

Dynamics in Quality of Care: The Case of Readmission Rates

By

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Declaration of Originality

I, Rocco Friebe, declare that this thesis is solely my own work written with the guidance of my thesis supervisors, Professor Paul Aylin and Doctor Katharina Hauck, and mentor, Doctor Adam Steventon. All other works are appropriately referenced and acknowledged. All stated views and conclusions are my own, and I bear full responsibility thereof.

Rocco Friebe

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In Erinnerung an die Brieskower, Günter und Manfred Schurade.

Abstract

The robust measurement of quality in healthcare is a pre-requisite for monitoring health system performance and is key in driving health system improvements. Despite the rise in process and outcome indicators, little agreement exists amongst health experts regarding the suitability of a single metric to measure quality in healthcare across multiple dimensions, such as safety, effectiveness and efficiency. However, over the past decade, hospital emergency readmission rates have developed into a prominent marker of healthcare quality, with an enhanced policy focus on reducing readmission to improve quality. Particularly, in England following the 2010 government white paper *Equity and Excellence: Liberating the NHS*, several policies were introduced, including financial penalties for hospitals with excess readmission rates, or funding transfers to social care services to reduce future hospital readmissions. Despite this effort to reduce readmission rates, little is known in the literature about the impact of this enhanced policy focus in England and thus, in this thesis, I examine the dynamics in quality of care based on changes in readmission rates. Following a review of the literature on the methodological consideration when using readmission rates as a measure for healthcare quality, I assess trends and variation in readmission rates across NHS Trusts between 2006 and 2016. Next, I validate the readmission metric against patient-reported outcome measures in hip and knee replacement patients in chapter 4. The final two substantive chapters present an impact evaluation of two English health policies on quality of care, one national-level payment reform (i.e. financial penalties for hospitals with excess readmission rates), and one area-level health system reorganisation (i.e. centralisation of stroke care in London).

Table of Contents

Declaration of Originality.....	2
Copyright Declaration.....	3
Acknowledgements	4
Abstract	6
List of Tables.....	11
List of Figures	13
List of Abbreviations	14
 Chapter 1 Introduction	 14
1.1 Prologue.....	16
1.2 Quality in the context of healthcare	19
1.3 The financial impact of poor quality in healthcare.....	21
1.4 Causes of errors in healthcare	22
1.5 Managing quality of care in the NHS.....	27
1.6 Measuring improvements in quality of care	29
1.7 The focus on readmission rates in the English NHS.....	31
1.8 Motivation for this thesis.....	33
1.9 Aims and contributions of this thesis	36
1.10 Contribution of the candidate to the thesis	39
1.11 Other important contributions	43
1.12 Structure of the remainder of this thesis	43
 Chapter 2 Literature review on the measurement of quality of care using readmission rates	 44
2.1 Introduction.....	44
2.2 Methods.....	50
2.2.1 Search strategies.....	50
2.2.2 Selection criteria	51
2.3 Results	53
2.3.1 Threat to validity	53
2.3.1.1 Link with other outcome measures	54

2.3.1.2	Adjustment for patient-characteristics	56
2.3.2	Data	58
2.3.2.1	Reliability of good coding practices.....	58
2.3.2.2	Accountability of cross-provider readmissions	60
2.3.2.3	Accuracy of data sources.....	61
2.3.3	Association of readmission rates with other indicators of quality	62
2.4	Conclusion	64

Chapter 3 National trends in emergency readmission rates: A longitudinal analysis of administrative data for England between 2006 and 2016

		68
3.1	Preamble to Chapter 3	68
3.2	Introduction	69
3.2	Methods	71
3.2.1	Study population	71
3.2.2.	Statistical analysis plan	74
3.3	Results	77
3.3.1	Study sample	77
3.3.2	Trends and variation in national emergency readmission rates for all NHS patients	79
3.3.3	Trends and variation in emergency readmission rates for patient subgroups.....	81
3.4	Discussion	89
3.4.1	Strengths and limitations.....	92
3.5	Conclusions	95

Chapter 4 The relationship between readmission rates and changes in patient-reported outcome measures

4.1	Preamble to chapter 4	97
4.2	Introduction	98
4.3	Methods	102
4.3.1	Study sample	102
4.3.2	Readmission rates.....	106
4.3.3	Patient-reported outcome measures.....	106
4.3.4	Risk-adjustment of patient-reported outcome measures	108

4.3.5	Statistical analysis.....	109
4.3.5	Approach to missing data and sensitivity analysis.....	110
4.4	Results	111
4.4.1	Index discharges	111
4.4.2	Trends in readmission rates and health gain	113
4.4.3	Panel data models.....	120
4.4.4	Sensitivity analyses	123
4.5	Discussion	128
4.5.1	Strength and limitations	129
4.6	Conclusion.....	131

Chapter 5	Do financial penalties reduce readmission rates? A continuous treatment effect evaluation.....	133
5.1	Preamble to chapter 5.....	133
5.2	Introduction.....	134
5.3	Setting financial penalty threshold.....	137
5.4	Data	140
5.4.1	Financial penalties	140
5.4.2	Study sample	141
5.4.3	Outcome measures	142
5.4.4	Study covariates	143
5.5	Econometric framework.....	146
5.5.1	Generalised Propensity Score.....	147
5.5.2	Diagnostic tests.....	148
5.5.3	Estimating the relationship between treatment levels and financial penalties	149
5.4.5	Subgroup and sensitivity analyses	150
5.5	Results	150
5.5.1	Study sample and patient characteristics.....	150
5.5.2	Outcome measures and study covariates.....	153
5.5.3	Generalised Propensity Score and diagnostic testing.....	153
5.5.4	Estimation of the relationship between treatment levels and financial penalties ...	161
5.5.5	Subgroups and sensitivity analyses	164
5.6	Discussion	173

Chapter 6	The impact of centralisation of stroke services in London on quality of care: Impact evaluation using two treatment groups	177
6.1	Preamble to chapter 6.....	177
6.2	Introduction.....	178
6.4	Data	183
6.5	Econometric framework.....	189
6.6	Results	192
6.6.1	Results from main model specification.....	199
6.6.2	Alternate specifications and sensitivity analysis	203
6.7	Discussion	211
6.7.1	Strengths and Limitations	213
6.8	Policy implications and Conclusions	214
Chapter 7	Conclusion	216
7.1	Summary of findings	218
7.1.1	Chapter 3	218
7.1.2	Chapter 4	219
7.1.3	Chapter 5	220
7.1.4	Chapter 6	221
7.2	Strength and limitations of the thesis	223
7.3	Policy implications	228
7.3.1	Chapter 3	228
7.3.2	Chapter 4	229
7.3.3	Chapter 5	230
7.3.4	Chapter 6	231
7.4	Future research.....	232
References		235
Appendix A:	Approvals for using my own work in this thesis.....	263

List of Tables

Table 1: Primary diagnosis codes (ICD-10 codes) and procedure codes (OPCS-4 codes) used for the identification of patients for subgroup analyses.....	73
Table 2: Summary statistics of all patients in the study sample by financial year.....	78
Table 3: Ordinary Least Squares regression analysis for readmission rates between 2006/07 and 2015/16	81
Table 4: Descriptive statistics of crude, 30-day readmission rates and SCV for selected patient subgroups	83
Table 5: Sensitivity analysis for 7-day and 90-day emergency readmission rates.....	88
Table 6: ICD-10 codes and OPCS-4 codes for hip replacements and knee replacements...	104-105
Table 7: Summary statistics of the study sample for each procedure and three financial years..	113
Table 8: Hausman model specification test for hip and knee replacements	121
Table 9: Unbalanced panel data analysis for the association between changes in readmission rates and PROMs	122
Table 10: Unbalanced panel data analysis for association between readmission rate and PROMs with adjustment for response rate	124
Table 11: Unbalanced panel data analysis for associations between readmission rates and PROMs while restricting sample to Trusts with minimum response rates of 60%	125
Table 12: Strictly balanced and unbalanced panel data model for association between readmission rates and PROMs.....	126
Table 13: Unbalanced panel data analysis for association between readmission rate and PROMs with adjustment for response rate and 6-month mortality rate	127
Table 14: Summary statistics of the study sample and for seven financial years.....	152
Table 15: Ordinary Least Squares regression output of the observed treatment level (financial penalties).....	154-155
Table 16: Balancing statistics showing differences in means and t-statistics across three groups based on distribution of the financial penalty variable	156-158
Table 17: Model output of the conditional expectation of the risk-adjusted, 30-day readmission rates in 2012/13, given the level of financial penalty and the estimated Generalised Propensity Score.	162
Table 18: Definitions of selected stroke processes and outcome measures	186
Table 19: Summary statistics for all London Trusts and Trusts in the rest of England, and London HASU Trusts and London non-HASU Trusts	187-188

Table 20: Panel data model using two treatment groups for London HASUs and London non-HASUs.....	200
Table 21: Fixed effect models versus random effect models (two treatment groups) for London HASUs and London non-HASUs.....	201
Table 22: Panel data model using random effects and replicating Morris et al. (2014).....	204
Table 23: Panel data model comparing London HASUs and London non-HASUs to Trusts in seven English metropolitan areas as control group	205
Table 24: Lead analysis testing for parallel trends in the pre-policy period	207
Table 25: Panel data analysis weighted for the average number of quarterly stroke admissions observed in quarter 1 to quarter 16.....	210

List of Figures

Figure 1. Flow chart depicting the article selection process of the literature review	53
Figure 2. Trends in risk-adjusted, 30-day emergency readmission rates and variation in England from 2006/07 to 2015/16.....	80
Figure 3. Trends in risk-adjusted, 30-day emergency readmission rates for indexed acute conditions, indexed chronic conditions, and surgical interventions, from 2006/07 to 2015/16.	85-87
Figure 4. Trends in risk-adjusted, 30-day emergency readmission rates following hip and knee replacements.....	114
Figure 5. Variation in change of risk-adjusted, 30-day readmission rate by trust.....	115
Figure 6. Trends in patient-reported outcome measures	117
Figure 7. Variation in change of health gains (EQ-5D, EQ-VAS, Oxford Hip Score and Oxford Knee Score) by Trust	118-1119
Figure 8. Distributions of financial penalties in 2012/13	141
Figure 9. Balancing statistics – plots of t-statistics across groups before and after GPS adjustment.....	159
Figure 10. Overlap of GPS distributions by tertiles of the treatment level (i) level 1; (ii) level 2; and (iii) level 3	160-1161
Figure 11. Main dose-response model relating different levels of financial penalties to risk-adjusted, 30-day readmission rates.....	163
Figure 12. Sensitivity analysis, comparing quadratic, cubic and quartic estimator	165
Figure 13. Subgroup analysis for risk-adjusted, 30-day readmission rates following (i) indexed emergency admissions and (ii) indexed elective admissions	166-167
Figure 14. Sensitivity analysis using risk-adjusted, 30-day readmission rates for the period of 1 st April 2011 to 28 th February 2013	169
Figure 15. Subgroup analyses for the risk-adjusted, 30-day readmission rate following indexed admissions for (i) acute myocardial infarction, (ii) heart failure, and (iii) pneumonia.....	170-172
Figure 16. Proportion of stroke admissions divided by London HASU Trusts and London non-HASU Trusts.....	193
Figure 17. Trends in stroke specific process and outcome measures weighted by the number of admission	195-198

List of Abbreviations

A&E	– Accident and Emergency
ACA	– Affordable Care Act
CI	– Confidence interval
CMS	– Centres for Medicaid and Medicare Services
COPD	– Chronic obstructive pulmonary disease
CT	– Computed tomography scan
DID	– Difference-in-difference
ER	– Expected Emergency Readmission Rate
EQ-5D	– EuroQuol five dimensions questionnaire
EQ-VAS	– EuroQuol visual analogue scales
GDP	– Gross Domestic Product
GP	– General Practitioner
GPS	– Generalised Propensity Score
HASU	– Hyper Acute Stroke Unit
HES	– Hospital Episode Statistics
HRRP	– Hospital Readmission Reduction Programme
HSCIC	– Health and Social Care Information Centre
ICD-10	– International Classification of Diseases version 10
IMD	– Index of Multiple Deprivations
IRDES	– Institute de recherché et documentation en economie de la santé
NAO	– National Audit Office
NHS	– National Health Service
NHSLA	– The National Health Services Litigation Authority
NQF	– National Quality Forum
OECD	– Organisation for Economic Co-operation and Development
OHS	– Oxford hip score
OKS	– Oxford knee score
OLS	– Ordinary Least Squares
ONS	– Office for National Statistics
OPCS-4	– Classification of Interventions and Procedures version 4
OR	– Observed Emergency Readmission Rate
PCT	– Primary Care Trust

PROMs – Patient reported outcome measures

QoF – Quality and Outcomes Framework

SAS – Analytical software package

SCV – Systematic component of variation

SES – Socio-economic status

STATA – Statistical software package created by StataCorp

Std. Dev. – Standard deviation

UK – United Kingdom

US – United States

WHO – World Health Organisation

Chapter 1 Introduction

1.1 Prologue

It is a priority across Organisations for Economic Co-operation and Development (OECD) countries to provide not only high quality healthcare, but also care that is tailored to patients' clinical needs, and delivered in the most efficient and effective manner (OECD, 2017). However, achieving these objectives and sustaining a high performing healthcare system has become increasingly difficult, particularly as most healthcare systems face a significant rise in multi-faceted pressures (Colombo *et al.*, 2011). These include public health issues, such as the rise in non-communicable diseases often linked to an ageing population and lifestyle choices (World Health Organisation or WHO, 2010). For example, in the United Kingdom (UK) the average life expectancy has risen from 47 years in 1901 to 81 years in 2017 (Public Health England, 2016), and life expectancy at birth is projected to increase further to 88 years by 2064 (Office for National Statistics or ONS, 2015). At the same time, the number of people living with long-term conditions and multi-morbidity that is associated with an increase in life expectancy has reached 15 million, and is projected to increase to 18 million by 2025 (House of Commons Health Committee, 2014). According to the same report, long-term conditions already present the single largest burden for health services, with 55% of all General Practitioner (GP) visits and 77% of all in-patient bed days linked to the treatment of people with long-term conditions, and demand is expected to rise in the future. On the supply side, healthcare systems experience rises in health labour costs (National Audit Office or NAO, 2016), and rising costs associated with new medical technology, including pharmaceutical products (Health & Social Care Information

Centre, 2015). These pressures are representative of healthcare systems across all OECD countries (OECD, 2013).

