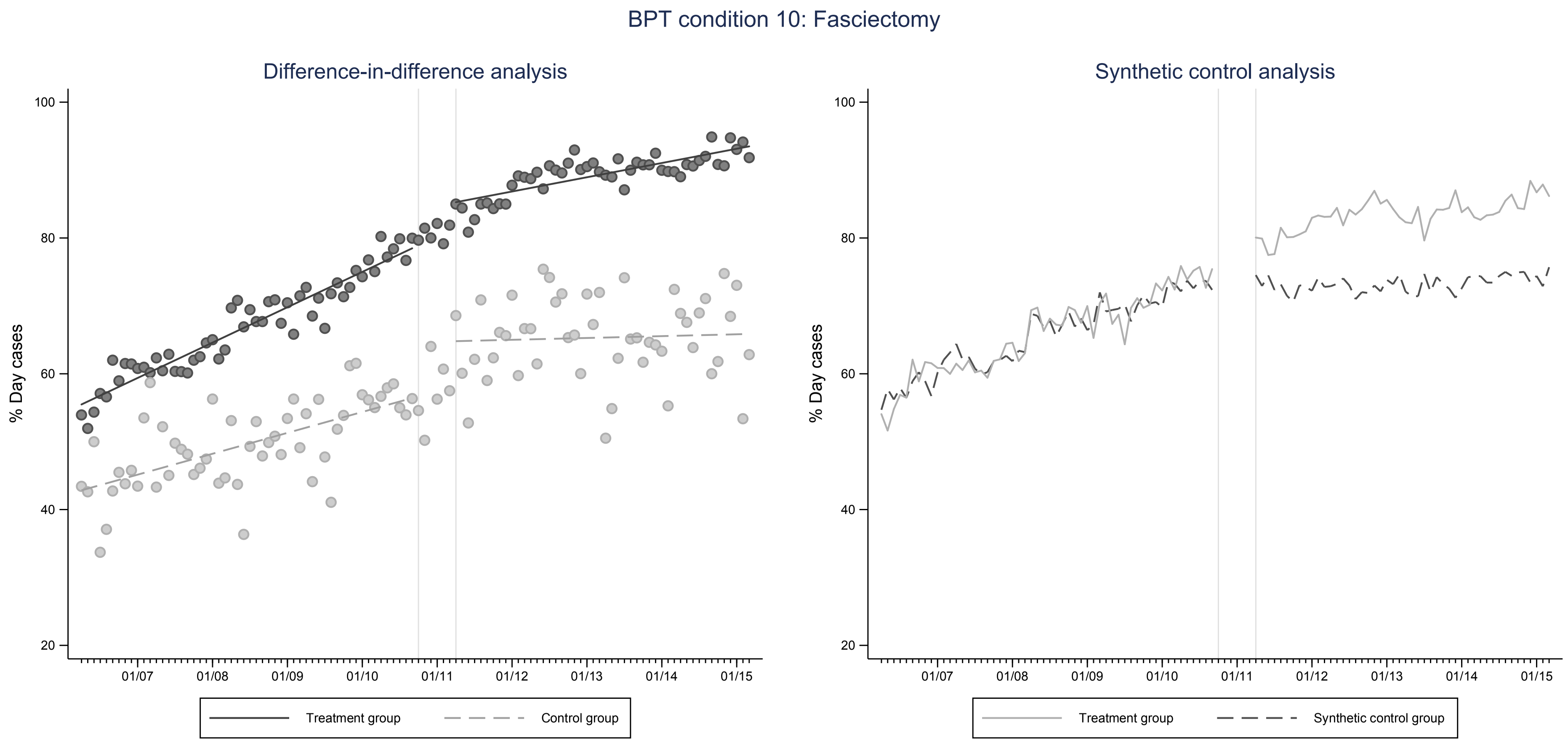
BPT condition 8: Shoulder decompression



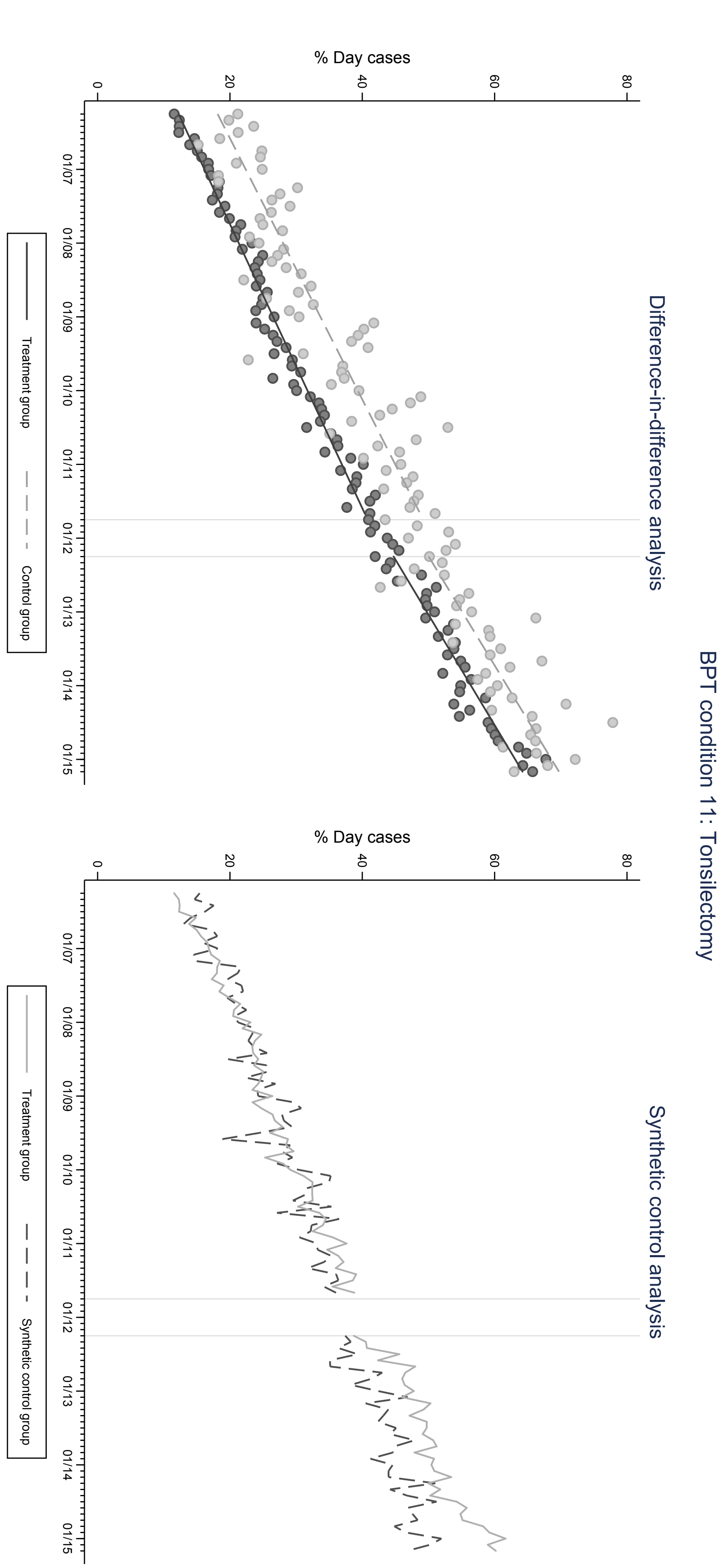

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*



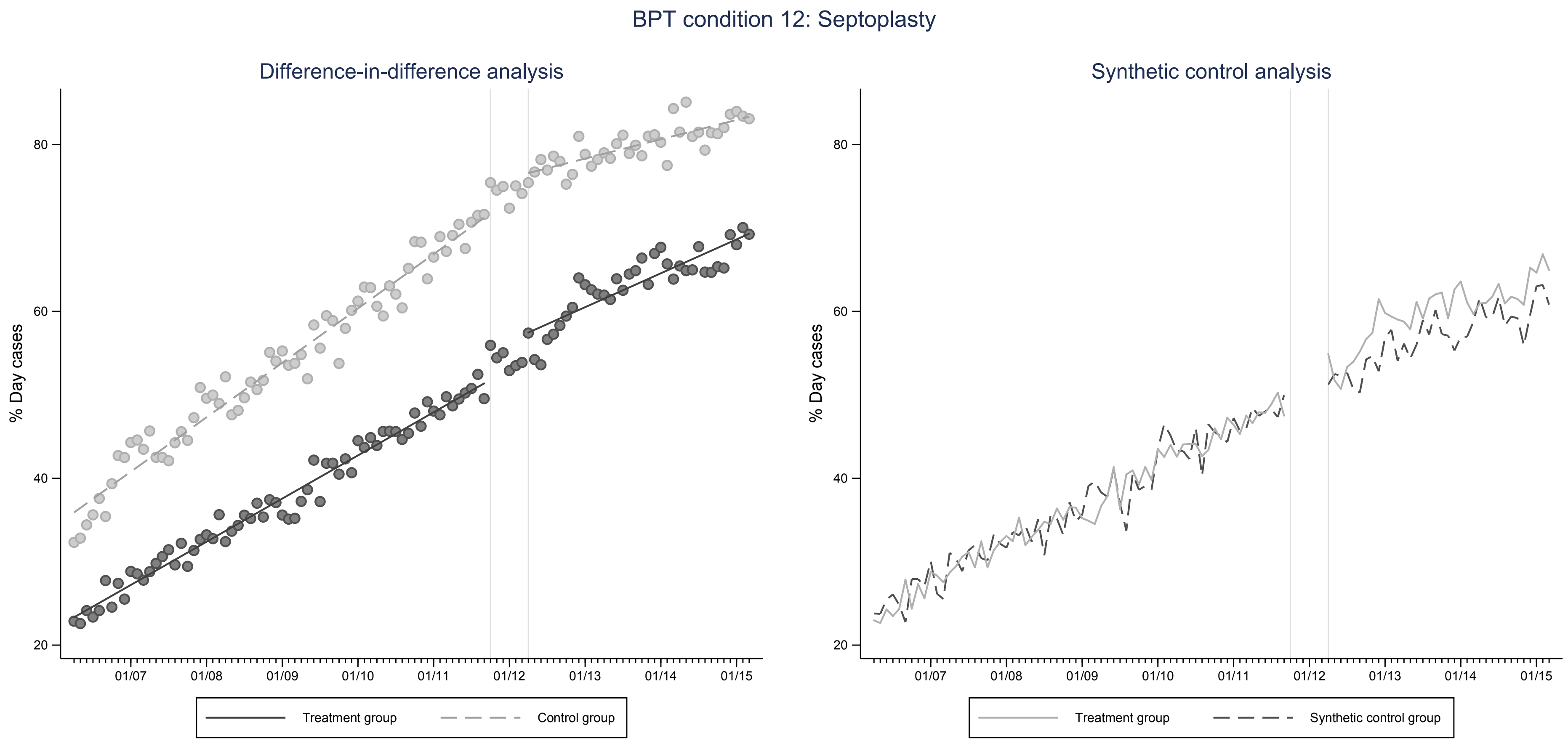

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*



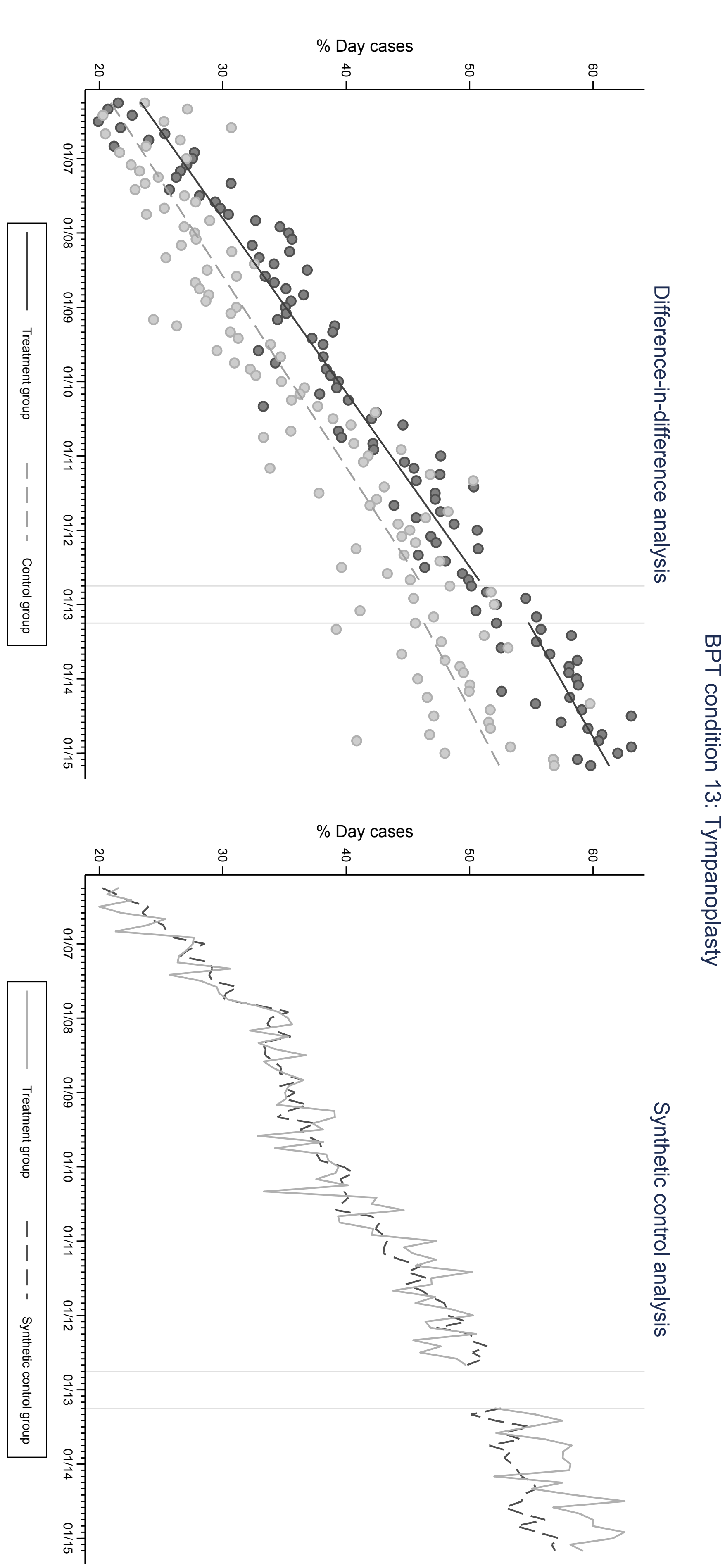

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*




*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