While healthcare demand and healthcare spending have been increasing dramatically over the past decades, the average real-term spending per capita in OECD countries have risen by 1.4%, from an average 7.8% in 2000 to an average 9.3% in 2011 (OECD, 2015). However, significant variation in spending on healthcare exists between OECD countries; for example, in 2011, Turkey spent 5.1% of their Gross Domestic Product (GDP) on healthcare in comparison to the 16.4% spent by the United States (US). However, caution is warranted with regards to inferences between GDP spent and the quality of healthcare. Despite being one of the most expensive healthcare systems in the world, healthcare provision in the US is often referred to as inefficient and subject to high variation in quality across geographies and patient groups (Garber and Skinner, 2009). On the other hand, a recent Commonwealth Fund report highlighted that the UK healthcare system performed consistently well (within the top percentile) across several quality of care domains, such as care co-ordination, safety and patient centeredness (Davis *et al.*, 2014), even though healthcare expenditure decreased to one of the lowest levels in European comparisons.

Healthcare expenditure, as a share of GDP, decreased across many countries with the beginning of the global financial crisis in 2009. The greatest reductions were observed for healthcare systems in countries hit the hardest by the financial crises, including Greece (-7.2%), Portugal (-3.3%) and Italy (-1.6%) (OECD, 2015). Similarly, in the UK, real-term expenditure as a share of GDP decreased by 1.6%, from 8.9% in 2009 to 7.3% in 2014. This decline is projected to continue, reaching an expected real-term expenditure of 6.6% as a share of GDP by 2020. By 2021, this decrease in expenditure in

combination with a rise in demand, is expected to lead to a funding gap of £30 billion annually (Monitor, 2015¹).

A lack in future funding that matches projected increases in demand was highlighted as a major concern for the long-term sustainability of the National Health Service (NHS; House of Lords, 2016). Despite average efficiency gains of 0.4% per year and increases in NHS productivity (Lafond, Charlesworth and Roberts, 2015), critics argue that such rises will not compensate for the future gaps resulting from decreased funding (The Health Foundation, 2014). In fact, health experts have warned that as a potential consequence, quality of healthcare may deteriorate, adversely affecting patients accessing the English NHS (NAO, 2016).

Based on these multi-faceted pressures, policy-makers in the NHS are required to consistently innovate and initiate improvements at the local and national levels, through processes that aim at achieving the provision of high quality care, given a fixed and government-controlled healthcare budget. Such processes are two-fold: first, at the higher level, assessing the structure of the healthcare system and whether service provision operates at levels of allocative efficiency (*e.g.* through healthcare service re-designs), and second, at the lower level, assessing whether individual processes operate at levels of optimum technical efficiency (*e.g.* through incentives, penalties, monitoring and regulations). Arguably, both sets of processes are required to happen simultaneously, with complex interventions being evaluated, and the results from these evaluations fed directly into quality improvement initiatives to achieve best possible outcomes. Moreover, to understand the ways in which high quality care can be achieved and sustained in the long run, quality in the context of healthcare needs to be defined, the

¹ Monitor is a regulatory body of the NHS

development of measuring quality of care in the NHS has to be recognised, and challenges in improving quality within the context of the NHS need to be understood.

1.2 Quality in the context of healthcare

The Oxford Dictionary (2017) defines quality as “*the degree of excellence of something*”, highlighting that quality is subject to interpretation and depends heavily on its embedded context. For example, within the automotive industry, quality can describe the actual or perceived merits of a car in comparison to a similar car produced by other manufacturers. In this instance the actual merits may refer to the physical outcome, *i.e.* lower variation in quality, which can be achieved through, for instance, the automation of processes, whereas the perceived merits may relate to the consumer experience. A lack of quality in either of those two domains can quickly result in a reduction of demand, as customers shift their buying preferences to other manufacturers that provide better quality products.

Healthcare differs from classic competitive markets – a market where the majority of people are entering the system involuntarily at a stage where they are at their most vulnerable. As highlighted by Kenneth J. Arrow (1963), factors that distinguish the healthcare market from other economies include asymmetric information that can lead to principal-agent problems, market entry barriers, uncertainty, the need for government intervention and externalities. However, despite these fundamental differences compared to other markets, the WHO’s health system responsiveness framework highlights that healthcare systems operate on a similar principle – namely, to meet the population’s, or consumers’ expectations (Darby *et al.*, 2003).

As such, policy-makers in England introduced two policy initiatives to promote competition between suppliers of healthcare to subsequently improve healthcare quality; the internal market between 1991 and 1999, allowing for price negotiations between hospitals and buyers, and the introduction of a market-based competition system under the newly elected Labour government in the 2000s. While the former policy resulted in a reduction in prices and quality measured through mortality in heart attack patients, but reductions in waiting times (Propper, Burgess and Gossage, 2008), evidence on the impact of the latter policy showed decreases in mortality, with greatest reductions observed in areas with high provider competition (Cooper *et al.*, 2011; Gaynor and Town, 2011). While the referenced studies investigated the effect of competition on mortality as a quality outcome indicator, many definitions for quality in healthcare exist, challenging the generalisability of such impact evaluations on inferring effects on healthcare quality as a whole.

The most widely referred to definition of quality in healthcare was published by the Institute of Medicine (2001), and acknowledged in a key report on quality of care published by the WHO (2006). Based on this, quality in healthcare is a top-level description of a framework containing six domains. Each domain reflects on a distinct area of health system performance and patient care, yet combined, the framework can guide policy-makers in the selection of targeted interventions and strategies for improving quality within any healthcare system. The six domains include:

1. **Safe** – minimising the risk of harming patients through the delivery of healthcare that is intended to help them;
2. **Effective** – service provision that uses evidence based clinical practices;

3. **Patient-centred** – providing health services that are tailored to each individual patients' need, requirements and preferences and ensuring that clinical decisions are guided by patient values;
4. **Timely** – avoiding delays within the care pathway that could result into adverse events for the patient;
5. **Efficient** – using resources (equipment, supplies and energy) in a way that avoids waste; and,
6. **Equitable** – providing health services that are not subject to quality variation due to patient characteristics or geographic locations.

1.3 The financial impact of poor quality in healthcare

A lack of quality in healthcare can have potentially catastrophic and life-changing consequences for patients, families and the wider society. However, errors occur frequently during day-to-day healthcare practices, whether detected or undetected, consequential or inconsequential, and they have been recorded for more than a century. Amongst many terrible impacts on patients, such as causing disability or mortality, poor quality of care may also result in direct monetary losses for the healthcare system. To this effect, negligence has been a popular term, frequently covered by the national media over the years. And indeed, data from the NHS Litigation Authority (NHSLA) reflects that while activity in the NHS increased by more than 26% during the past nine years, the reporting of harmful incidents (moderate, severe or fatal) increased by more than 410% (NHSLA, 2014). The same report also showed that the total claim value rose by approximately £1.102 billion, from £354.1 million in the financial year 2004/05 to £1.456 billion in the financial year 2014/15. Even though these numbers could suggest a

worsening of quality of care in the NHS, interpretations of rises are ambiguous, with increases possibly resulting from improved reporting practices (Chacko, 2009), but may also be representative of the higher likelihood for submitting claims due to a cultural shift within the legal profession through the offering of ‘*no win, no fee*’ legal services. According to the NHS LA (2012), most claims were related to clinical negligence, with the clinical speciality of Obstetrics reporting the highest value of claims and the second highest number of claims. Total pay-outs accounted for £1.04 billion in 2014/15, a significant increase by £393 million from £651 million in 2009/10. Similarly, compensation for non-clinical claims such as falls in an NHS facility, increased by £7.2 million, from £34 million in 2009/10 to £41.2 million in 2014/15. Negligence claims are potentially avoidable, and could save an equivalent of up to 1.22% of the NHS’ annual budget (reference NHS budget of £116.4 billion in financial year 2015/16). However, due to the hazardous hospital environment, every admission to a hospital as well as every extra day spent in hospital increases the risk of incurring an adverse event (Hauck and Zhao, 2011). Thus, by introducing initiatives that improve quality of care, costs may be redeemed by reducing unnecessary secondary care admissions, duplications, and readmissions, subsequently leaving less room for errors.

1.4 Causes of errors in healthcare

A report published by the Institute of Medicine, *To Err Is Human* (Kohn, Corrigan and Donaldson, 2000), put patient safety under the spotlight, and concluded that in the US, more people die per year due to medical errors in hospitals than from car accidents, breast cancer, or AIDS combined. However, unlike car accidents, patients who receive treatment in hospitals are often complex in nature, which includes the existence

of underlying health conditions, or comorbidities, which might affect the outcome and effectiveness of the treatment. Thus, some “errors” may be unavoidable given the high patient complexity, and not directly related to poor quality of care.

Since the publication of *To Err Is Human*, researchers have focussed increasingly on disentangling the factors that are leading to errors in healthcare, and while several opinions exist within the literature, it is widely believed that they fall within three broad categories: **human failure**, **health system failure**, and a **combination of both** (Carayon and Wood, 2010).

Human failure: The foundation of any healthcare system is its staff (Horne, Khan and Corrigan, 2013), and it is likely for errors to occur at any given point simply due to human nature. In most cases, errors resulting in adverse outcomes happen unintentionally, but either because of the high risk carried by healthcare procedures (Neale, Woloshynowych and Vincent, 2001), or because of not following or not being aware of best practice (Weinger *et al.*, 2003). A recent qualitative study by Bari *et al.*, (2016) stated that every medical professional has made mistakes during the course of their career, potentially leading to patient safety concerns and compromised quality of care. It is assumed that due to a lack of experience and still remaining in training, residence and junior doctors have a particularly high risk of committing medical errors. For example, a study by Jen *et al.* (2009) compared mortality rates in England and found that patients had a higher risk of dying on days when newly qualified doctors started their first shift after reaching their qualification. Similarly, researchers have found evidence to suggest that patients treated in hospital during the weekend are more likely to die due to the provision of poorer services (Palmer, Bottle and Aylin, 2015), while others attributed this to patient complexity and case-mix (Meacock *et al.*, 2016). While medical errors can impact adversely on the patient, studies have also highlighted that it is important not to

discount the effect that errors might have on young doctors (Mankaka, Waeber and Gachoud, 2014), particularly in terms of psychological distress (Wears and Wu, 2002; Waterman *et al.*, 2007) and their future behaviours in dealing with errors and reporting them (Wu *et al.*, 2003).

Despite an increase in awareness about medical errors caused by staff, it is believed that in the majority of instances, medical errors remain undisclosed, which in part, is driven by a culture of shame and an associated fear of reporting negligence (Wami *et al.*, 2016). While most information on medical errors was derived from reporting databases, such as the National Reporting and Learning System in the NHS, it is unsurprising that in fact, the real number of patient safety incidences is considered to be much higher than currently stated.

Example of a human failure

In February 2008, Dr Urbani, a qualified doctor from Germany who provided out-of-hour services in the English NHS, administered a fatal dose of an opioid painkiller to David Gray. An investigation into the death of David Gray concluded that he was unlawfully killed, with one of the main reasons for the error being the limited English language skills of Dr Urbani and a resulting misunderstanding. He was subsequently trailed for clinical negligence in Germany and received a suspended jail sentence (Care Quality Commission, 2010).

Health system failure: Errors can also occur because of the way in which the healthcare system is designed, which for instance, includes capacity constraints (Carayon and Wood, 2010), or an inefficient service organisation (McKay and Deily, 2008).

Example of a health system failure

One example of an inefficient service design was the introduction of health information technology, including electronic prescribing and clinical decision support. While a computer-based electronic health record system is often seen as a way to improve efficiency, and hence to raise quality of care (Yanamadala *et al.*, 2016), research has pointed at concerns regarding potential patient safety hazards due to an increased reliance on information technology. In the US, Bowman (2013) referred to a patients' delay in cancer treatment due to a system fault that only reported old cancer testing results, rather than the results following the most recent test.

Such events may be rare, but they exemplify how a careful design of a healthcare system, which includes the adaptation to new technologies or service designs, can play a crucial role in the quality of care provided to patients. Moreover, it also shows the importance of paying close attention to the increasing digitalisation of health services and the need to implement standards that could help prevent errors from occurring in the future.

Combination of human failure and health system failure: There is an increasing recognition that errors are likely to occur at the intersection between human and health system components – conceptualised under the 'Swiss cheese model' by Reason (2000). Based on this framework, the health system consists of different layers ('cheese slices'), with holes that can be seen as active or underlying errors. If quality of care within one layer of the health system is compromised within a 'safe' environment, the following layer will compensate for the error. However, major patient safety incidences will occur at times when errors along several layers of the health system appear simultaneously.

Example of a combined clinical and organisation failure

One such example in the NHS was the death of 29 babies undergoing complex cardiac surgery at the Bristol Royal Infirmary between 1984 and 1995 (The Bristol Royal Infirmary Inquiry, 2001). This example of a major shortfall in quality of care was caused by a number of errors, including the clinical culture, low levels of clinical safety and deficiencies in performance monitoring – all components that individually could have potentially prevented such large-scale damage if worked appropriately.

The NHS is a health system with a memory, and many of the past patient safety and quality of care incidents triggered initiatives to prevent similar failures from happening in the future. These ranged from recommendations following public enquiries (Francis, 2013), to the establishment of national bodies like the Care Quality Commission for systematic surveillance of quality of care (NAO, 2011), or the formation of the National Patient Safety Agency to develop a standardised reporting system of patient safety incidents within hospital Trusts (Panesar, Cleary and Sheikh, 2009). Furthermore, over the last 15 years there has been a notable shift towards public reporting as a way to scrutinise the quality of care provided by health services, to allow for informed decision-making for patients, and to trigger quality improvement at the system and provider-levels. This includes the publication of the Dr Foster Hospital Guide beginning in 2001 (Kmietowicz, 2001), the collection and publication of patient and staff surveys, and the public reporting of healthcare acquired infection rates such as methicillin-resistant staphylococcus aureus or clostridium difficile by hospital Trusts since 2009.

1.5 Managing quality of care in the NHS

The first universal concept of managing quality was introduced by Juran (1986), and contains three distinct elements: *quality planning*, *quality control*, and *quality improvement*. The framework highlights that in order to maximise the effectiveness in quality of care improvements, all three elements, due to their inter-relatedness, must be in equilibrium. However, achieving an optimal balance in a real-world environment can be challenging, particularly as healthcare systems and the division of responsibilities span across multiple stakeholders. In England for instance, accountabilities are divided between the national-level (*e.g.* Department of Health), regional-level (*e.g.* Clinical Commissioning Groups), institutional-level (*e.g.* NHS Trusts), and individual-level (*e.g.* front-line staff). Adhering to the ‘Swiss cheese model’, past policies and improvement strategies addressed each body of the healthcare system, recognising that individually, they all play a role in providing high quality care.

The publication of Lord Darzi’s review ‘*High Quality Care For All*’ was recognised as a milestone in managing the quality of care provided in the NHS, thereby putting quality of care at the heart of decision-making (Department of Health, 2008). The report set out the government’s ambition to improve quality of care through decentralising target-based managements and to shift towards locally driven improvement initiatives. This involved the strengthening of patient choice, supporting care for people with long-term conditions by introducing personalised healthcare budgets, and to encourage commissioner-driven partnerships to improve public health through prevention.

In 2010, the then coalition government published a white paper, *Equity and Excellence: Liberating the NHS* (Department of Health, 2010), outlining the next steps in driving quality improvements that were built upon the core principles outlined by Lord

Darzi. This included strategies of shifting powers towards NHS Trusts for initiating improvement strategies at the local-level that would lead to increases in quality, safety and clinical effectiveness. Furthermore, reinvestments of £20 billion from efficiency savings until 2014 into programmes that improve quality of care and outcomes were promised. In response to the white paper, the Department of Health published the NHS Outcomes Framework in the same year. The framework was developed to “*provide national level accountability for the outcomes that the NHS delivers*”, and particularly to trigger quality of care improvements by setting quality criteria (p.22, Department of Health, 2010).

The latest addition to a range of government strategies for improving the performance of the NHS was the *NHS Five Year Forward View*, outlining three key ambitions to be achieved by 2020 (NHS England, 2014). First, addressing the health and well-being gap, particularly health inequalities; second, addressing the funding and efficiency gap, especially the imbalance between funding required to match demand of health services; and third, addressing the care and quality gap. With regards to quality of care, the document states: “*...unless we reshape care delivery, harness technology, and drive down variation in quality and safety of care, then patients’ changing needs will go unmet, people will be harmed who should have been cured, and unacceptable variation in outcomes will persist*” (p.7).

Over the past decade, the overarching theme in English health policy-making has been the increased focus on improving quality of care for patients accessing the English NHS. Government ambitions, and the formulation and implementation of improvement strategies captured mainly two components of the Juran trilogy – ***quality planning*** and ***quality improvement*** – and are a pre-requisite for driving quality in healthcare. However, a key challenge is the robust measurement of changes in quality of care and safety (or ***quality control*** according to Juran’s trilogy) that can inform the impact and

success of already introduced quality improvement strategies, but also guide future efforts to drive quality improvements.

1.6 Measuring improvements in quality of care

The first concept of measuring quality of care goes back to the 1850s, with Florence Nightingale discovering the causation between sanitation and hygiene standards, and a decrease in mortality rates (Kudzma, 2006). Since then, numerous milestones in the measurement of quality of care have been reached, most notably the shift to electronic recording of patient information as well as treatments and the subsequent advent of derivable indicators for measuring health system performance. In England, the use of such indicators has widely informed decision-making at each layer of the system. For example, process and outcome measures are being used for day-to-day monitoring of performance at the individual-level, while the National Quality Board uses indicators to compare health system performance of the NHS against other countries.

The introduction of electronic administrative health records, which hold information on patient demographics, diagnoses and treatment, presents a great opportunity to fulfil the third component of the Juran (1986) trilogy, *quality control*. Moreover, utilising this information allows to uncover aspects of quality affecting patients across the healthcare system, as compared to being restricted in focus to one individual provider. However, despite the elevated importance for robustly measuring changes in healthcare system performance as a tool for quality improvement, few derived indicators for measuring quality of care are universally accepted (Releigh and Foor, 2010). Common problems in measuring quality of care often relate to first, data issues such as poor reporting and inadequate patient case-mix adjustment (which is the

accounting for systematic underlying patient complexities due to demographics such as age and ethnicity, or pre-existing medical conditions that might affect treatment outcomes); and, poor adjustment for influences of primary, community, and social care, or simply other stakeholders in a healthcare system that may not be under the control of the hospital.

Policy-makers expressed the growing need for developing robust quality indicators that are “*clearly defined, cost-effective, and designed in a way that counter-productive behaviour is discouraged*” (p.2, Bird *et al.*, 2005). Previous research has made use of electronic health records and investigated quality with the help of indicators such as mortality rates (Goodacre, Campbell and Carter, 2015) and length of hospital stay (Bueno *et al.*, 2010). However, both measures have limitations, for instance while length of stay can indicate the efficiency of care co-ordination between the hospital and post-discharge services in older patients, it may be affected by disease severity. However, staying in hospital longer extends the period that a patient is exposed to substantial physiological and psychological stress, leading to adverse health impacts that may be unrelated to the quality of care (Krumholz, 2013). Moreover, by using mortality rates, length of stay or other indicators such as infections rates, studies are often not able to examine the complexity of healthcare systems with its entangled causalities between quality of care provided at different stages along the patient pathway. For example, if a patient dies outside the hospital due to an infection resulting from poor wound management during the post-discharge period; it is likely to not being picked up in commonly used data of in-hospital mortality. Similarly to the poor provision of post discharge services in primary care.

On the other hand, hospital readmission rates, which describe the proportion of patients returning to hospital following the receipt of an initial treatment within a pre-defined period of time – often 30 days, have been shown to correlate with quality

provided to patients at the initial hospital stay (Ashton *et al.*, 1997; Hansen, Williams and Singer, 2011), transitional care services (Feltner *et al.*, 2014; Lee *et al.*, 2015; Rennke and Ranji, 2015), and post-discharge support (Phillips *et al.*, 2004; Harrison *et al.*, 2014), making it a useful metric to support quality improvement through **quality control**. Moreover, the readmission metric has been endorsed through an increasing policy focus on reducing readmission rates as a way to improve quality of care across healthcare systems internationally (Kristensen, Bech and Quentin, 2015), including the Hospital Readmission Reduction Programme (HRRP) in the US, or the readmission reduction policies in England, introduced following the 2010 government white paper, *Equity and Excellence: Liberating the NHS*.

1.7 The focus on readmission rates in the English NHS

In 2010, the government white paper, *Equity and Excellence: Liberating the NHS*, outlined a substantial programme of healthcare reforms in England, including a new priority to reduce avoidable readmissions and encourage more collaborative working between hospitals and social care following hospital discharge (Department of Health, 2010). The white paper was in part a response to concerns that readmissions had been steadily increasing: indeed, between 1998 and 2008, the number of emergency readmissions within 30-days of discharge rose by more than 50% in England (Department of Health, 2011). Emergency readmissions include admissions from emergency departments as well as unplanned, direct and urgent admissions from primary care practitioners² (Department of Health, 2012).

² Operational definition of emergency readmission rates as used throughout this thesis.

Reasons for the rise in readmissions are complex, but could relate to changes in population case-mix, including the rising number of an older population living with multi-morbidity (Hewitt *et al.*, 2016), improved survival rates at the initial hospitalisation (Laudicella *et al.*, 2015), and a lack of coordination between agents along the patient pathway (Jones *et al.*, 2015). Thus, observed rises in readmissions might reflect a failure to adopt evidence-based practices, and in particular the lack of a comprehensive approach to healthcare delivery that combines high quality disease-specific care within hospital settings with enhanced multi-disciplinary working, improvements in transitional care services, and prolonged post-discharge support (Dharmarajan, 2016).

The white paper introduced, from April 2011, mandatory financial penalties for all readmissions occurring within 30 days of hospital discharge that resulted from insufficient quality of care or inadequate preparation for discharge (Department of Health, 2011). A differential approach was taken to the reimbursement of readmissions depending on whether they followed an admission that was an emergency (*e.g.* through an emergency department or a direct and urgent admission from a GP) or non-emergency (*e.g.* admissions for elective care, day cases, and regular day or night attendances). For readmissions following emergency admissions, reimbursement was linked to locally agreed thresholds, which national policy stipulated should be set with an ambition to reduce these readmissions by 25%, compared with the previous financial year. Initially, Trusts received no reimbursement whatsoever for readmissions that followed a non-emergency indexed admission, although from April 2012, reimbursement of those readmissions was also linked to the threshold agreement as for emergency admissions (Department of Health, 2012). For the 2012/13 financial year, financial penalties accumulated to a total of £248 million in savings.

Unlike the financial penalties issued for hospitals in the US under Hospital Readmission Reduction Programme (HRRP), in England savings resulting from penalisation had to be reinvested into post-discharge rehabilitation services (*i.e.* those which fall to community services and local authority-funded social care), which are not always within the direct control of the discharging hospital. Areas of reinvestment had to be guided by recommendations determined in a clinical review. For example, in the financial year 2012/13, reinvestments were made into ‘re-ablement’ services, *i.e.* services that help patients to regain physical strength and confidence required for performing every-day activities (33% of total reinvestment from savings accumulated through financial penalties), community services (26%) and intermediate care services (12%). Reinvestments of penalties had the objective to reduce readmissions to occur in the future. The impact of this policy will be examined in Chapter 5.

1.8 Motivation for this thesis

The English NHS is experiencing significant pressures, with rising demands for its healthcare services, in part due to a demographic change of the population that lives longer and with multi-morbidity. At the same time, NHS funding is increasing at a much slower rate, leaving a large funding gap, with some fearing that this may lead to deteriorations in quality of care, and subsequently adversely impact patients who are accessing the healthcare system. Staff and policy-makers alike have been focusing great efforts into holding up the currently provided high level of quality care in the NHS, and most certainly, the learning derived from several high-profile patient safety incidences in the past (Dyer, 2013) has helped transform the NHS to one of the best healthcare systems in international comparison (Schneider *et al.*, 2017).

Continued innovative contributions towards improving quality of care at the local and national levels are required to uphold the high standard of care provided by the NHS. Initiatives such as those outlined in the 2010 white paper, *Equity and Excellence: Liberating the NHS* (Department of Health, 2010) have already put an emphasis on reducing readmissions as a way to improve quality of care, and strategies outlined in the *NHS Five Year Forward View* described the reduction of variation in quality and outcomes as one of three key ambitions to be achieved by 2020 (NHS England, 2014). Despite this increasing policy focus on healthcare quality, surprisingly little is known about the current state of quality in the NHS, its changes over time, and the impact of past efforts to improve quality of care.

While measuring some aspects of quality of care and their visualisation have undoubtedly led to greater transparency and a better understanding of variation among healthcare service providers, the focus on **quality control** through quality indicators also holds unintended consequences (Casalino, 1999). These include a ‘target fatigue’ among managers and clinical staff (Releigh and Foor, 2010), whose day-to-day routines are dictated by target-driven bureaucracy, an increased level of gaming, whereby clinical processes are optimised to improve certain indicators while other areas of the clinical pathway are subject to negligence (Mears and Webley, 2010), and increasing patient selection to avoid high risk procedures (Lovaglio, 2012).

Policy-makers widely relied on mortality rates, infection rates and length of stay as quality indicators in the past, yet all of them carry significant limitations (Raleigh and Foot, 2010). One in particular is their restricted scope in reflecting care provided to patients along the clinical pathway, which goes beyond the quality and safety of the initial hospital stay. This fact has been acknowledged by policy-makers internationally and addressed through an enhanced focus on reducing readmission rates to trigger

improvements in quality at different stages of the clinical pathway (Kristensen, Bech and Quentin, 2015). This includes improved communication between the discharging hospital and providers of post-discharge care, or better co-ordination between primary care services and secondary care services. To reflect the widespread policy interest into measuring care quality along the pathway and to address the limitations of previously used quality indicators, this thesis focuses on readmission rates as a first motivation.

As mentioned in previous sections, several policies have been introduced to improve quality of care, specifically to reduce readmission rates in England since 2010, but also others targeting a range of quality metrics. Despite this focus, often no robust evaluation is conducted to assess the impact of a particular policy. In the past, policy-makers often relied on qualitative evaluations, case studies, or if quantitative evaluations were conducted, they used before-and-after comparisons. These assume that the gradient change in the outcome is caused by the policy change, yet underlying secular trends may introduce significant biases in results. Therefore, hospitals impacted by the policy change would ideally be compared to a natural control group that remained unaffected by the policy. The lack of good and methodological sound evaluations in the NHS becomes apparent when considering that the first evaluation unit that uses robust and scientific matching methods to evaluate major NHS programmes was set up in a joint venture between NHS England and The Health Foundation in 2016. This was in response to a growing need to underline policy changes with robust evidence on their effectiveness; a need voiced from within the NHS. This provides the second motivation for this thesis, namely to improve the robustness of methods to analyse the impact of policy initiatives aimed at improving quality of care.

The 2010 government white paper *Equity and Excellence: Liberating the NHS* introduced a number of policies focussing on the reduction of readmission rates. Despite

their use as an outcome metric, their usefulness as a quality of care measure has been questioned before (Friebel and Steventon, 2016), not least because of evidence suggesting that only approximately 30% of readmission rates are actually preventable through improvements in quality of care (Van Walraven, Jennings and Forster, 2012). This lack of clear evidence leads to the third motivation of this thesis, namely to critically assess the suitability of readmission rates as an outcome measure.

1.9 Aims and contributions of this thesis

The aim of this thesis is to examine the impact of quality improvement efforts on quality outcomes in the English NHS, particularly focussing on readmission rates and their validity as a metric due to the enhanced 2010 national policy focus on reducing readmissions as a way to improve quality of care.

This PhD thesis carries several theoretical and applied econometrical contributions:

Review of the literature

To develop a clear understanding of issues surrounding readmission rates before they can be applied as a measure to evaluate healthcare quality, and in particular, interventions meant to improve quality of care (Chapter 2).

Trends and variation in quality of care

To examine trends and variation in quality of care in the English NHS, using risk-adjusted readmission rates and the systematic component of variation to evaluate their changes from 2006 to 2016 (Chapter 3). This can be seen as the starting point to

investigate the state of quality in the English NHS, measured through readmission rates as well as a stock take of whether quality improved both in the aggregate and on provider level. This chapter presents the most comprehensive overview of trends in readmission rates in England over ten years, and for nine clinical subgroups to date.