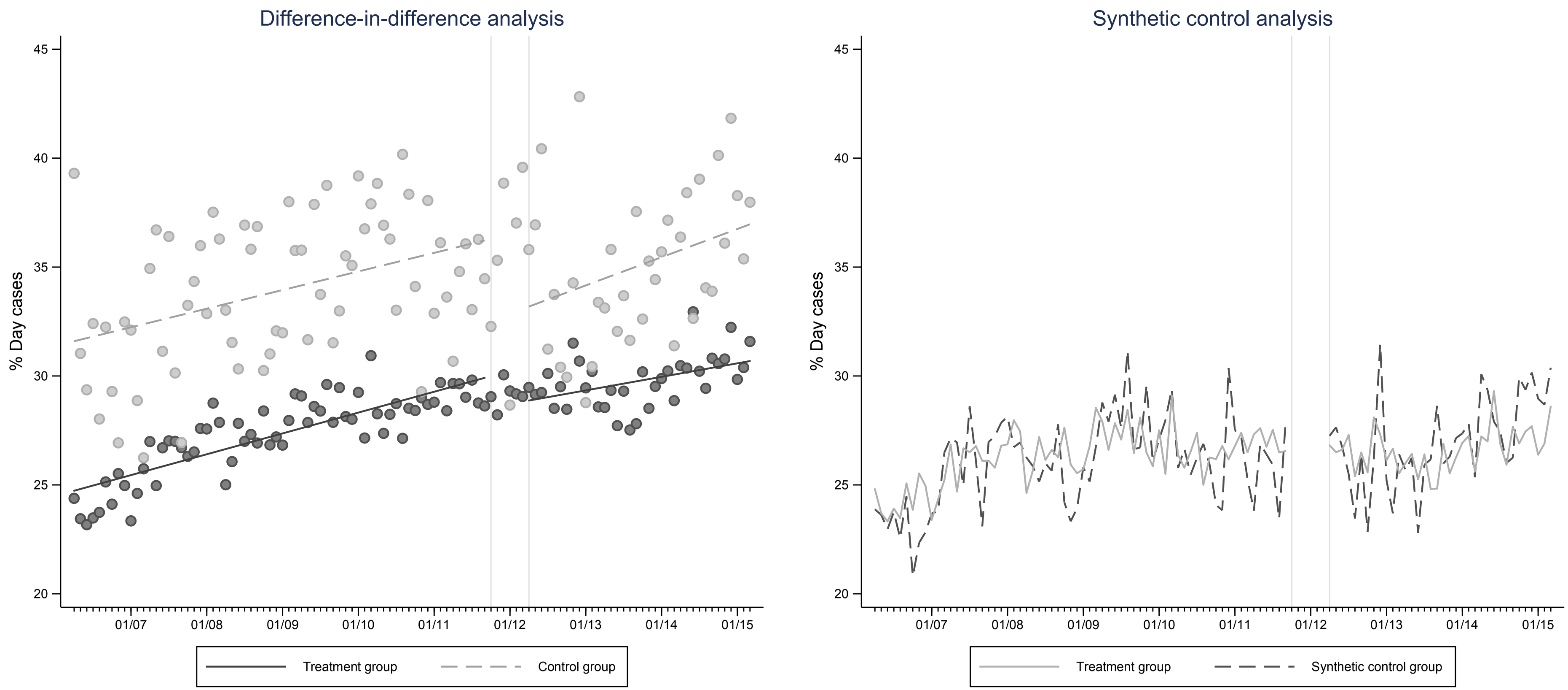



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*



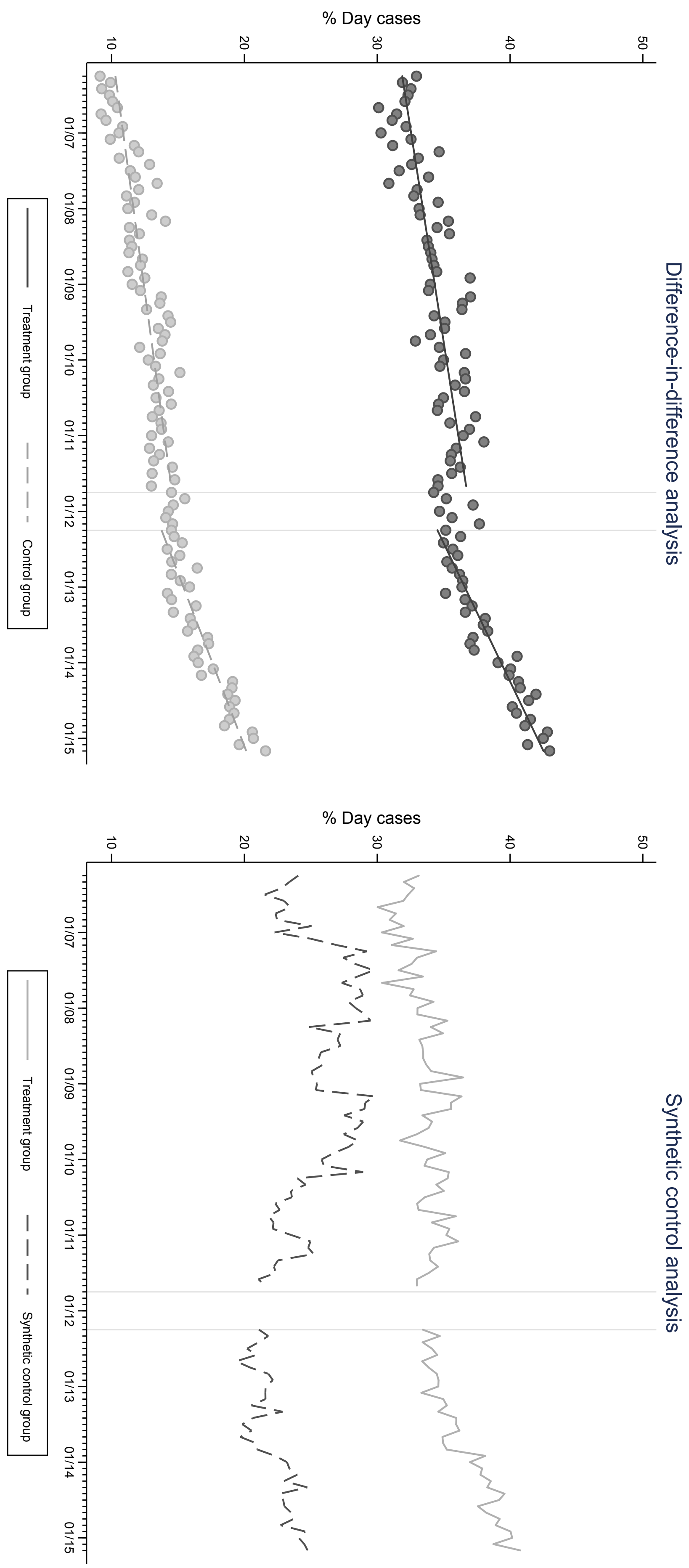

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

## BPT condition 14: Epilepsy



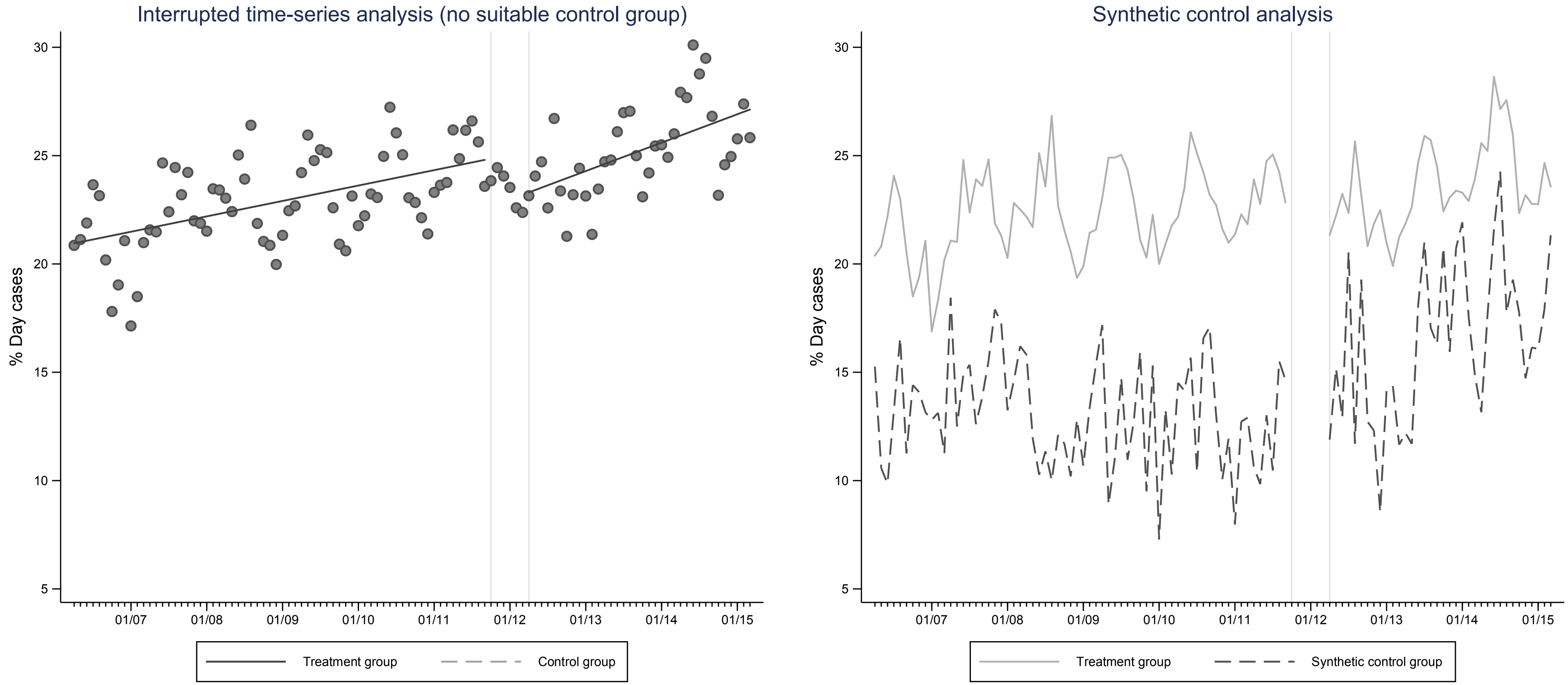

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

BPT condition 15: Acute headache



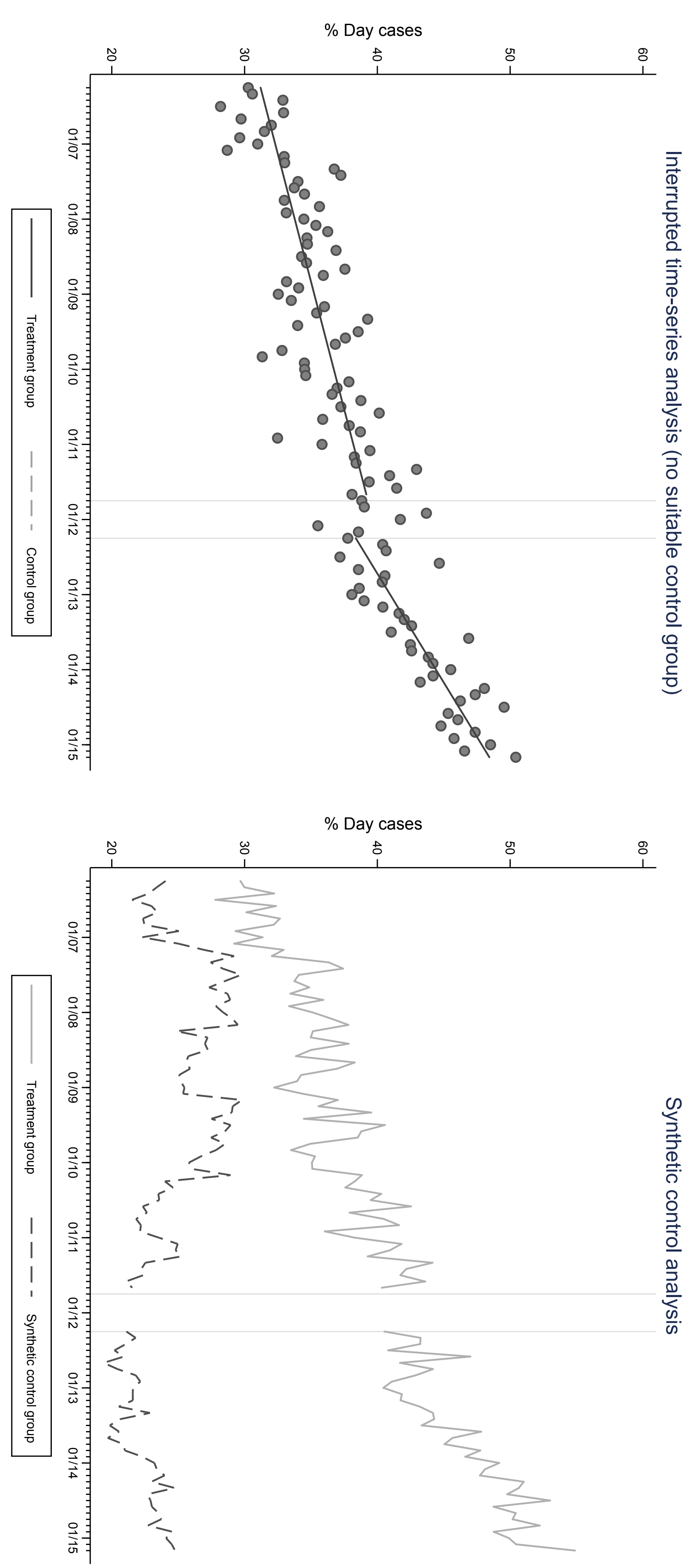