Unintended consequences of a policy focus on 30-day readmission rates

Healthcare systems globally have implemented policies aimed at reducing readmissions, including financial penalties on hospitals with high readmission rates in the US and England. The penalties have been controversial, and there have been concerns that such a focus on readmissions might distract from other efforts to improve care or might inappropriately displace activity from inpatient to other settings. What is needed is information regarding the wider impact of readmission reduction initiatives on patient-reported health and well-being. These measures can capture the effect of ‘unintended consequences’ and align with the aims of any healthcare system. Thus, the contribution of this chapter is to examine the relationship between changes in risk-adjusted, 30-day readmission rates and measures of self-reported quality of life in hip and knee replacement patients in England (Chapter 4).

Evaluation of health policies aimed at improving quality of care

The third and fourth contributions relate to the innovative evaluation of two healthcare policies, aiming to improve quality of care in the NHS. I begin by analysing the impact of a national policy that introduced financial penalties for hospitals with excess readmission rates. While financial penalties are now widely used for hospitals with excess readmission rates, there have been concerns about unintended consequences of such pay-for-performance policies, for example through funding shortages resulting from too large financial penalties. However, the evidence base for the effectiveness of

financial penalties in reducing readmission rates is sparse and previous studies relied mainly on before-and-after study designs that make strong identifying assumptions. What is needed is robust information on the unbiased causal impact of financial penalty policies. The aim and contribution of this chapter is to apply the Generalised Propensity Score methodology to English administrative patient-level data to allow for a robust estimate of the causal relationship between the size of financial penalty and future readmission rates (Chapter 5).

The second healthcare policy evaluation focuses on the impact of an area-level health service reorganisation, namely the centralisation of acute stroke services in London and their effect on quality of care. Service centralisation is now widely seen as an effective mechanism to improve quality of care, mainly by bundling clinical expertise in specialist treatment centres. The centralisation of acute stroke care in London has received great interest from policy-makers in the past, with several evaluations performed to date. However, all conducted impact evaluations carry significant limitations, for example, including the focus on changes in one specialist treatment centre without comparison to a control group that was unaffected by the policy intervention, or comparing London as a whole to the rest of England by pooling all Trusts located in the London catchment area into one treatment group. While these types of evaluations can provide some indication about the impact of an area-level service reorganisation, previous research failed to account for the heterogeneity in provider performance and variation in patient flow. Therefore, the aim and contribution of this chapter is to evaluate the centralisation of stroke care using seven stroke specific process and outcome indicators (inclusive of 30-day readmission rates), by applying a difference-in-difference analysis with two treatment groups (Chapter 6). This methodology allows investigating potentially systematic differences between patients receiving care in London specialist

units and non-specialist units that can result from varying levels of clinical engagement or availability of specialist medical equipment. These differences are disguised in previous evaluations. Moreover, this chapter expands the focus on readmission rates by also considering six process and outcome measures.

The research combined in this thesis fills an important gap in the existing literature. Despite the great focus on reducing readmission rates in the English NHS since 2010 and elsewhere, little is known about the suitability of readmission rates as a metric for measuring quality of care, the unintended consequences of a focus on reducing readmission rates, and the impact of policies aimed at improving healthcare quality, such as readmission reduction policies. By examining each of these points, this thesis provides a comprehensive overview, which could help guide policy decisions in the future.

1.10 Contribution of the candidate to the thesis

All objectives have been met through analyses presented in individual chapters. Research papers have been derived from chapters 3 to 6, which have either been published, are forthcoming in peer-reviewed journals, or currently under review. All journals agreed in the reuse of adapted and extended versions of the published papers to form a substantive part of this thesis (see Appendix A). The following papers have been published prior to submission of this thesis:

1) Friebe R, Hauck K, Aylin P and Steventon A., 2018 “Emergency readmission rates across nine patient subgroups: A longitudinal analysis of administrative data in England between 2006 and 2016” *BMJ Open* 8:e020325. doi: 10.1136/bmjopen-2017-020325. (Chapter 3)

2) Friebe R, Dharmarajan K, Krumholz H and Steventon A., 2017. Reductions in readmission rates are associated with moderate improvements in patient-reported health gains following hip and knee replacement in England. *Medical Care*, 55 (9), pp. 834-840. (Chapter 4)

3) Friebe R, Hauck K and Aylin P., 2017 “Centralisation of acute stroke services in London: Impact evaluation using two treatment groups“ *Health Economics*, pp. 1 - 11. (Chapter 6)

4) Friebe R and Steventon S., 2016. The multiple aims of pay-for-performance and the risk of unintended consequences. *BMJ Quality and Safety*, 25, pp. 827-831. (Chapter 7)

A summary of my contribution to each chapter is presented in the following paragraphs, and again included in the preamble preceding every individual chapter. I would like to acknowledge Professor Paul Aylin and Doctor Katharina Hauck for their invaluable and supportive supervision throughout the period of this PhD research. I would also like to thank Doctor Adam Steventon for his support and mentorship. Finally, this PhD thesis would have not been possible without the financial support received by the NIHR Patient Safety Translational Research Centre at Imperial College London.

Objective 1: Review of the literature

I was the sole contributor to this chapter.

Objective 2: Examining trends and variation in quality of care for English Trusts and across 10 financial years (2006 to 2016).

The research paper derived from this chapter was published in the *BMJ Open* (Friebe *et al.*, 2018). The work was conducted between December 2016 and October

2017. My contribution was the overall study design, performing the analysis, interpretation of findings and write-up of both, the chapter and the derived journal article. The final versions contain comments incorporated from my co-authors and two independent peer-reviewers.

Objective 3: Assessing the relationship between readmission rates and patient-reported quality of life measures to inform the debate about unintended consequences of readmission reduction programmes.

A research paper derived from this chapter has been published in *Medical Care* (Friebel *et al.*, 2017). The initial idea of this chapter was provoked by a discussion with Professor Harlan M. Krumholz and Doctor Kumar Dharmarajan from Yale University (both belonging to the Center for Outcomes Research and Evaluation), and their previous work on the risk-adjustment of hospital readmission rates in the US. The Center for Outcomes Research and Evaluation was responsible for providing evidence used to decide on the risk-adjustment approach used by the Centers for Medicare and Medicaid Services (CMS) and also played a key role in introducing the financial penalty policy for hospitals with excess readmission rates in the US.

My contribution to the chapter and research paper was the overall study design, obtaining, cleaning and linking of publicly reported patient reported outcomes data and readmission rates derived from the Hospital Episode Statistics (HES) database. I conducted the analyses and prepared the chapter as well as the initial manuscript of the research paper. The produced chapter incorporates co-authors comments and peer-reviewer feedback.

Objective 4: Evaluation of the English financial penalty policy on reducing risk-adjusted, 30-day readmission rates, using the Generalised Propensity Score methodology.

Work for this chapter was conducted between January 2016 and May 2017, and the findings were presented at the American Health Economics Association conference in Philadelphia (US) in June 2016, presented and discussed at the 3rd IRDES Workshop on Applied Health Economics and Policy Evaluation in Paris (France) in June 2017, and presented at the Boston 2017 Congress of the International Health Economics Association (US) in July 2017. The idea for this chapter was inspired by the lack of robust evidence on estimating the causal relationship between financial penalties used in many healthcare systems and their impact on reducing future readmission rates. My contribution was the initial idea for this study, including the use of Generalised Propensity Scores and estimating dose-response functions. The produced chapter incorporates feedback from my co-author and reviewer feedback.

Objective 5: Evaluation of an area-level health service reorganisation and its impact on quality of care.

A research paper for this chapter has been published in *Health Economics* (Friebel, Hauck and Aylin, 2017), with the work conducted between July 2014 and May 2017. Professor Paul Aylin and Doctor Katharina Hauck proposed the research question, which was answered in this chapter. My contributions were the initial analysis of aggregated HES data and expansion of the difference-in-difference approach to accommodate two treatment groups. I prepared the chapter and the first draft of the research paper. The produced chapter and the published research paper incorporate comments and feedback provided by co-authors and peer-reviewers.

1.11 Other important contributions

During my work on this thesis, I have been involved in several projects at The Health Foundation. This included the first English application of an innovative tool for estimating distinct hospital trajectories for the quality of care in elderly and frail patients, and a particular focus on trends in length of stay and readmission rates. In parallel, I worked on a research paper that investigated the association of daily changes in bed occupancy rates on readmission rates, which is currently under peer-review in *Health Policy*. These papers are not reproduced in this thesis. Beginning from February 2018, I was named Visiting Fellow at the Center for Global Development in Washington DC to work on quality of care in low- and middle-income countries and I have produced a research paper on the potential lessons learnt on quality improvement in the NHS, which is currently under peer-review at the *International Journal for Quality in Health Care*.

1.12 Structure of the remainder of this thesis

Chapter 2 critically reviews the literature. Chapter 3 examines changes in trends and variation of readmission rates between April 2006 and February 2016. Chapter 4 estimates the relationship between readmission rates and patient self-reported measures of quality of life for patients undergoing hip and knee replacement in England. Chapters 5 and 6 evaluate the impact of two health policies, one national-level policy and one local-level health service reorganisation, on quality of care. Chapters 3 to 6 are each preceded by a short preamble that puts each chapter into the context of the thesis. Chapter 7 summarises the main findings from preceding chapters, highlights future areas for research and concludes.

Chapter 2 Literature review on the measurement of quality of care using readmission rates

2.1 Introduction

The aim of measuring healthcare quality is to ultimately improve patient outcomes; however, different stakeholders tend to give importance to different aspects of quality measurements (McGlynn, 1997). For example, while the focus for payers of healthcare services is likely to be on the value for money (Carlos, 2008), hence the cost-effectiveness of their healthcare spending and its impact on outcomes, patients tend to value access to medicines and respective health outcomes (Brown, 2007; Elwyn *et al.*, 2007), whereas clinicians often define outcomes as biological markers (Ofri, 2010). In fact, clinicians tend to be caught between the interest of payers and patients, having to align cost control with judgements of best practice and patient demands (Weinstein, 2001). Thus, healthcare quality requires to be measured objectively, combining the interests of all stakeholders, which in turn will ensure the development of strategies for successful quality improvement (Derose *et al.*, 2002).

Over the past decade, unplanned readmission rates, *i.e.* those readmissions that occur as an emergency and not as a planned or elective readmission, have developed into a prominent marker for the measurement of healthcare quality. For instance, policy-makers in Denmark, Germany, England and the United States (US) incorporated readmission rates into their quality frameworks (Kristensen, Bech and Quentin, 2015), partly because of the relative ease of derivation from large administrative health data sources (Benhassat and Taragin, 2000; Fischer *et al.*, 2014), and based on evidence that they reflect on healthcare quality provided to patients along the clinical pathway. This

includes a link with the quality of care services provided at the initial hospital stay, such as the perceived climate of safety (Hansen, Williams and Singer, 2011), the efficiency and organisation of transitional care services (Feltner *et al.*, 2014; Lee *et al.*, 2015; Rennke and Ranji, 2015), and the quality of post-discharge support, for example through initiatives aimed at people with highest risk of readmission (Phillips *et al.*, 2004; Harrison *et al.*, 2014). Moreover, readmission rates are believed to be undesirable for patients (Eide *et al.*, 2016; Curtis *et al.*, 2017), impose additional strain on hospitals and clinicians (Leppin *et al.*, 2015), and are costly for the payers of healthcare services (Cary and Stefos, 2016); thus, to some extent capturing the interests of all three stakeholders.

There are several possible reasons for why a patient has to return to hospital for further treatment after discharge from an indexed admission (Donze *et al.*, 2013; Holly *et al.*, 2015). This may include situations where the patient returns for a scheduled appointment to continue treatment or, after a period of time at home, enters into another hospital, which may provide specialist services. Thus, not all readmissions are representative of healthcare quality and the focus should therefore be on unplanned hospital readmissions (Gruneir *et al.*, 2011; Bradley *et al.*, 2013; Kim *et al.*, 2015). These are further distinguished into subcategories, such as entered as an emergency or being disease-specific (Van Walraven *et al.*, 2012).

Policies such as the Hospital Readmission Reduction Programme (HRRP) in the US (CMS, 2016), or those introduced under *Equity and Excellence* in the English National Health Service (NHS; Department of Health, 2010), focus on unplanned hospital readmissions; however, it is not always clear whether the unplanned readmission is related to healthcare quality (Zhan *et al.*, 2016), or indeed is related to other factors outside the control of the discharging hospital (Zhang *et al.*, 2014), and/or stakeholders in the healthcare system (Lopes *et al.*, 2017). For instance, infections following surgical

interventions, such as hip and knee replacements may also occur due to the patients' inherent ability to self-care, or the patients living arrangements (Ibrahim *et al.*, 2013; Carroll *et al.*, 2014). Under those instances, readmissions may in fact be inappropriate as a metric for healthcare quality, as the additional readmission describes a positive interaction with the healthcare system that supports the patient in regaining the desirable health status (Priebe *et al.*, 2009). To reduce any potential bias resulting from this, several studies suggested to make a further distinction into readmissions that are thought to be preventable due to changes in the delivery of healthcare quality (Dharmarajan, 2016), and those that are not preventable and hence, outside the control of the healthcare system (Goldfield *et al.*, 2008; Lindquist and Baker, 2011; Lavenberg *et al.*, 2014; Sills *et al.*, 2016).

It is estimated that approximately 30% of all unplanned hospital readmissions in the NHS are preventable (Blunt *et al.*, 2015), and while large uncertainty exists around the definition of preventability (Hasan, 2001; Vest *et al.*, 2010; Soong and Bell, 2015), research has shown that unlike for unplanned readmissions, variability of preventable readmissions across providers tends to be small (Walraven *et al.*, 2011; Van Walraven, *et al.*, 2012). Though there are many possible determinants of preventable readmissions, a systematic review by Vest *et al.* (2010) found that preventable readmissions strongly associated with the quality of discharge support following the indexed admission. This includes the level of communication between the discharging hospital and providers that offer follow-up care outside the hospital environment, a lack of clearly defined milestones that will help patients with serious health conditions in managing the recovery process, but also the doctor's propensity to readmit patients when they present in the Accident and Emergency (A&E) department (Vest *et al.*, 2010). Thus, for readmission rates to reflect on healthcare quality, they should be limited to a clearly defined criterion of preventability, *i.e.* being preventable through appropriate high quality healthcare

delivery (Saunders *et al.*, 2015). Interestingly, the financial penalties introduced for hospitals with excess readmission rates in the English NHS have the objective to reduce a specifically predetermined set of preventable readmissions (Department of Health, 2011). These are readmissions that could have been avoided through an improved availability of social care services, better reablement services, or those that could have been dealt with in a primary care setting.

Another important consideration regarding the definition of readmission rates is the follow-up period between discharge from an indexed admission and the readmission (Heggestad and Lilleeng, 2003; Fischer *et al.*, 2014). This is particularly important since a period chosen too short may limit the metrics scope in measuring quality of care provided to patients along the clinical pathway, *e.g.* the quality of post-discharge support services. Similarly, a period chosen too long may pick up readmissions that are unrelated to quality of healthcare services (Kurtz *et al.*, 2016). Research has shown that 7-day readmission rates are likely to be more appropriate in the measurement of healthcare quality received at the initial hospital stay (Eastwood *et al.*, 2017), while 90-day readmission rates were found to correlate with the quality of healthcare provided to patients in settings such as rehabilitation centres (Galloway *et al.*, 2016). However, mostly a 30-day time window is chosen for policy purposes, despite some variation across healthcare systems, *e.g.* 28-days in Australia (Kilkenny *et al.*, 2013). Some studies have called for the timeframe to be determined based on the cause of the indexed admission (Demir *et al.*, 2008), yet no standardised follow-up period exists in the literature. Given the described evidence, it is possible that a longer follow-up period may be chosen in instances where researchers might want to study the quality of out-of-hospital services, such as those provided in primary care settings, or during rehabilitative care.

In the US, approximately 13% of Medicare patients were readmitted following discharge from any indexed admission in 2015 (Salerno *et al.*, 2017), with associated annual costs estimated at \$17 billion (Jencks, Williams and Coleman, 2009). In the English NHS about 7% of patients were readmitted to hospital following discharge from any indexed admission in 2010 (Blunt *et al.*, 2015), at an estimated cost of £1.6 billion (Davison *et al.*, 2016). In other words, spending on emergency readmissions in England accounted for approximately 1.3% of the annual NHS budget as of 2017. Moreover, emergency readmission rates have been increasing slowly across most healthcare systems; for example in the English NHS, readmissions increased slightly from 6.8% in April 2004 to 7.2% in April 2009 (Blunt *et al.*, 2015). While some of these rises may be linked to improved hospital survival (Dharmarajan *et al.*, 2017), which could partly be triggered by the adoption of new innovative processes such as thrombolysis treatment in stroke patients (Majhadi *et al.*, 2013), the degree of change in readmissions has been found to be heterogeneous across regions, hospitals and patient groups (Horwitz *et al.*, 2015; Singh *et al.*, 2015; Ramey *et al.*, 2016). In fact, these variations could suggest that a significant proportion of emergency readmissions is associated with varying levels of healthcare quality and thus, be potentially amenable to quality improvement efforts. This argument was supported through evidence presented in a systematic review by Walraven *et al.* (2011), which found a median rate of avoidable (*i.e.* preventable) emergency readmissions of 27.1%, ranging from 5.0% to 78.9%.

While there might be many possible reasons for the ambiguity in findings for variation in readmission rates, one of the reasons for the generally higher readmission rates reported in the US is the common focus on patients captured by the Medicare programme, the federal health insurance scheme in the US for people aged 65 years or over. This patient population is likely to carry more long-term health conditions,

naturally making them more prone to being readmitted following discharge from an indexed admission. In comparison, the reported readmission rates for England usually cover the whole population, with possible exceptions for any patients below the age of 18.

Evidence on the potentially avoidable number of hospital readmissions has sparked great interest from policy-makers for its use in healthcare quality measurement (Kripalani *et al.*, 2014). In fact, to reduce avoidable readmission rates, policy-makers in England and the US have introduced financial penalties for hospitals with excess readmission rates in 2011 and 2012, respectively (Department of Health, 2012; CMS, 2016). While the Hospital Readmission Reduction Program (HRRP) in the US originally covered patients with an indexed admission for acute myocardial infarction, pneumonia and heart failure, it has since been expanded to also cover hip and knee replacements, and chronic obstructive pulmonary disease (Barrett *et al.*, 2015; Zuckerman *et al.*, 2016). Surprisingly, despite this large policy attention on reducing readmission rates, the validity of readmission rates as a measure for healthcare quality remains limited (Huesch *et al.*, 2013; Alverson and Callaghan, 2014; Wish, 2014; Khanna *et al.*, 2015), and has been questioned in light of the contradicting evidence on the impact of financial penalties for certain hospital groups in the US (Friebel and Steventon, 2016). In particular, a study by Figueroa *et al.* (2016) found evidence suggesting that safety-net hospitals in the US, which are hospital providers primarily serving patients coming from poor socio-economic backgrounds, have been receiving disproportionately high financial penalties compared with hospitals serving patients from more affluent areas. The authors considered this mismatch in distribution of penalties to be a consequence of poor accounting for patient case-mix, specifically the lack of adjustment for the patient's socio-economic background. However, despite large financial penalties, a recent study found that safety-

net hospitals showed greatest reductions in readmission rates following the introduction of HRRP (Salerno *et al.*, 2017). Alongside the patient's socio-economic background, case-mix adjustment for other predictors of readmission rates plays a crucial role, specifically in cross-provider comparisons. Due to the patient's inherent characteristics such as age, gender, or number of underlying comorbidities, the likelihood of being readmitted following discharge from an indexed admission that is unrelated to the quality of care provided varies and has to be accounted for to avoid unduly penalising hospitals, which are treating more complex patient groups. The methods used for risk-adjusting readmission rates and the patient-level information entered into the predictive models will be further discussed in chapters 3 to 5.

Reliability and validity of a metric such as readmission rates are the key criteria for its use as a suitable measure of healthcare quality (Fischer *et al.*, 2014). This includes that readmissions need to be reflective of a patient's health status, have a significant importance for policy-makers and are amenable to changes in the healthcare system. Furthermore, any used quality metric is required to be scientifically sound and feasible (Kelley *et al.*, 2006), which includes that benefits associated with measuring quality outweigh the costs associated with collecting them. This literature review serves the purpose of developing an understanding about the issues surrounding the use of readmission rates as a measure for healthcare quality.

2.2 Methods

2.2.1 Search strategies

A review of the literature was conducted to examine the utility of readmission rates as a valid measure for healthcare quality. Formal methods usually employed for

systematic reviews were used for the identification and selection of relevant articles, data abstraction, quality assessment and synthesis of results. However, while this chapter adopts these formal methods, some deviation exists regarding the selection of relevant articles, as described in the following section.

In October 2017, the bibliotic databases (1) MEDLINE/PubMed and (2) SciVerse (Science Direct) were searched for publication in the period of 1st January 2001 to 1st October 2017. The employed search terms were designed in a way to capture readmission rates, along with metrics for quality in healthcare, as well as the measurement of such. The following search algorithm was used: [“readmission” OR “rehospitalisation” OR “revisit” OR “return”] AND [“indicator” OR “metric” OR “measure” OR “outcome” OR “marker” OR “endpoint” OR “performance”] AND [“quality” OR “safe” OR “patient-centred” OR “efficiency” OR “effectiveness” OR “equitable” OR “timely”].

I designed the search strategy in a way to maximise sensitivity and to allow for a direct comparison between search outcomes from sources (1) and (2). Moreover, reference lists of key review articles and all articles meeting the inclusion criteria were searched. The reference manager software Mendeley was employed for the download and storage of identified articles. One researcher reviewed all articles.

2.2.2 Selection criteria

The minimum quality requirement for study inclusion in the literature search were: (a) their publication following 1st January 2001; (b) articles had to be written in English language; (c) published following a peer-review; (d) available as full-text; and (e) on human subjects. To avoid publication bias through only including peer-reviewed articles in the literature search, I also complemented this review with ad hoc website

searches via Google and .org websites, but also searched the reference lists of selected articles. All included articles were required to be relevant to the research question, hence to focus on the usefulness of readmission rates as a valid measure for healthcare quality. Articles examining trends of readmission rates, or using readmission rates as a quality of care measure when studying policy impacts, were excluded from this literature search. Moreover, impact evaluation studies are reviewed via a narrative review of specific papers, and will be discussed in the following chapters of this thesis where I present impact evaluations of local and national-level policies to improve quality of care, specifically chapters 5 and 6. The selection criteria chosen for this literature review were designed to develop a clear understanding of issues surrounding readmission rates before they can be applied as a measure to evaluate quality, and in particular interventions meant to improve quality of care.

Based on the adoption of the outlined search strategy, 1590 articles were identified. Following the title/abstract review, 567 articles were full-text reviewed. Using the same criteria described above, 117 studies were identified as eligible for inclusion into the examination of readmission rates as a measure for healthcare quality. Figure 1 depicts a flow chart, outlining each individual step in the article selection process with the associated number of articles.

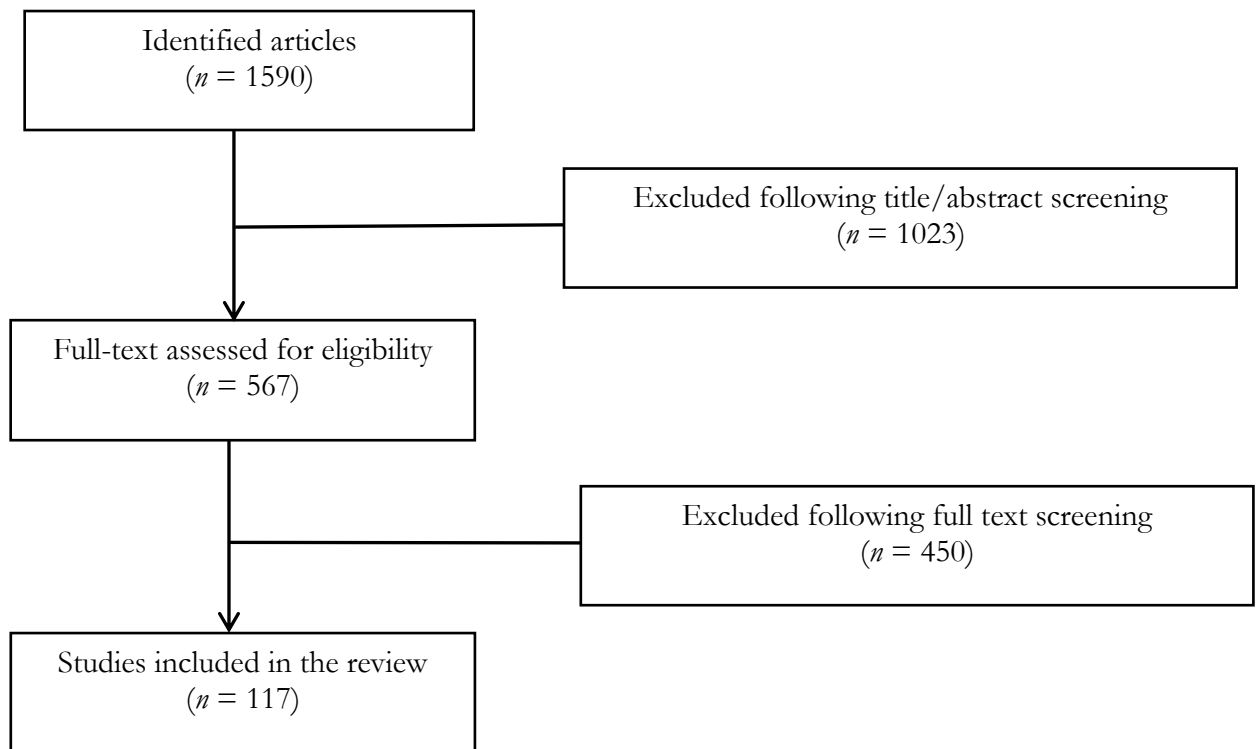


Figure 1. Flow chart depicting the article selection process of the literature review

2.3 Results

A total of 117 articles met the inclusion criteria, which can be classified into three distinct clusters: first, the threat to validity of readmission rates as a measure for quality of care; second, data; and third, the association of readmission rates with other quality metrics. The following paragraphs provide a summary of the literature within each cluster.

2.3.1 Threat to validity

The literature search revealed several threats to the validity of readmission rates as a measure for healthcare quality, namely the effect of competing healthcare quality indicators, and concerns regarding case-mix adjustments. The following sections report and discuss findings for both threats.

2.3.1.1 Link with other outcome measures

Alongside hospital readmission rates, mortality rates are widely used for the measurement of healthcare quality, including quality dimensions such as the effectiveness of clinical processes (Kobewka *et al.*, 2017). Yet, mortality is seen as an opposing endpoint to a hospital readmission given their natural relationship: a patient who died, whether inside or outside the hospital, cannot be readmitted (Grocott, 2010; Gheorghiade *et al.*, 2013). Subsequently, when calculating readmission rates from administrative health data, patients who died need to be excluded from the study sample. Despite this seemingly natural relationship between both metrics, findings from previous research on the relationship between mortality rates and readmission rates remains inconclusive, and is highly disease-specific (Krumholz *et al.*, 2013). For example, while no relationship between both measures was found for patients with an indexed admission for pneumonia and acute myocardial infarction (Krumholz *et al.*, 2013), a study by Laudicella, Li Donni and Smith (2013) established an inverse relationship for hip fracture patients. Recent research by Dharmarajan *et al.* (2017) also reported a small, yet significant association between changes in readmission rates and 30-day mortality post discharge from hospital. Based on these findings, an enhanced policy focus on reducing readmission rates might therefore increase the potential for perverse incentives and thus, readmissions should be considered alongside changes in mortality rates (Shwartz, Restuccia and Rosen, 2015). Others have suggested constructing a composite measure that takes into account changes to both measures when comparing hospitals (Glance *et al.* 2017). This recommendation even holds when considering that both measures are independent of each other, and thus, are reflecting on different aspects of healthcare quality.