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

BPT condition 16: Asthma



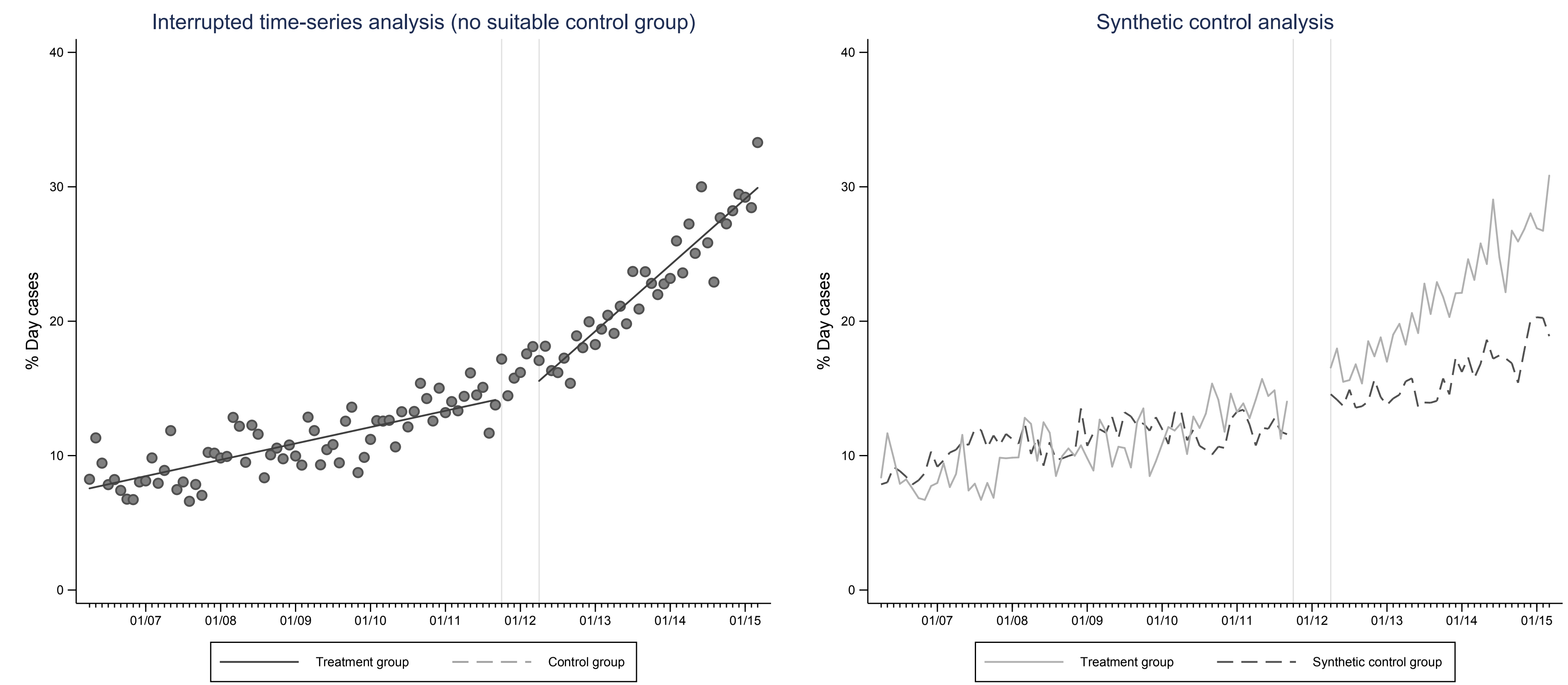

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

BPT condition 17: Respiratory

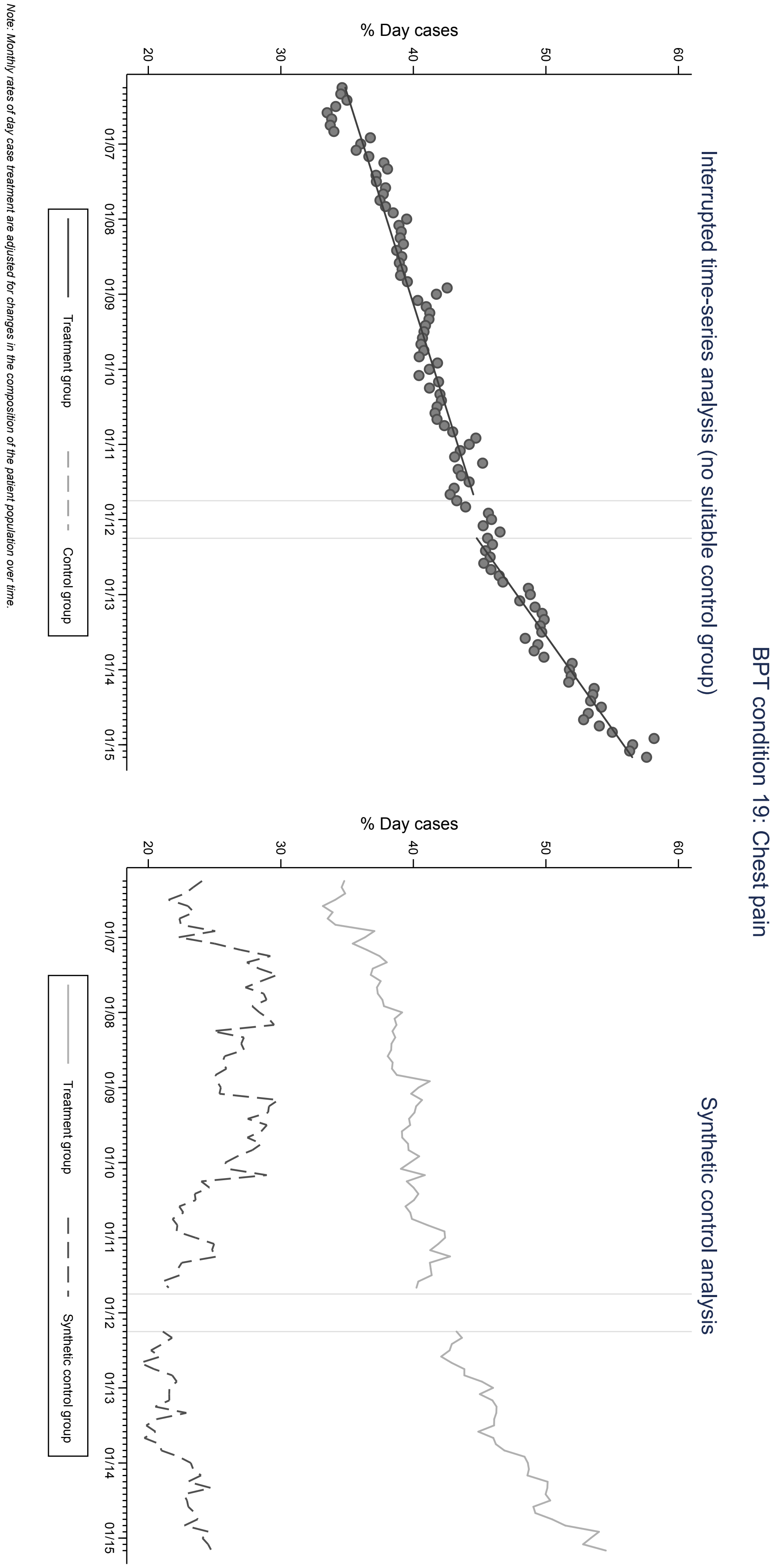



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

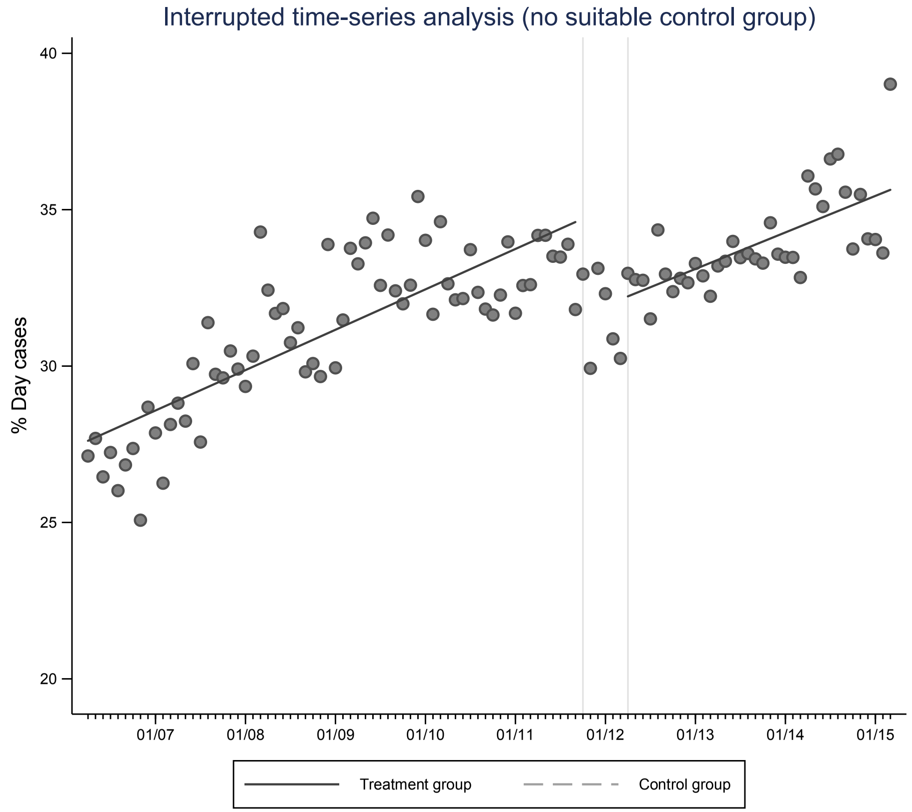
BPT condition 18: Pulmonary embolism

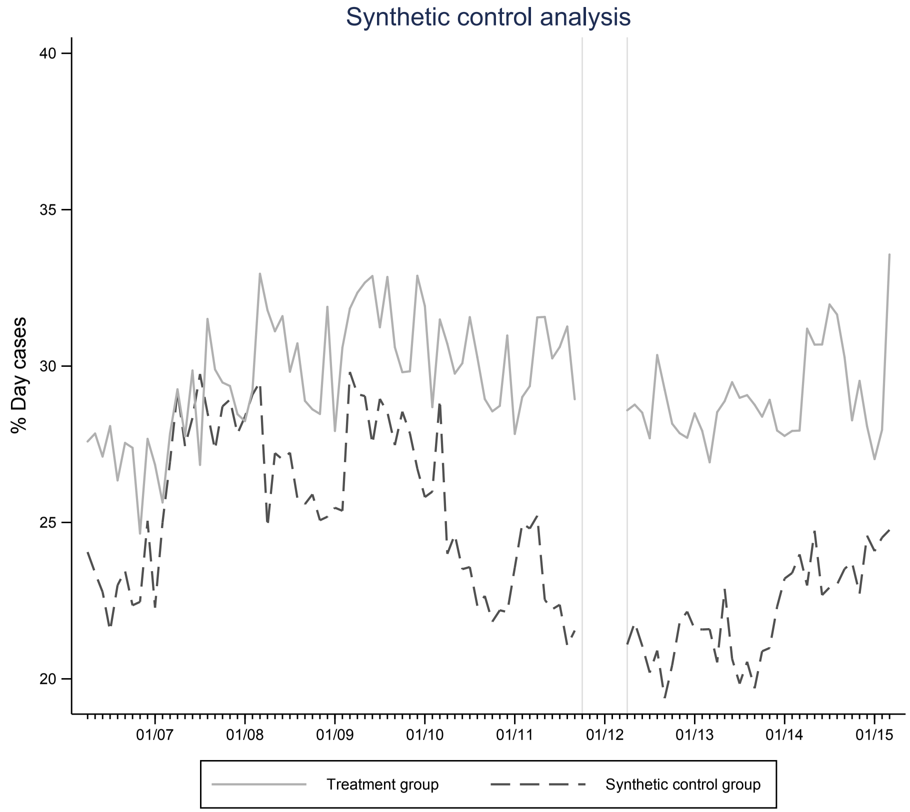