Across most healthcare systems, overall length of stay and length of stay for particular patient subgroups has been decreasing (Bueno *et al.*, 2010; Kalra, Fisher and Axelrod, 2010; Li *et al.*, 2015; Sogaard *et al.*, 2015). For example, in the English NHS overall length of stay has reduced from 6.2 days in 2005/06 to 4.8 days in 2015/16 (NHS Digital, 2016). While there are many possible reasons that could explain this decline (Borghans *et al.*, 2008; Lewis and Edwards, 2015), research pointed at technical advancements that have led to efficiency gains (Sorenson, Drummond and Khan, 2013), but also to a general shift towards providing care to patients admitted as day-cases in the NHS (NHS Digital, 2016). Moreover, NHS hospitals have seen significant declines in the number of available hospital beds (*i.e.* reduction from 300,000 beds in 1987/88 to 131,000 beds in 2015/16) (British Medical Association, 2017), with NHS staff likely to discharge patients earlier to free up additional bed capacity. Some research suggests an inverse relationship between length of stay and readmission rates, for instance, Kaboli *et al.* (2016) reported that each day spent less in hospital increases the probability of a readmission by approximately 6%. It is possible that some patients are being discharged before reaching sufficient levels of clinical fitness, or are being discharged without adequate post-discharge care plans put into place (Parliamentary and Health Service Ombudsman, 2016), potentially leading to an increased risk of a readmission. However, the findings reported by Kaboli *et al.* (2016) might not be generalizable to the whole population, since the study sample was significantly older (mean age = 65.5 years) and thus, carried a considerable higher risk of readmission. Furthermore, being discharged quicker not only means having to spend less time in the hospital environment, but it might also reduce the risk of incurring adverse events (Hauck and Zhao, 2011), and lead to a reduced exposure to other physiological and psychological strain that is associated with a hospital stay (Krumholz, 2013). Therefore, several studies have found that

reductions on length of stay leads to a lower readmission risk (White *et al.*, 2014; Kunisawa *et al.*, 2016).

2.3.1.2 Adjustment for patient-characteristics

Using readmission rates as a measure for quality of healthcare requires making a distinction between readmissions that are in fact caused by the healthcare quality provided to the patients, and those readmissions that are unrelated to quality, but linked to the patient characteristics (García-Pérez *et al.*, 2011). This is particularly important when comparing hospitals based on their readmission rates, and could lead to potentially unfair penalisation of hospitals when predictive patient-level characteristics are not sufficiently taken into consideration and when case-mix vary systematically between hospitals (Amarasingham *et al.*, 2013; Marang-van de Mheen and Shojania, 2014). For example, following the introduction of financial penalties under HRRP in the US, research reported that hospitals serving patients from the most deprived socio-economic backgrounds faced the largest proportion of financial penalties (Epstein, 2012; Joynt and Jha, 2013; Figueroa *et al.*, 2016). Subsequently, some researchers have argued that by not taking the individuals socio-economic status into account when risk-adjusting readmission rates, hospitals serving this patient group may be unfairly penalised (Fiscella, 2014). This follows the assumption that patients from poorer socio-economic backgrounds have a higher propensity of being readmitted due to for instance, being less able to self-care, or lacking the social support network that will help in the recovery process (Philbin *et al.*, 2001; Noori *et al.*, 2014; Glance *et al.*, 2015; Martsolf *et al.*, 2016). However, others have argued that if hospitals that serve patients from more socio-economically deprived backgrounds are in fact providing lower healthcare quality, by incorporating some measure of deprivation into the risk-adjustment process would effectively set the quality standard measured through readmission rates lower for poorer

patients, potentially embedding some degree of health inequalities. Interestingly, research by Langagergaard *et al.* (2011) found that patients from very socio-economically deprived backgrounds are less likely to receive high quality stroke services compared with patients from least deprived socio-economic backgrounds, thus providing support for the argument of not risk-adjusting for the patient's socio-economic status.

Although many risk-adjustment models have been developed in the past (Forthman *et al.*, 2010; Billings *et al.*, 2012, 2013; Lenzi *et al.*, 2016), little consensus exists regarding the inclusion of case-mix variables (Kansagara *et al.*, 2011; Lee, 2012; Futoma *et al.*, 2015). While patients that are sick and old present with the highest likelihood for being readmitted following discharge (Silverstein *et al.*, 2008; Kruse *et al.*, 2013), often adjustment models rely on patient-level information available from administrative data sources (Tabak *et al.*, 2017). For example, the Hospital Episode Statistics (HES) database in England includes deprivation proxies, *i.e.* the Index of Multiple Deprivation (IMD), which is based on the patient's area of residence (Department for Communities and Local Government, 2015); yet, no such information is readily available within Medicare data in the US, even though it could be added as the patients' residential postcode is recorded (Blum *et al.*, 2014). Other studies have highlighted how the severity of the disease at the indexed admission is of high predictive value for being readmitted (Wang *et al.*, 2016), yet no such link was found for patients with anaemia (Garlo *et al.*, 2015). However, administrative databases tend to not collect this information as the available data is often only used to inform reimbursement purposes, and not with an evaluative purpose in mind. Of those patient-level characteristics currently employed, Fischer *et al.* (2014) highlighted that for most, the predictive value remained small (c-statistics between .70 and .80). The same study concluded that currently there is only limited guidance regarding the use of information for the case-mix adjustment of readmission rates.

However, healthcare systems could improve the threat to validity of readmission rates linked to case-mix adjustment by collecting additional information, which might lead to improved comparisons between hospitals, or patient groups.

2.3.2 Data

A reason for the widespread use of hospital readmission rates as a measure for healthcare quality is their derivability from large administrative data sources. Often, administrative data sources combine information that is entered manually at individual hospitals for reimbursement purposes and collated at a specialist data centre (*e.g.* NHS Digital in the case of England), or held by insurance companies (*e.g.* in Germany). Subsequently, the appropriate use of readmission rates is highly linked to the data it is derived from, and the following sections discuss some of those aspects.

2.3.2.1 Reliability of good coding practices

Similar to mortality, a hospital readmission is a binary outcome; either the patient has been readmitted, or s/he has not been readmitted over a defined period of time. However, the coding practices of how a readmission is recorded (*i.e.* the method of admission) can have a significant impact on their usefulness as a healthcare quality indicator. As discussed in an earlier section (see Section 2.1), policy-makers primarily focus on emergency hospital readmissions, *i.e.* those readmissions that are unplanned. Policy-makers in England consider unplanned emergency admissions to be any admission recorded with a method of admission code via A&E, general practitioner, bed bureau, consultant outpatient clinic, or other means, such as arriving via ambulance from an A&E of another provider where the patient had not been admitted. Inconsistencies in recording the method of admission may therefore lead to an under, or overestimation of

the real hospital readmission rate (Hannan *et al.*, 2011). Several studies have pointed out that the source of admission can be used as a proxy for the acuteness of a readmission, thus patients who are being transferred from A&E departments to inpatient settings may be more likely to be unplanned, compared to admissions from the patient's usual place of residence (Fischer *et al.*, 2014). However, the source of admission may never be used as a sole indication to judge whether the admission was in fact unplanned or planned, as in many instances it provides imprecise information, such as when the admission was via the GP (*i.e.* it can be both, planned or unplanned).

Other concerns relate to hospital-level gaming, which may lead to biases in the estimation of hospital readmission rates, particularly when focussing on a specific patient group (Lagu and Lindenauer, 2015). For example, Sjoding *et al.* (2015) have found that hospitals in the US were able to proactively code indexed admissions for pneumonia into sepsis or respiratory failure. The subsequent impact was that those patients were not considered as a denominator when calculating readmission rates for ranking hospitals to determine financial penalties under the HRRP in the US. Thus, hospitals were able to reduce the reported readmission rate and possibly gain unfair advantages over hospitals not engaged in gaming. The study concluded that the CMS may wish to reconsider the definition of patient groups, for example by applying disease codes that capture a wider scope of the clinical disease.

Finally, Fischer *et al.* (2014) pointed out that while good coding practice is required for the recording of readmission rates, the importance for other patient-level information should not be underestimated. Particularly, researchers and policy-makers rely on the entered patient characteristics that are used for the case-mix adjustment of readmission rates. Falsely entered information on patient demographics may lead to

biased prediction estimates (Amin *et al.*, 2013). However, this may only be problematic if there are systematic differences in coding across providers.

2.3.2.2 Accountability of cross-provider readmissions

Accounting for cross-provider readmissions can pose a major concern for the examination of changes in readmission rates at the hospital-level, particularly when focussing on readmission rates at a single hospital alone (Davies *et al.*, 2013). Several studies have highlighted that patients undergoing planned or elective surgery tend to receive such care at specialist hospitals, for example at providers that are specialised in Orthopaedic surgery (Moscelli *et al.*, 2016). Another example includes the provision of acute stroke care services in eight London Hyper Acute Stroke Units since 2010 (Healthcare for London, 2014). In many instances, those treatment centres are not in direct proximity of the patient's place of residence, making it unlikely that in case of an emergency during the post-discharge period, the readmission will occur to the hospital of the indexed admission. It is therefore possible that the actual readmission rate would be underestimated if focussing on readmissions to the hospital of the indexed admission alone (Henke *et al.*, 2015; Khan *et al.*, 2015), and thus, the linking of information across hospitals is a prerequisite for an accurate use of readmission rates as a measure for healthcare quality. This is a benefit of administrative NHS health data, which allows tracking patients across providers, even if they changed the hospital during their initial stay to receive specialist care, or if they were not being readmitted to the hospital of the indexed admission.

2.3.2.3 Accuracy of data sources

Most studies derive readmission rates from electronic health databases, with the available information on patient characteristics, diagnoses and treatment being used for reimbursement purposes. The use of administrative health data has numerous benefits (Rubin *et al.*, 2001; Shenkman, 2003; Rothbard, 2015). For example, available data usually covers a large number of patients; information spans across different clinical specialities that are not disease-specific; and data contains standardised information, which allows for direct comparisons between healthcare providers. While the standardisation of information is a requirement determined by reimbursement bodies and offers some consistency for cross-provider comparisons, in turn this information was often collected for reimbursement purposes alone and without the objective to be processed any further (Thorn *et al.*, 2016). Therefore, data points contain granular information, with large variation in accuracy (Adeyemo and Radley, 2007; Sellers *et al.*, 2013; Muzerengi *et al.*, 2017), and with available information changing across financial years based on reimbursement practices. For example, thrombolysis treatment in stroke patients has seen significant increases over the past decade (Flynn *et al.*, 2014). However, it remains unclear how much of this rise is due to an increased uptake of this new technique, and how much is due to improved recording caused by linked reimbursement of hospitals in the NHS. Moreover, for the case of readmission rates, some studies have argued for an additional collection of information that will help distinguishing whether the observed readmission is unplanned or as part of the treatment plan (Adeyemo and Radley, 2007).

It could also be made clearer whether the readmission is related to the health condition at the indexed admission and thus, help improve the identification of readmissions that are amenable to healthcare quality (Fischer *et al.*, 2014). Policy-makers in England considered some of these problems when introducing financial penalties for

hospitals with excess readmission rates in 2011, for instance by excluding patients that are readmitted due to having had a transportation accident (Department of Health, 2011). However, it remains unclear how accurately this information is recorded at the hospital-level.

Several studies suggested that linking data across different sources may be advantageous (Jasinarachchi *et al.*, 2009; Jonas *et al.*, 2012; Meyers *et al.*, 2014; Thompson, Kurian and Luft, 2015); first to develop a better understanding about the care provided at different parts along the clinical pathway that could help uncover causalities between secondary care utilisation and healthcare quality (Røstad *et al.*, 2013), and second, to link in patient-level information that could predict future readmissions and hence, will enrich the risk-adjustment of readmission rates (Parker, McCombs and Graddy, 2003; Colais *et al.*, 2014; Blagburn *et al.*, 2015). This might include information such as the patients living arrangements, for example whether the patient is living alone or in a combined household, but may also relate to clinical information such as primary care utilisation, or prescriptions (Lichtman *et al.*, 2010; Richmond, 2013; Bradford *et al.*, 2017). While less granular information would improve practices of case-mix adjustment, often policy-makers and researchers face significant problems in linking information across different sources, due to inconsistencies in patient identifiers (Bohensky *et al.*, 2010), or data governance issues (OECD, 2015).

2.3.3 Association of readmission rates with other indicators of quality

The validity of readmission rates as an indicator for healthcare quality depends upon the methodological considerations discussed in the previous sections. Published findings regarding this topic are inconclusive, with large heterogeneity in the literature and hence, no definite established link between healthcare quality and readmission rates.

While many studies examined possible relationships, findings fluctuated depending on the chosen healthcare system, patient group, and clinical speciality (Halfon *et al.*, 2006; Jha, Orav and Epstein, 2009; Chen *et al.*, 2010; Axon and Williams, 2011; Kangovi and Grande, 2011; Berenson, Paulus and Kalman, 2012; Joynt and Jha, 2012). For example, in a validation study based on Medicare data, Jha *et al.* (2009) investigated the association between the quality of discharge processes and readmission rates. While they found no correlation between the documentation of discharge instructions for patients and readmission rates, the same study found a modest association between readmissions and the patient-reported experiences of discharge planning. In another study, the same authors found a substantial positive link between regional hospitalisation rates and readmission rates in the US (Epstein, Jha and Orav, 2011). Others investigated the impact of different levels of care provision along the patient pathway, specifically the continuity of care provided to patients. While a recent study based on the NHS found that patients that see the same primary care doctor more frequently when visiting a GP practice show lower rates of hospitalisation (Barker, Steventon and Deeny, 2017), similarly in the Taiwan healthcare system, continuity of care was found to be closely related with readmission rates (Cheng, Chen and Hou, 2010). Moreover, in the US, 55% of all readmissions were found to be linked to poor in-hospital quality of care, whilst the same study reported that one in twelve readmissions for patients with lung diseases are a result of poor healthcare quality (Axon and Williams, 2011). Interestingly, Horwitz *et al.* (2015) investigated the relationship between readmission rates and hospital volume and found that risk-adjusted readmission rates were lowest in hospitals with the lowest patient volume, which is contrary to the relationship with mortality rates or complications that were previously found to be lowest in high-volume hospitals. Overall though, the majority of reviewed articles found an inverse relationship, *i.e.* between low quality healthcare and high readmission rates, yet at varying magnitude (Benhassat and

Taragin, 2000; Ly, Jha and Epstein, 2011; Tsai *et al.*, 2013; Horwitz *et al.*, 2015; Dharmarajan, 2016). For example, a systematic review by Benhassat and Taragin (2000) found that 9% to 48% of all readmissions could be prevented through improvements in care for the condition treated from at the initial hospital stay, better discharge planning and post-discharge support. The same study cites evidence from randomized prospective trials, which showed that 12% to 75% of all readmissions relate to low levels of patient education and ability to self-care, poor determination of discharge needs at the hospital level, and substandard home care.

Compared with indicators such as mortality rates, readmission rates offer the opportunity to signal quality along different stages of the clinical pathway, as they were found to correlate with healthcare quality at the initial hospital stay (Hansen, Williams and Singer, 2011), quality of transitional care services (Feltner *et al.*, 2014; Lee *et al.*, 2015; Rennke and Ranji, 2015), and post-discharge support (Phillips *et al.*, 2004; Harrison *et al.*, 2013). Yet, several authors have called for additional analyses that will help uncover the determinants of hospital readmissions and also to investigate whether readmission rates associate with other outcome measures (*i.e.* in addition to length of stay and mortality), for instance patient-reported outcomes. Moreover, additional research needs to be conducted to understand whether efforts to reduce readmission rates by employing financial penalties for hospitals with excess readmission rates in the US and England can alter future readmission rates through incentivising improvements in healthcare quality.