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

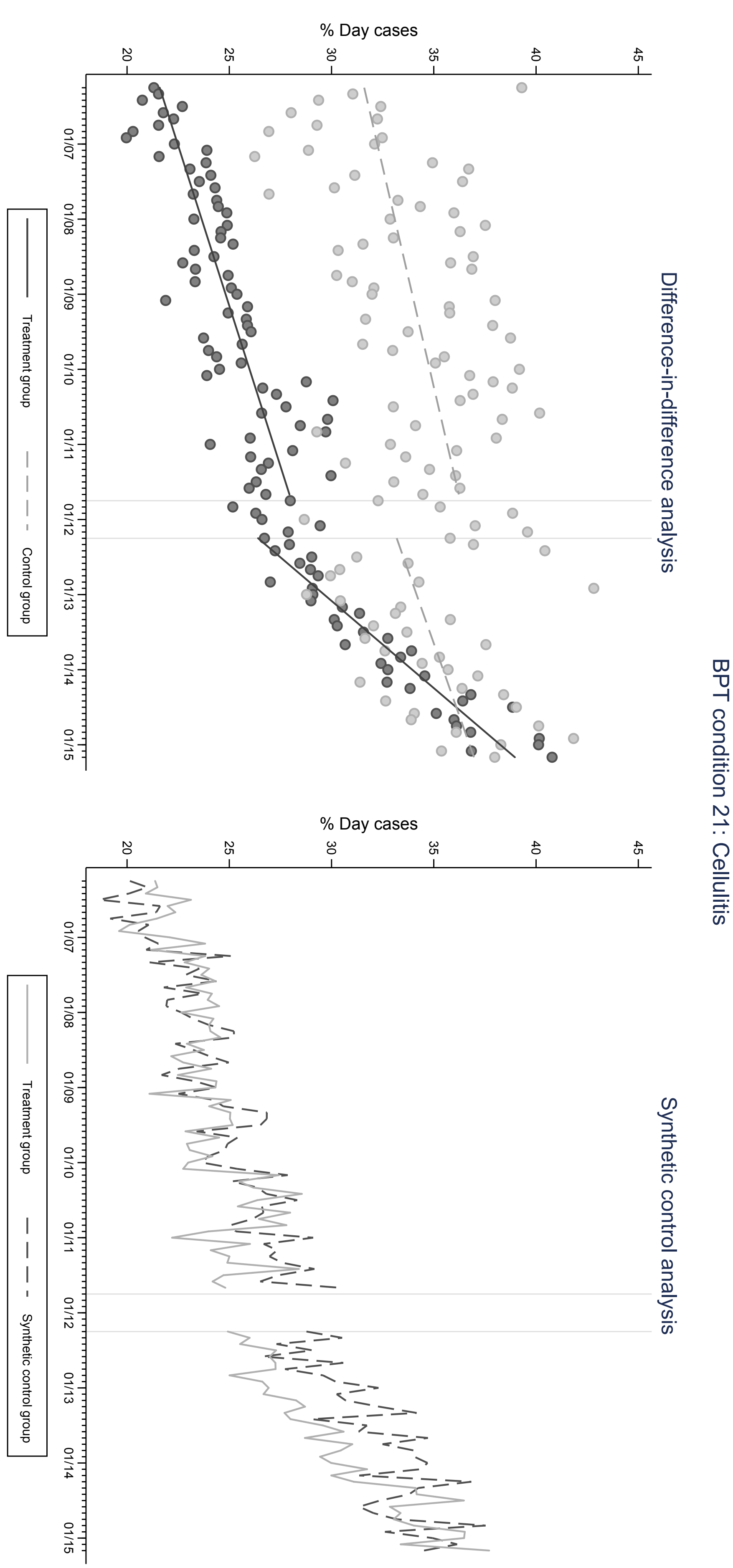

BPT condition 19: Chest pain
Interrupted time-series analysis (no suitable control group)
% Day cases
20
30
40
50
60
01/07
01/08
01/09
01/10
01/11
01/12
01/13
01/14
01/15
Treatment group
Control group
Synthetic control analysis
% Day cases
Treatment group
Synthetic control group
Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.