2.4 Conclusion

This literature review aimed at examining the current state of research regarding the considerations needed prior to using readmission rates as a measure of healthcare

quality. While a definition of readmission rates based on evidence was provided in the introduction section of this chapter, the review focussed on three main aspects of readmission rates: first, the threat to validity of readmission rates as a measure for quality of care, including the need for risk-adjustment; second, data; and third, the association of readmission rates with other quality metrics.

The literature presented in this chapter makes a clear argument for the risk-adjustment of readmission rates. This is particularly important to separate readmission rates that are caused by patient-characteristics, including the number of underlying comorbidities or long-term conditions, from those readmissions that are under the control of the discharging hospital, or the healthcare system (García-Pérez *et al.*, 2011). Risk-adjustment is particularly important when making comparisons between providers, because not accounting for factors that lie outside the control will lead to a disadvantage in hospitals that are treating more complex patients with a resulting higher readmission rate. To address this concern, all analyses presented in chapters 3 to 6 use risk-adjusted readmission rates as an outcome measure.

Furthermore, one reason for the widespread use of readmission rates as a quality indicator is the relative ease of derivability from existing health data sets. Thus, data plays a pivotal part in the use of readmission rates, and specifically the reliance on good quality coding practices to identify respective readmissions. Moreover, information recorded on patient demographics and other clinical and non-clinical characteristics is widely used for risk-adjustment, yet their usability depends on availability in the first place, but also the quality of the record.

Finally, despite the use of readmission rates as an outcome measure, it is accepted that only a fraction of the observed number of readmission can be prevented through improvements in quality of care, which includes high quality in-hospital care, need-

assessments prior to patient discharge, adequate post-discharge support, and access to primary care services. Preventability of readmission rates varies by patient group and condition treated for at the initial hospital stay, but is believed to be on average about 30%. This is low, and other metrics such as infection rates or mortality rates might therefore be better suited as quality indicators. However, while these two metrics are highly correlated with the quality of the in-hospital stay, they offer little value for the assessment of care quality along the patient pathway, unlike readmission rates.

Several authors have investigated the relationship of readmission rates with other measures for quality of care, with generally mixed outcomes. For instance, evidence pointed at a link with length of stay, specifically an increased risk of a readmission with increases in length of stay due to the adverse physiological and psychological impacts of a hospital stay. However, it is also possible that length of stay reflects on the disease severity, which may not be picked up appropriately in the risk-adjustment. Further research has found a relationship of readmission rates with the hospital's inherent likelihood of admitting patients, whereas others have found no relationship with the hospital volume, which is commonly linked to procedure performance and mortality. The findings from this literature review show that there are no perfect measures for quality of care, especially none that are easily available in existing health datasets. This also leads to limitations in validating readmission rates as an appropriate outcome measure, as often, studies tried to establish associations with other metrics captured within the same datasets and over time. To address this problem, chapter 4 uses a linked dataset to investigate the association between readmission rates and patient reported outcome measures. This helps to validate readmissions with a measure directly capturing the experience of the patient, arguably information that describe what patients really care about with regards to quality of care.

Research within each aspect highlighted challenges, which if not addressed carefully, could introduce possible biases into the estimation of readmission rates as well as their interpretation. While arguably there is no perfect measure for healthcare quality, findings of this review suggest that quality should be assessed using a set of available measures (Press *et al.*, 2013), rather than focussing solely on readmission rates. This goes against the policy practices of several healthcare systems, which introduced an enhanced policy focus specifically on reducing readmission rates as a way to improve healthcare quality. However, findings of this review are not implying that reducing readmission rates are not associated with improvements for patients, rather that policy-makers should be careful in interpreting observed changes in readmission rates, particularly when combining them with an incentive system. I address this concern by expanding the use of quality measures to evaluate a health service reorganisation in chapter 6.

Chapter 3 National trends in emergency readmission rates: A longitudinal analysis of administrative data for England between 2006 and 2016

3.1 Preamble to Chapter 3

Policy-makers across several healthcare systems have placed great emphasis on reducing readmission rates as a way to improve quality of care. For example, the English National Health Service (NHS) introduced financial penalties for hospitals with excess readmission rates in 2011; yet, a recent Healthwatch analysis reported a 22.8% rise in the number of readmissions over the past five years. Despite the salience of this issue for policy-makers and clinicians, no study has examined the latest trends of emergency readmission rates and their changes in variation across providers.

The following chapter uses national hospital administrative data to investigate trends of emergency readmission rates and the degree of variation due to unobservable factors for 150 hospital trusts over a ten-year period (April 2006 to February 2016). Moreover, the chapter reports on changes in trends and variation for nine clinical subgroups. I find encouraging signs of improvement in healthcare quality provided to patients across England, however a large heterogeneity across clinical subgroups was also identified, with some clinical groups experiencing marked increases in readmission rates.

A research paper derived from this chapter has been published in the *BMJ Open*. I would like to thank Doctor Katharina Hauck, Professor Paul Aylin and Doctor Adam Steventon for their invaluable discussions and comments on a previous draft version. The chapter also includes feedback received from two peer-reviewers.

3.2 Introduction

One of the top priorities of the English NHS is not only to provide suitable and high quality in-hospital health care, but also to follow it up by an efficient discharge process, with the overall aim of ensuring best possible outcomes for patients (Department of Health, 2015). Despite this, patients continue to receive care that varies based on where in the country they access the NHS (NHS England and Public Health England, 2015), and while some of the variation can be explained by differences in the complexity of the patients' medical needs (Mant, 2001), other variation remains unjustified, and presents an opportunity for improving delivery of care processes (Wennberg, 2002). In fact, the NHS Five Year Forward, as its key objective, has highlighted the need to close this 'quality gap' (NHS, 2014), and which has also been tackled by policies such as the Right Care Programme (NHS England, 2017) and Getting it Right First Time (Timmins, 2017).

As addressed in Chapters 1 and 2, emergency hospital readmissions rates carry significant limitations as a metric of assessing quality of care provided by healthcare systems (Fischer *et al.*, 2014). Yet, using readmission rates as a measure of care quality can be justified by two key arguments. First, and most importantly, readmission rates are included in the actual quality frameworks of the English healthcare system (Kristensen, Bech and Quentin, 2015), and are extensively used and documented by the English NHS as a quality indicator (Krumholz *et al.*, 2009; Lindenauer *et al.*, 2010; Stefan *et al.*, 2013). Second, they are able to demonstrate quality of care provided along the entire patient pathway (Phillips *et al.*, 2004; Hansen, Williams and Singer, 2011; Feltner *et al.*, 2014; Harrison *et al.*, 2014; Lee *et al.*, 2015; Rennke and Ranji, 2015), and are thus able to capture a comprehensive picture of care provided at a systemic-level.

Prior research investigating trends in readmission rates, used a method of analysis whereby national-level readmission rates were aggregated across all hospitals (Blunt *et al.*, 2015).

On the one hand, national readmission rates appear to be a good marker of overall improvement made within a healthcare system. On the other hand, and more importantly, such aggregation dilutes the differences in progress not only between hospitals, but also between various groups of patients. This dilution then has the opposite impact from wanting to improve the quality of care given to individuals irrespective of their clinical needs or the hospital they access, by disallowing the identification of the specific healthcare providers and clinical areas that in fact require policy attention. Supplementing national trends in readmissions with an exploration and analysis of the variation between providers and patient groups becomes extremely important to expose the hidden and complex dimensions in quality of care, since it can aid policy-makers in designing and implementing more targeted and cost-effective improvements.

In order to capture the variation in emergency readmission rates between and across hospitals, I employed an analytic method called the Systematic Component of Variation (SCV) (McPherson *et al.*, 1982). SCV is a commonly used metric of assessing variation within health systems (Aylin *et al.*, 2004; Bevan *et al.*, 2004; Care, 2007), and is described in more detail in the next section. To capture variation across different clinical areas, I analysed separately, nine groups of patients, each of whom had specific conditions and underwent specific procedures. In an attempt to provide a comprehensive assessment of readmission rates trends in England, I used a large dataset, derived from the Hospital Episode Statistics (HES) database, which consisted of records of all patients who had been admitted to a cluster of hospitals over a period of 10 years.

3.2 Methods

3.2.1 Study population

I studied all patients who received secondary care between April 2006 and February 2016 in 150 non-specialist NHS Trusts were included in the final analyses. NHS Trusts are providers of healthcare that typically combine several hospital sites. Patients were identified from pseudonomized and unidentifiable health care records in the HES database. To capture a patients' period of hospital stay, I constructed linked health records from the patients' admission to discharge, even when patients changed hospital as part of the hospital stay (NHS Digital, 2017; Busby *et al.*, 2017).

I included all adult patients admitted and discharged from a non-specialist NHS trust between 1 April 2006 and 29 February 2016. This included discharges following any elective (*i.e.* planned) or emergency (*i.e.* unplanned) indexed (*i.e.* original or first) admission. Moreover, I included any patient admitted as a day-case – a healthcare trend in the NHS that saw a rising shift of care from in-patient settings to outpatient settings over the observation period (Secondary Care Analysis Team (NHS Digital), 2016).

Any patient discharged in March 2016 was removed from the study sample, to ensure a sufficient follow-up period within the scope of the data for the calculation of readmission rates within 30-days from patient discharge. Moreover, I excluded a total of 56,401,750 admissions from an initial sample of 140,709,025 admissions. The number of specific admissions excluded from the study sample in this chapter can be broken down as follows: (a) 17,860,079 admissions from patients below 18 years of age; (b) 11,173,561 admissions from patients without complete records of variables required for the risk-adjustment process; (c) 12,085,711 admissions related to maternity, (d) 13,985,696 admissions related to cancer treatment, such as chemotherapy; and (e) 1,296,703 patients who did not survive the indexed admission were removed, because

naturally they could not result in a readmission. If in some instances, health records from patients showed several admissions to hospital, each admission was treated as an indexed admission if they occurred more than 30 days from discharge of the preceding admission. The definition of emergency readmission rates follows that stated in Chapter 1 of this thesis (see Section 1.7). I used the 30-day readmission rate metric, i.e. when the readmission occurs within 30 days of discharge from the indexed admission. The 30-day period follows widely used practice in the assessment of quality, and I only counted the first readmission within 30 days for each patient, even if several readmissions occurred within the defined follow-up period. Importantly, in this chapter I have not considered the cause for the readmission, possibly leading to some readmissions that are unrelated to the condition of the indexed admission.

First, I calculated annual readmission rates at the national-level by averaging across hospital-specific readmission rates. Second, I investigated annual readmission rate trends for patients with an indexed admission falling within nine specific clinical conditions. The selection of health conditions followed the underlying assumption that the patients' experience with the healthcare system is likely to vary depending on their reason for seeking healthcare in the first place. For instance, while acute conditions require hospital admissions and extensive rehabilitative care services, patients with long-term conditions are usually managed within the primary care setting (Goodwin *et al.*, 2010). Publicly available statistics on the use of 2015/16 healthcare services in the NHS based on the primary condition was used to select specific acute conditions and chronic conditions (NHS Digital, 2016a). Subsequently, I included patients with an indexed admission record for acute myocardial infarction, stroke and pneumonia as acute conditions; and patients with an indexed admission record for congestive heart failure, chronic obstructive pulmonary disease (COPD) and diabetes mellitus as long-term conditions. To identify relevant surgical interventions, I focussed on commonly performed surgeries in the

English NHS, and selected those belonging to different surgical subsections (Abbott *et al.*, 2017).

Thus, I chose hip and knee replacement, hysterectomy and cholecystectomy.

The selection of patients for the subgroup analyses was based on HES recorded primary diagnoses codes (International Classification of Diseases 10th edition, or ICD-10) and procedure codes (Classification of Intervention and Procedure Codes, or OPCS-4). Table 1 lists the applied ICD-10 codes and OPCS-4 codes for this chapter.

Table 1

Primary diagnosis codes (ICD-10 codes) and procedure codes (OPCS-4 codes) used for the identification of patients for subgroup analyses

Condition	ICD-10	OPCS-4
Acute Myocardial Infarction	I21, I210, I211, I212, I213, I214, I219, I22, I220, I221, I228, I229	-
Stroke	I60, I61, I62, I63, I64	-
Pneumonia	J12, J13, J14, J15, J16, J17, J18	-
Chronic Obstructive Pulmonary Disease	I278, I279, J40, J41, J42, J43, J44, J45, J46, J47, J61, J62, J63, J64, J65, J66, J67, J684, J701, J703	-
Heart Failure	I110, I130, I132, I50, I501, I509, J81X	-
Diabetes	E10, E11, E12, E13, E14	-
Hip and knee replacement	-	W371, W378, W379, W381, W388, W389, W391, W398, W399, W461, W468, W469, W471, W478, W479, W481, W488, W489, W931, W938, W939, W941, W948, W949, W951, W958, W959, W521, W528, W529, W531, W538, W539, W541, W548, O181, O188, O189, W400, W402, W403, W404, W410, W412, W413, W414, W420, W422, W423, W581, W582, W424, W425, W426, W520, W522, W523, W530, W532, W533, W540, W542, W544, O180, O182, O183, O184
Cholecystectomy	-	J18
Hysterectomy	-	Q07

3.2.2. Statistical analysis plan

For each Trust and financial year, I first estimated the average observed emergency readmission rate (*OR*) by aggregating information on readmissions from the patient-level data. I then adjusted for systematic differences in patient complexity across Trusts based on patient case-mix information recorded in HES, including on demographics and clinical history. For each Trust and financial year, I calculated the predicted emergency readmission rates (*ER*), using a logistic regression model that was applied to the patient-level. I entered the following patient case-mix information into the predictive model: patient age as recorded on admission, sex, ethnic origin, a score representing the level of socio-economic deprivation (i.e. the Index of Multiple Deprivation or IMD version 2010 that is based on small geographic areas, which contain on average 1,500 residents each) (Department for Communities and Local Government, 2015), the number of comorbidities based on the Charlson comorbidity index (Sundararajan *et al.*, 2004), and length of stay. The Charlson index used in this chapter was calculated according to a list of diagnoses codes that were recorded at the indexed (i.e. initial) admission and during indexed admissions that occurred within one-year prior (*i.e.* with a look-back period of one financial year). Because of evidence that the recording of diagnoses codes in HES has improved over the years (Navid *et al.*, 2015), it is possible that the number of comorbidities in the study sample increases, without real changes to the underlying number of comorbidities. To address this concern, I entered interaction terms between the Charlson index and the financial year into the prediction model. I also entered length of stay into the risk-adjustment model, due to literature indicating that every additional day spent in hospital increases the patients' risk of incurring an adverse event (Hauck and Zhao, 2011), possibly impacting on the probability of recovery. On the other hand, length of stay might also provide an indication of severity in the absence of any adequate measures recorded in HES. It is, however, possible that adjusting for length of stay might remove some of the variation in readmission rates, as length of stay is also frequently used as a measure of healthcare quality (Vermeulen *et al.*, 2016).