BPT condition 20: Appendicular



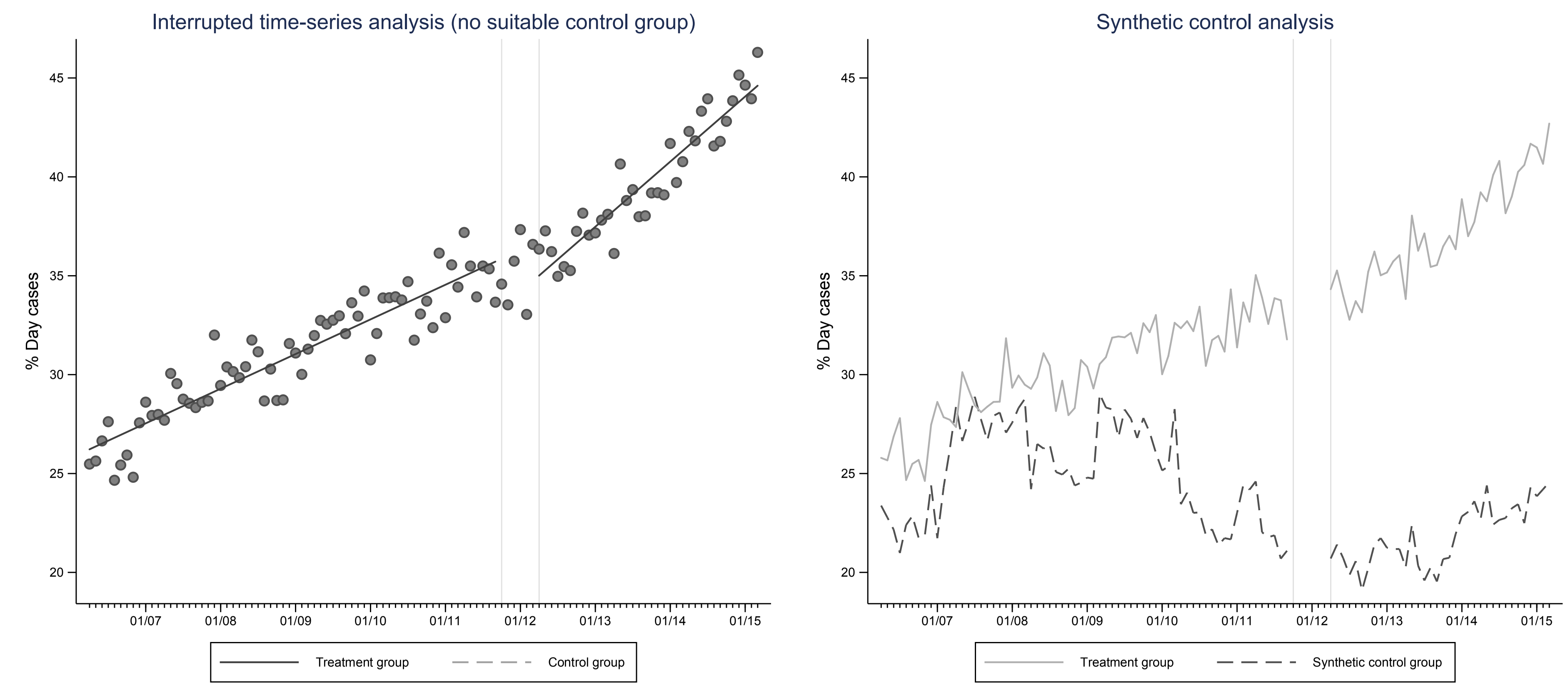




*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

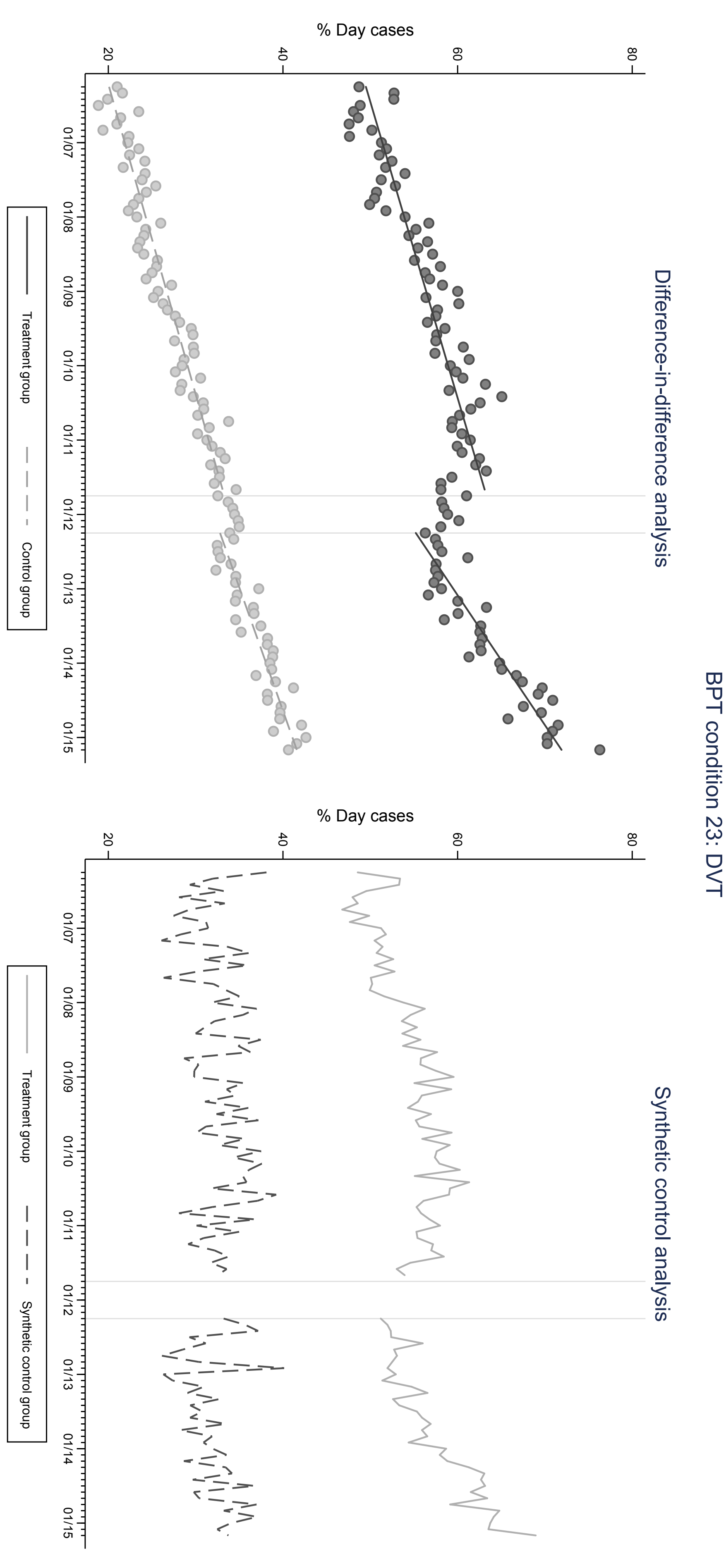



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

## BPT condition 22: Renal / ureteric stones

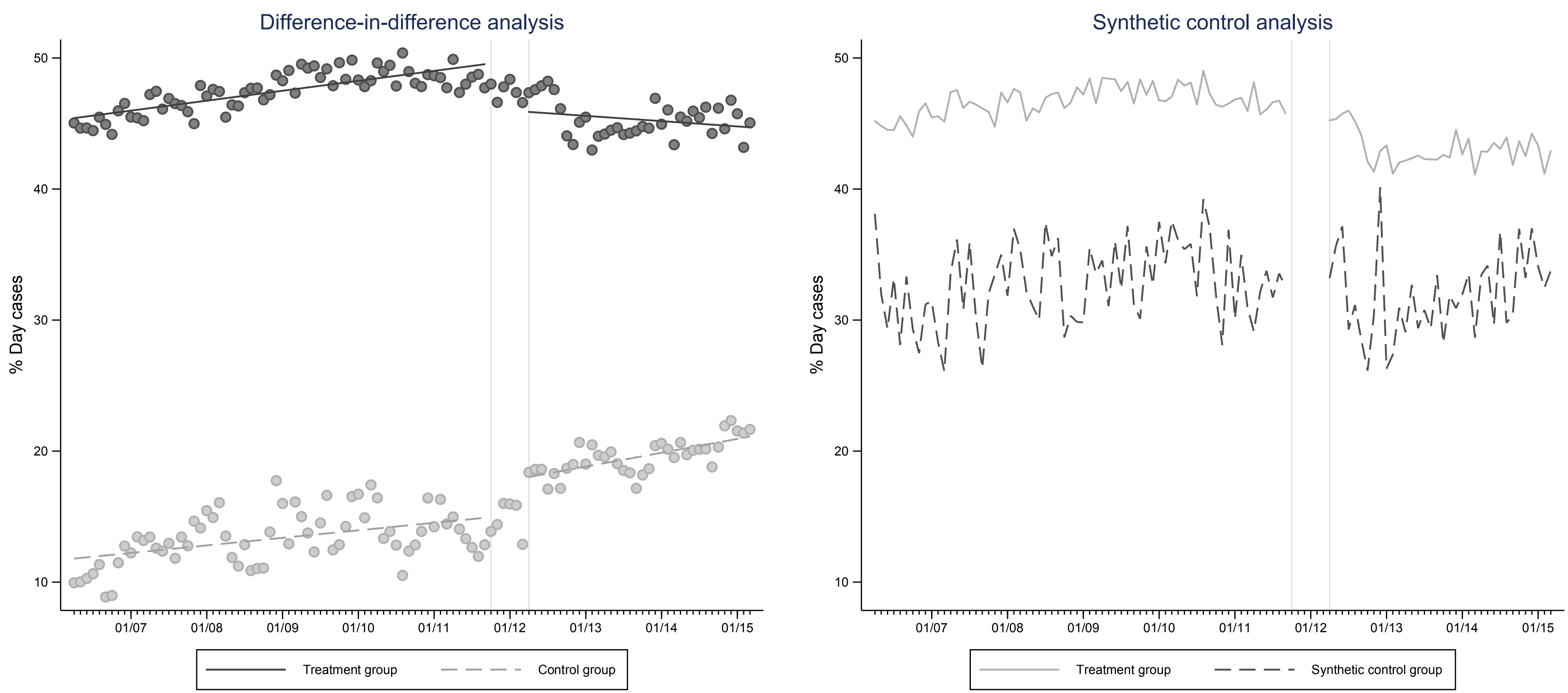



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*



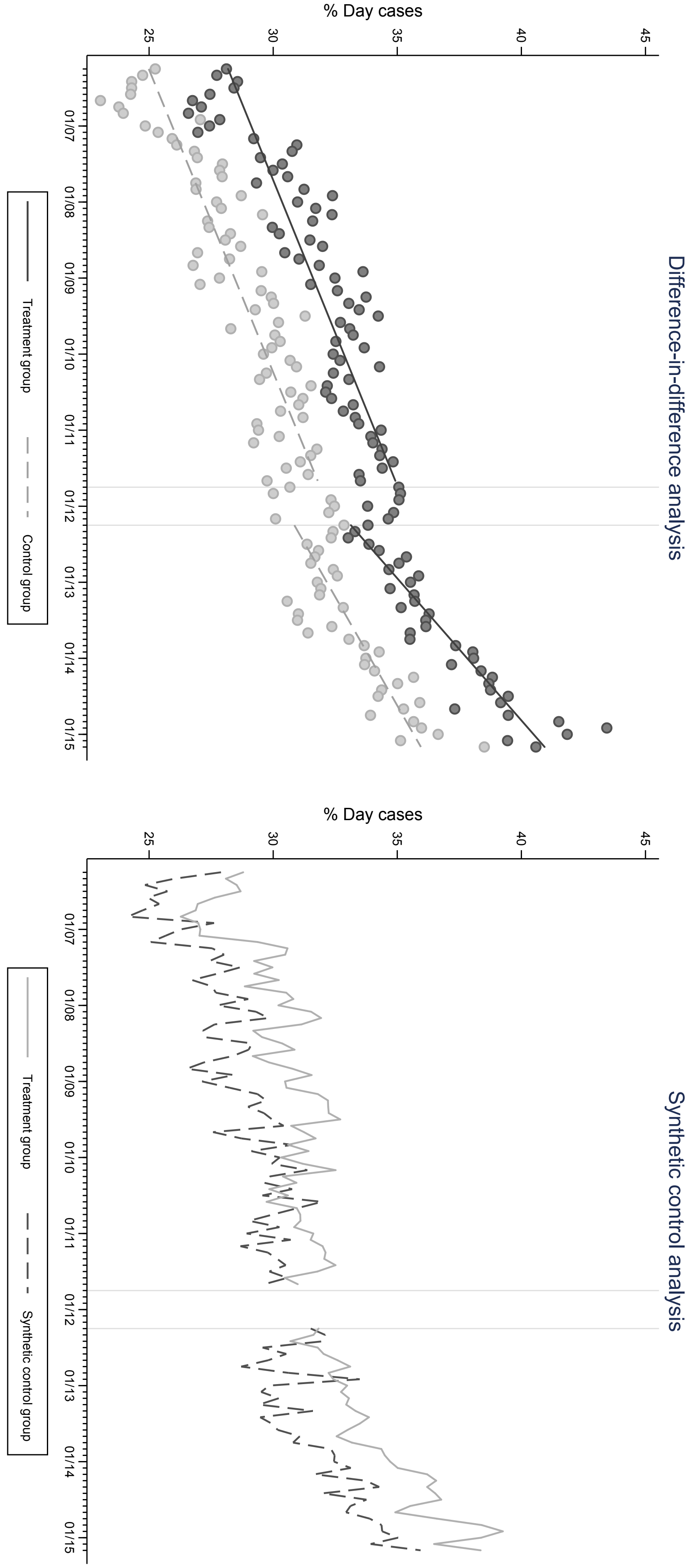

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

BPT condition 24: Self-harm



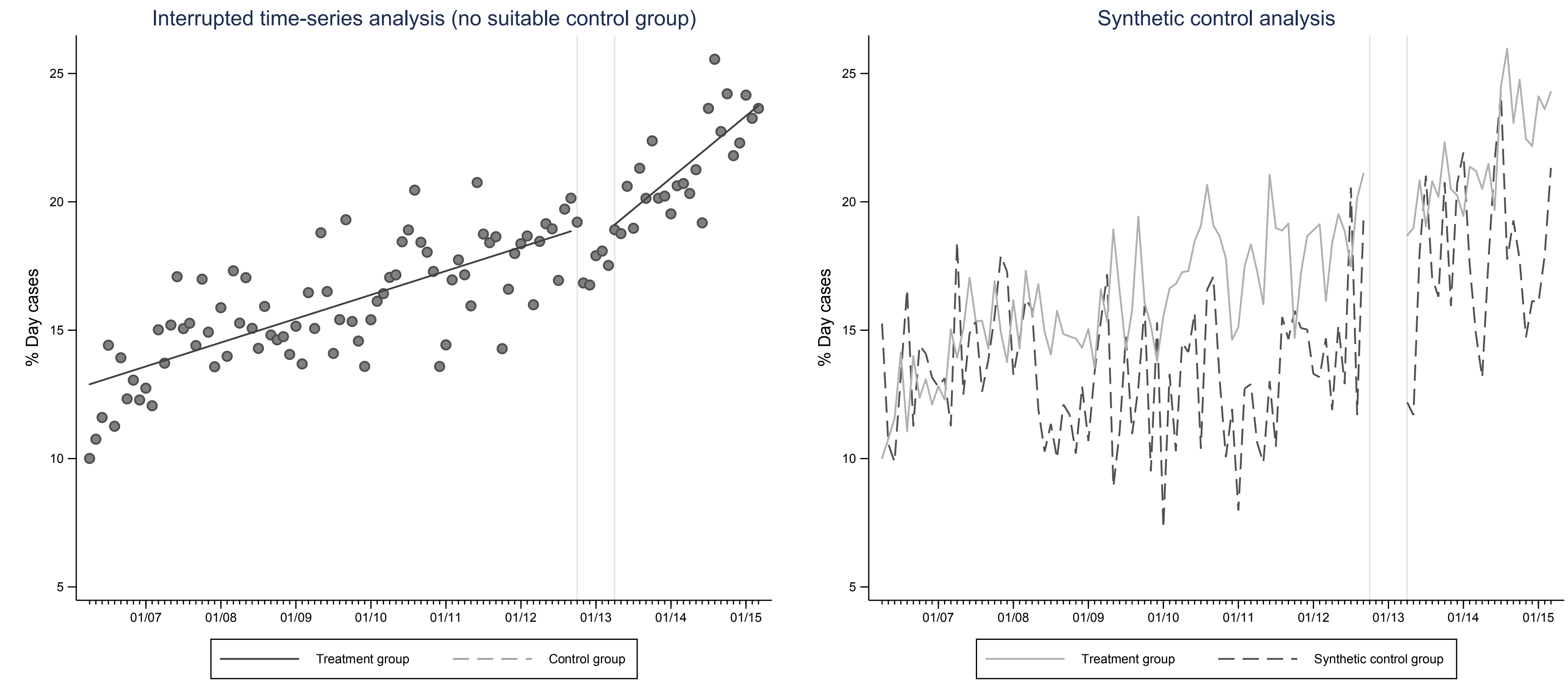

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

BPT condition 25: Falls



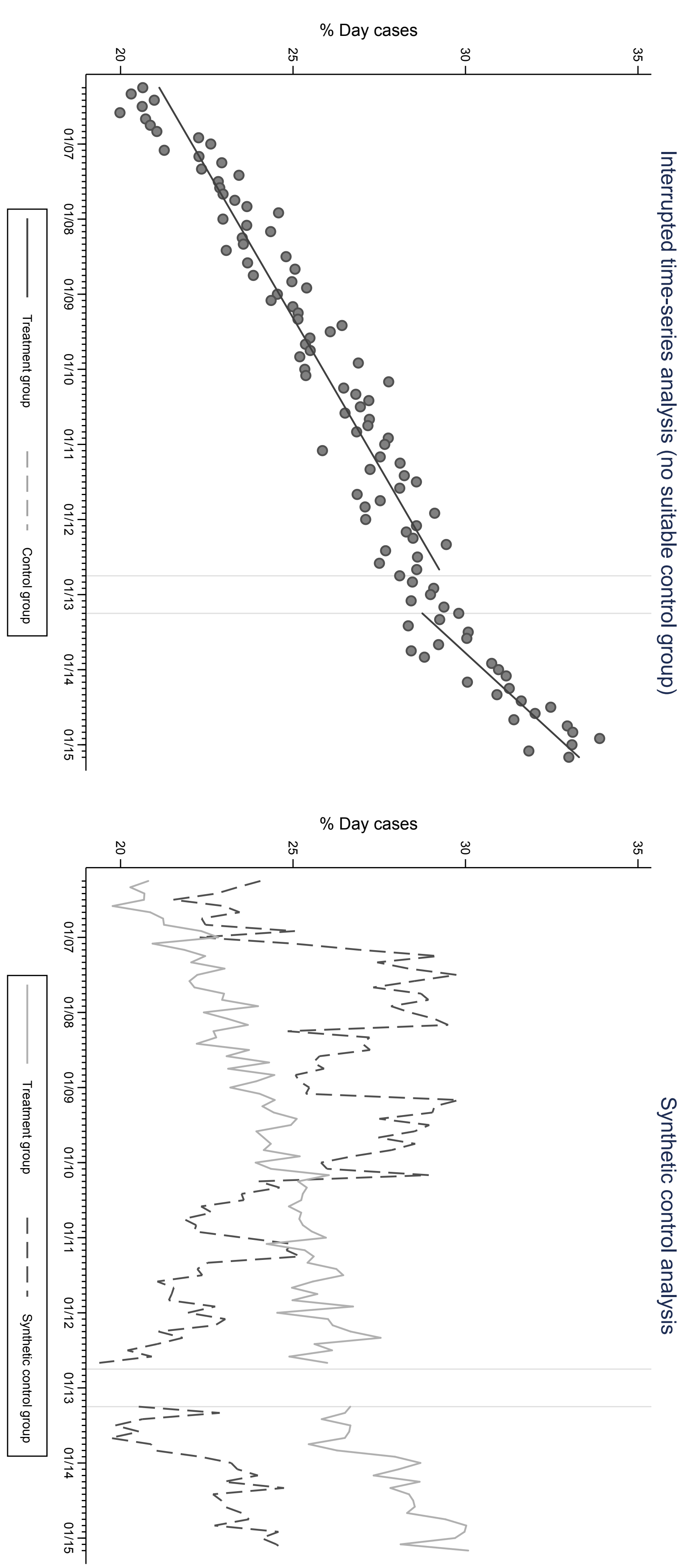

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

## BPT condition 26: Pneumonia



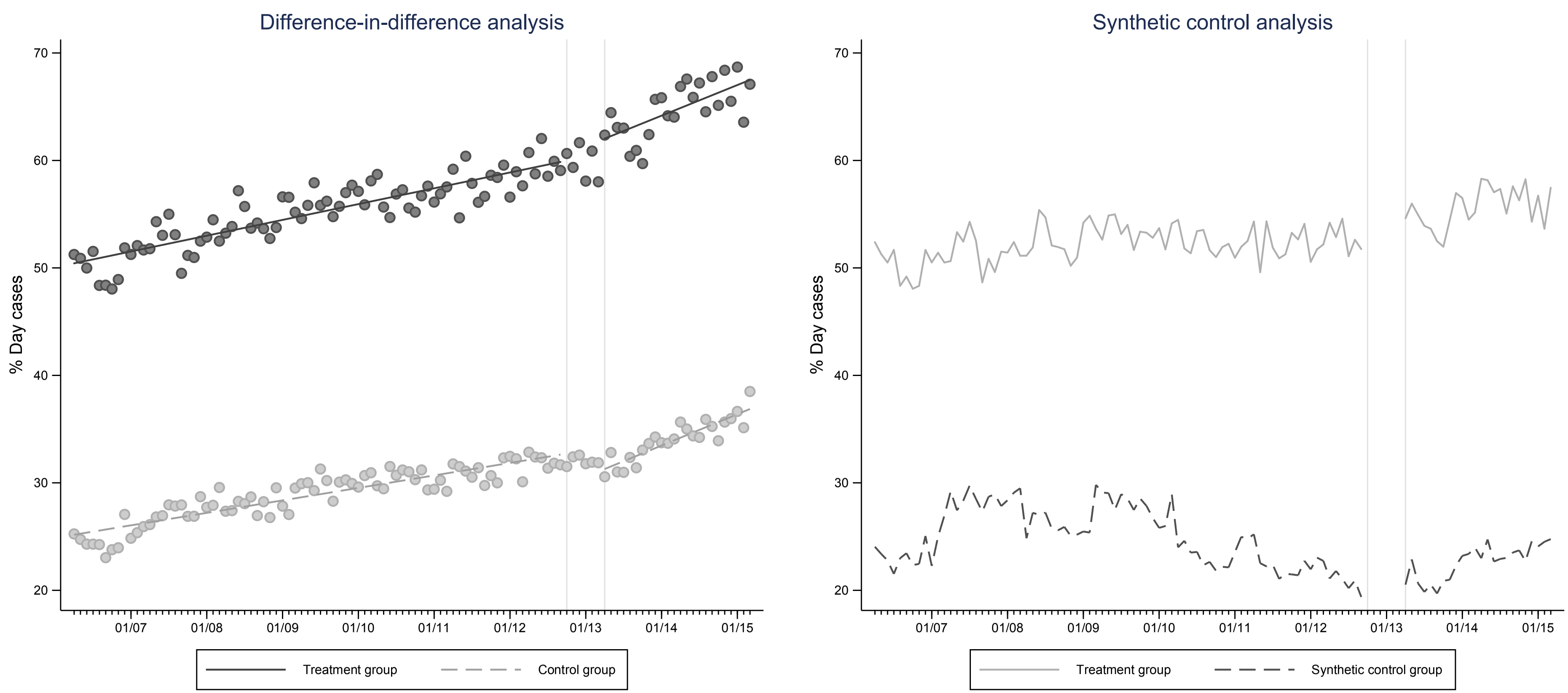

*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

BPT condition 27: Fibrillation

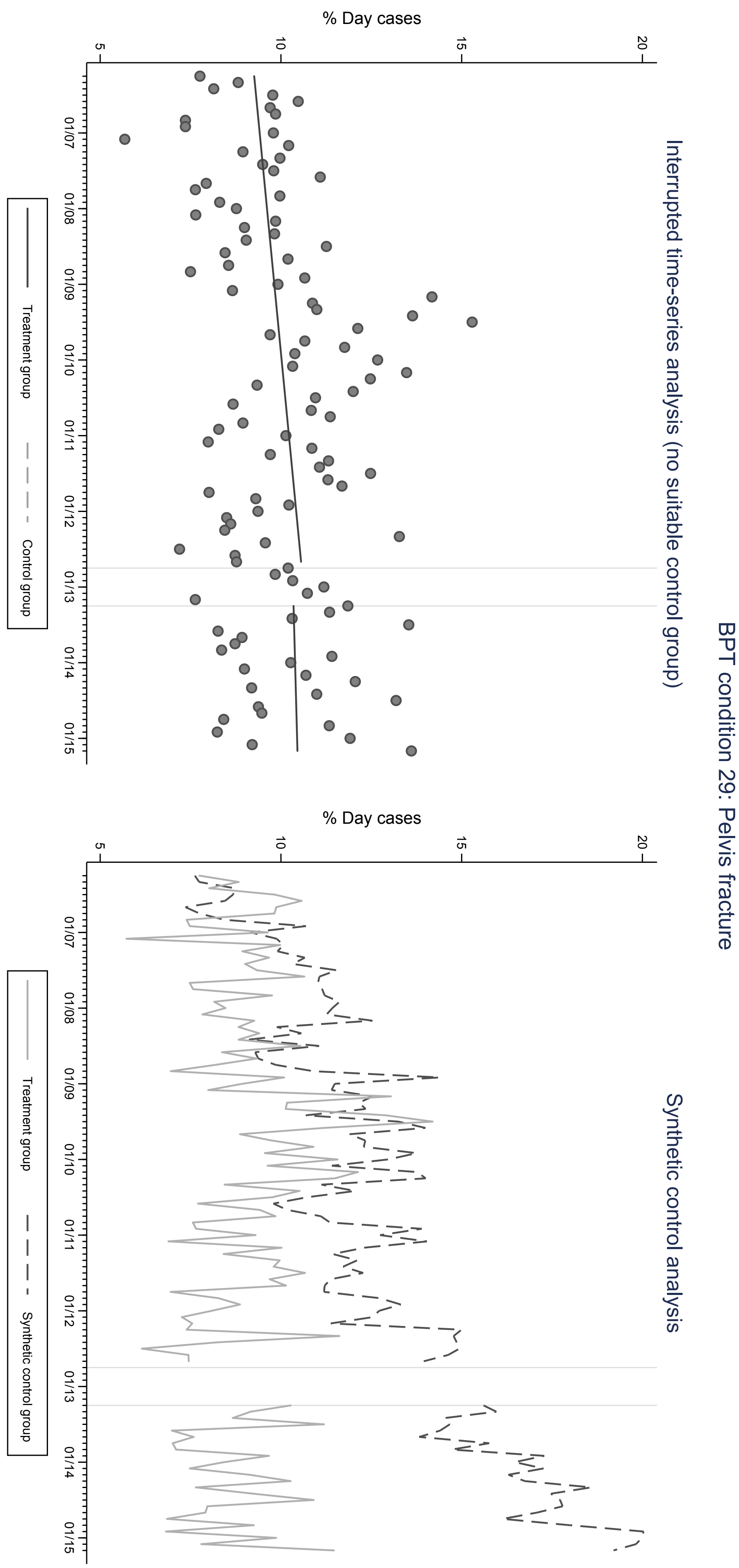



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

BPT condition 28: Head injury

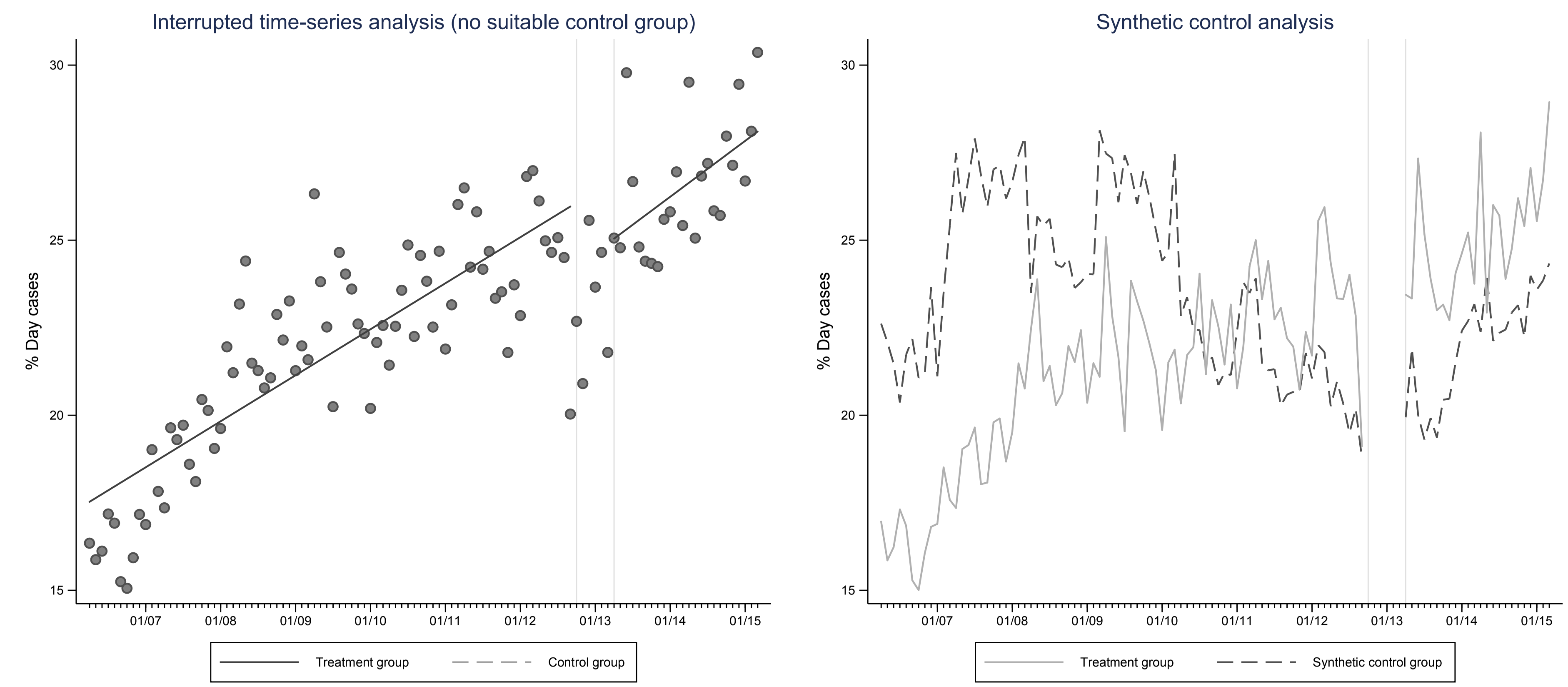



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

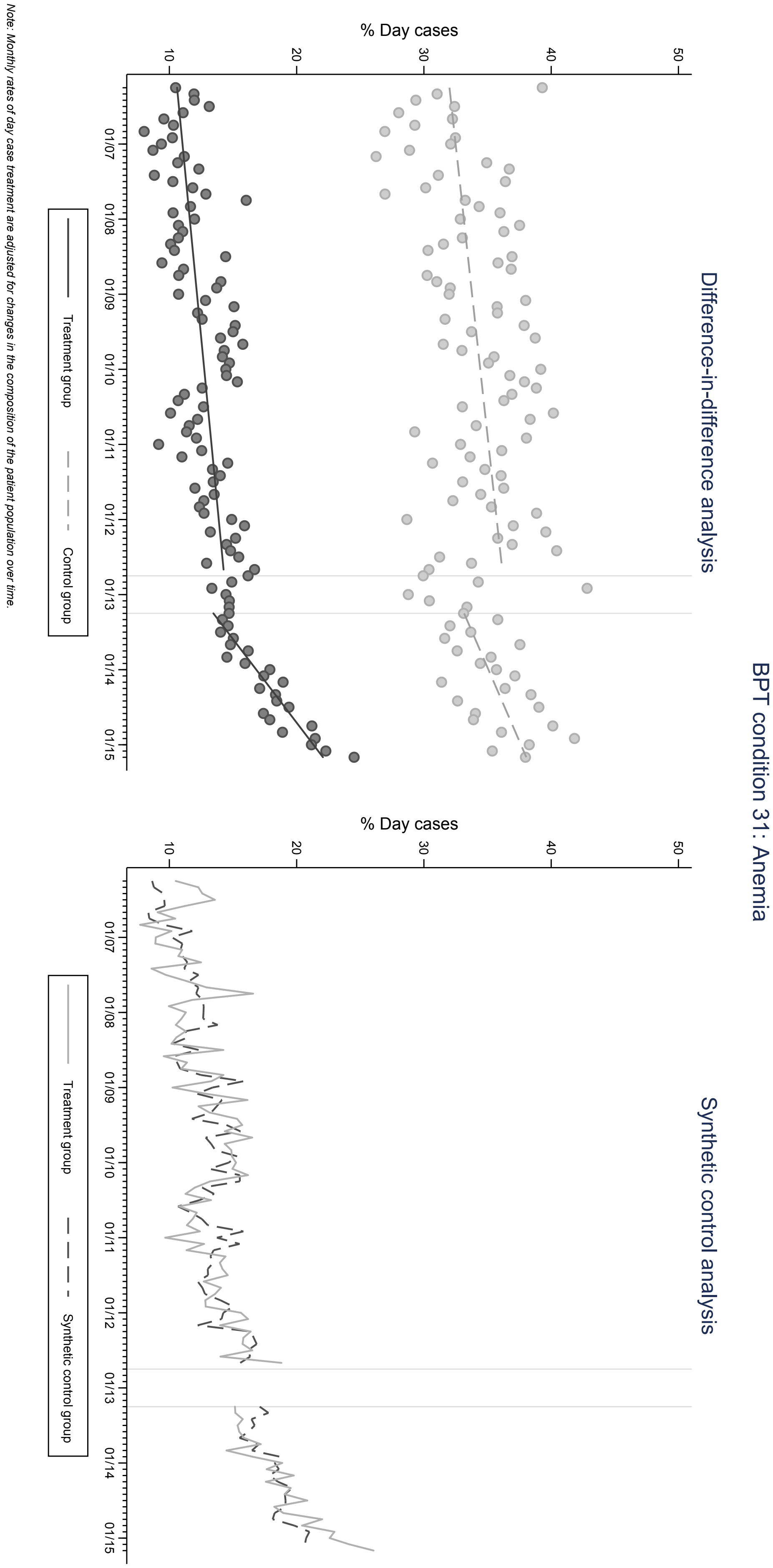



*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

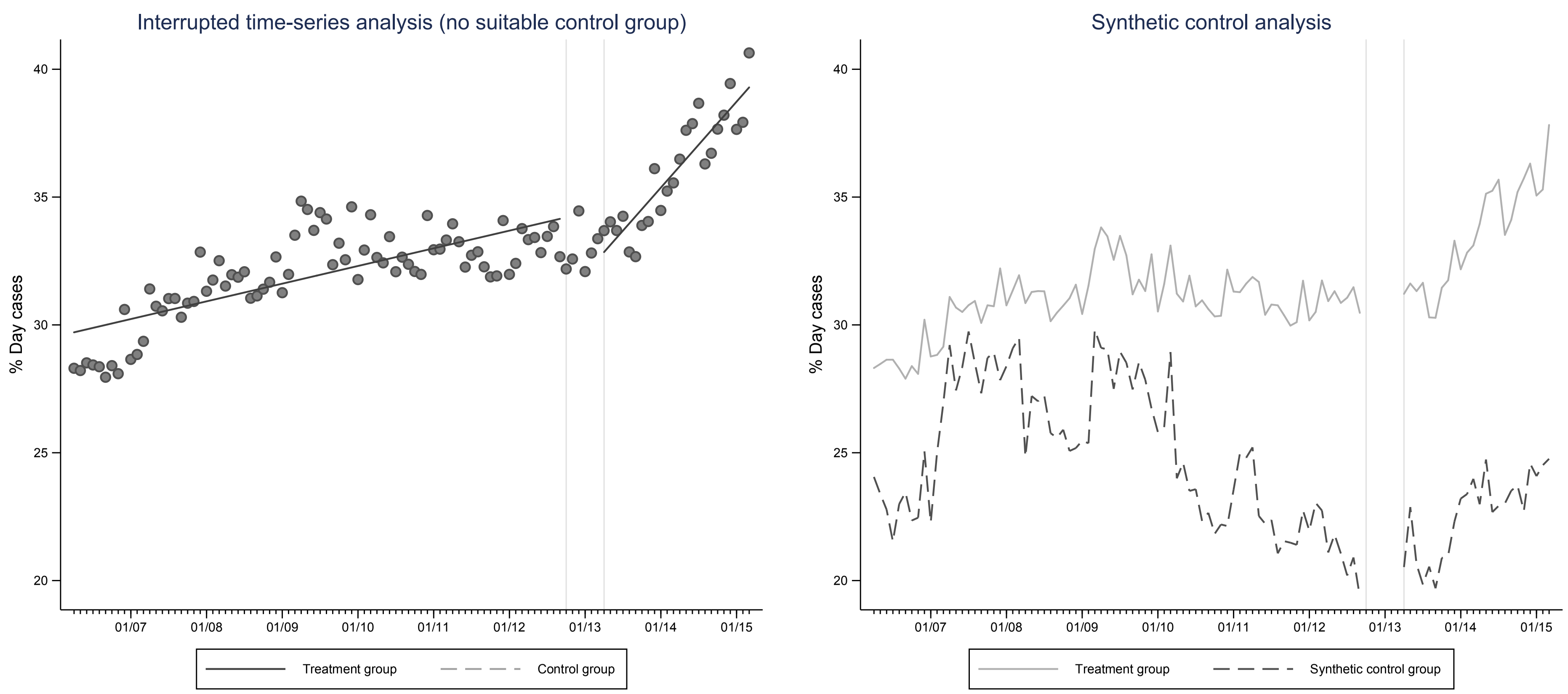
BPT condition 30: Bladder outflow




*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*


BPT condition 31: Anemia
Difference-in-difference analysis
% Day cases
10
20
30
40
50
01/07
01/08
01/09
01/10
01/11
01/12
01/13
01/14
01/15
Treatment group
Control group
Synthetic control analysis
% Day cases
10
20
30
40
50
01/07
01/08
01/09
01/10
01/11
01/12
01/13
01/14
01/15
Treatment group
Synthetic control group
Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.

BPT condition 32: Abdominal pain




*Note: Monthly rates of day case treatment are adjusted for changes in the composition of the patient population over time.*

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