The risk-adjusted, 30-day readmission rate for each Trust and in each financial year was calculated by dividing the *OR* by *ER*. In fact, this ratio allows an assessment of whether the Trust performed below or above what would have been expected given the types of patients treated in that financial year. I then multiplied this ratio for each Trust and financial year by the average emergency readmission rate observed at the national-level in that financial year.

The SCV methodology developed by McPherson *et al.* (1982) was used as a way to examine the amount of Trust-level variation in English 30-day emergency readmission rates. The SCV can be described as the variance of the ratios of *OR* and *ER*, minus the random component caused by Poisson variability (Newton, Seagroatt and Goldacre, 1994) times 100, and was calculated using the following equation:

$$SCV = \left[\frac{\sum_i \frac{(OR_i - ER_i)^2}{ER_i^2} - \sum_i \frac{1}{ER_i}}{n-1} \right] \times 100$$

Because hospital readmissions are relatively rare events (*i.e.* on average below 7 readmissions per 100 discharges), it is possible to assume that *ER* approximates a Poisson distribution. The SCV was calculated for each financial year, and each category of the indexed admission preceding the emergency readmission. More generally, the SCV measures the degree of variation caused by time-invariant, unobservable characteristics related to the hospitals, but also possibly the characteristics of populations treated in that financial year. Because of these variations in characteristics, hospitals diverge from the average emergency readmission rate observed at the national-level. If for a particular financial year, hospitals report very different emergency readmission rates due to unobservable characteristics that are not captured by the variables entered into the logistic regression model to calculate *ER*, then the SCV is high. These unobservable hospital characteristics might include factors such as good or poor management practices, and staff satisfaction, while unaccounted patient characteristics might include socio-

economic factors that correspond to medical need, but are not addressed through the IMD that is currently provided in HES (Sundararajan *et al.*, 2004).

According to studies published previously, the SCV score classifies into three distinct groups corresponding each to different levels of variation. For example, an SCV score valued below 3.0 represents small variation in emergency readmission rates; a score valued between 5.4 and 10.0 represents high variation in emergency readmission rates; and a score valued above 10.0 represents very high variation in emergency readmission rates (Murthy *et al.*, 2003; Bevan *et al.*, 2004; Appleby *et al.*, 2011). However, interpretations used in previous literature are ambiguous, for instance one study by Ibáñez *et al.* (2009) considered an SCV score above 16.0 to indicate high variation, while a more recent study by Coles *et al.* (2012) that examined variation in access to health services commissioned by the National Specialised Commissioning Team in England, considered high variability for an SCV score valued at or above 20.0.

I estimated a regression model with ordinary least squares estimators to test whether trends in risk-adjusted, 30-day emergency readmission rates changes across financial years. In the model, the risk-adjusted emergency readmission rate was entered as a dependent variable, and time dummies for each financial year entered as independent variables. The time dummy for the financial year 2006/07 was omitted as it represented the baseline case. Based on the direction of the coefficient estimates calculated from the regression model, I was able to show whether the trend in readmission rate in a respective financial year was significantly different from the trend in readmission rate at the baseline case, i.e. in the financial year 2006/07.

I also performed several sensitivity analyses that looked at readmission rates of alternated follow-up periods. Specifically, I investigated emergency readmission rates that occurred within 7-days and 90-days following discharge from an indexed admission. Alternate to the SCV score, I also report the standard deviation as a more intuitive measure of variation. The initial data

extraction for this chapter was done using SAS Enterprise Miner, followed by the statistical analysis with STATA version 13.

3.3 Results

3.3.1 Study sample

The data revealed a total of 62,584,297 indexed admissions, corresponding to 43,551 indexed admissions per Trust per financial year, with a range from 1,195 to 121,500. These admissions came from a total of 23,069,134 individual patients, highlighting that some patients experienced multiple indexed admissions between 2006/07 and 2015/16. As depicted in Table 2, the mix of patients treated in hospital changed slightly across the observation period. This included an increase in the average patient age by more than two years, from 57.4 years in 2006/07 to 59.4 years in 2015/16 ($p < .001$). Moreover, the average number of comorbidities based on the Charlson index increased slightly by .22, from .23 in 2006/07 to .45 in 2015/16 ($p < .001$). However, as discussed in the methods section, it is not certain whether these increases actually suggest that patients have become sicker over the years, but instead, the observed increase in the Charlson index may relate to improvements in coding of diagnoses codes. Other patient characteristics, such as the gender ratio, or the proportion of different ethnicities have remained relatively stable. However, the data also shows that patients admitted to hospital remained inpatients for a shorter period of time, specifically the average length of stay decreased by just under one day, from 3.16 days in 2006/07 to 2.25 days in 2015/16 ($p < .001$). This finding is supported by healthcare system trends to increase the number of day-cases, which are included in this analysis.

Table 2

Summary statistics of all patients in the study sample by financial year

Variable	FY 2006/07	FY 2015/16
	Mean (No)	Mean (No)
No of index discharges	5 204 263	6 219 153
Patient age (years)	57.42	59.46
Female (%)	54.02 (2 811 559)	54.48 (3 391 862)
White (%)	89.40 (4 652 641)	87.76 (5 463 584)
Black (%)	2.26 (118 127)	2.55 (158 949)
Asian (%)	4.13 (215 017)	5.03 (313 120)
Other (%)	1.48 (77 369)	2.17 (135 425)
Length of stay in days (Total days per year)	3.16 (16 461 340)	2.25 (14 029 556)
Patients discharged from quintile 1 - IMD score (least deprived)	20.90 (1 087 857)	19.33 (120 3376)
Patients discharged from quintile 2 - IMD score	20.39 (1 061 572)	19.74 (1 229 077)
Patients discharged from quintile 3 - IMD score	19.93 (1 037 591)	20.15 (1 254 540)
Patients discharged from quintile 4 - IMD score	19.49 (1 014 601)	20.17 (1 255 631)
Patients discharged from quintile 5 - IMD score (most deprived)	19.26 (1 002 642)	20.60 (1 282 480)
Charlson comorbidities	0.23	0.45
Crude 30-day readmission rate (%)	6.50 (338 565)	6.73 (418 949)
Number of NHS trusts	150	139

Note. Summary statistics across all patients for each financial year

3.3.2 Trends and variation in national emergency readmission rates for all NHS patients

The data revealed an increase in the total number of indexed admissions by 1,014,890, from 5,204,263 in 2006/07 to 6,219,153 in 2015/16 ($p < .001$). This was accompanied by a marked 80,384 increase in the number of emergency readmissions following discharge from an indexed admission, from 338,565 emergency readmissions in 2006/07 to a total of 418,949 emergency readmissions in 2015/16 ($p < .001$). However, the crude emergency readmission rate stayed relatively stable, by first increasing from 6.50% in 2006/07 to 6.75% in 2012/13 ($p < .001$), but then remaining constant until 2015/16. Similarly, the standard deviation measuring the variation in crude readmission rates between Trusts also remained constant, from .95% in 2006/07 to .93% in 2015/16 ($p = .30$). On the other hand, the risk-adjusted, 30-day emergency readmission rate increased slightly from 6.56% in 2006/07 to 6.76% in 2012/13 ($p < .01$), followed by a small decrease to 6.64% in 2015/16 ($p < .01$). While these changes appear relatively small, given the large sample size even small changes in the average readmission rate translate into a significant number of patients that either have to seek additional care, or are spared from this experience. In the case presented in this chapter, the seemingly small decrease in risk-adjusted, emergency readmission rates between 2012/13 and 2015/16 translated into an annual reduction of 7000 patients who did not have to be readmitted.

For the whole study period, the average SCV score for readmissions following any indexes admission was 15.11. However, the SCV score decreased slightly by 1.06, from 15.60 in 2006/07 to 14.54 in 2015/16 ($p < 0.001$). This finding shows that despite small increases in the readmission rates across the study period, the unexplained variation between trusts in England reduced significantly. This observation supports the reported reductions in the standard deviation. Trends in risk-adjusted, 30-day emergency readmission rates and the SCV score are depicted visually in Figure 2.

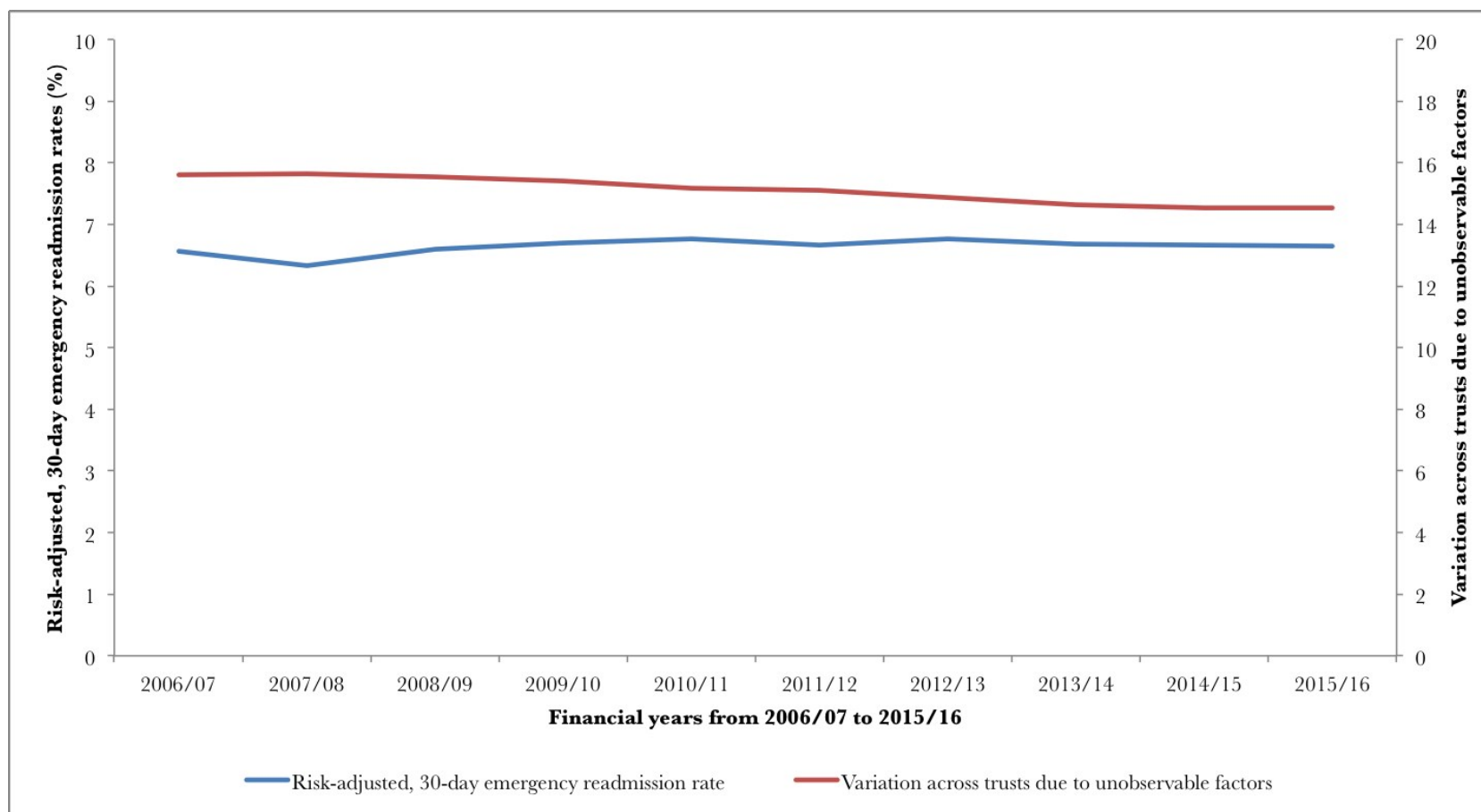


Figure 2. Trends in risk-adjusted, 30-day emergency readmission rates and variation in England from 2006/07 to 2015/16

As described in the method section, to test whether risk-adjusted, 30-day emergency readmission rates in each financial year differed from the baseline case in 2006/07, I performed regression analysis with ordinary least squares estimators. The model output reported in Table 3 shows a statistically significant decrease in risk-adjusted, 30-day readmission rates across the study period, with emergency readmission rates in 2010/11 being .21% ($p < .05$) above the baseline case. However, the risk-adjusted, 30-day emergency readmission rate was not significantly different for any of the other examined financial years.

Table 3.

Ordinary Least Squares regression analysis for readmission rates between 2006/07 and 2015/16

Variable	30-day readmission rates (adjusted)		
	Coefficient	Std. Error	t-statistics
Constant	6.56***	.08	80.95
FY 2006/07		Baseline	
FY 2007/08	-.23**	.11	-2.05
FY 2008/09	.03	.11	.32
FY 2009/10	.13	.10	1.20
FY 2010/11	.21**	.10	1.95
FY 2011/12	.10	.10	.96
FY 2012/13	.20*	.10	1.88
FY 2013/14	.12	.10	1.13
FY 2014/15	.09	.10	.89
FY 2015/16	.08	.10	.75
N	14.46		
R-squared	.01		

Note. *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5% and * for 10%.

3.3.3 Trends and variation in emergency readmission rates for patient subgroups

Despite generally stable risk-adjusted, 30-day readmission rates following discharges from any indexed admission, the subgroup analyses revealed heterogeneous trends. This information would have otherwise remained concealed, highlighting the value of analysing data beyond the aggregate. Findings of the subgroup analyses are depicted in Table 4. For example, I

find that risk-adjusted, 30-day emergency readmission rates following discharge from an elective (i.e. planned) indexed admission decreased only marginally, from 2.88% in 2006/07 to 2.61% in 2015/16 ($p < .05$) and was accompanied by a reduction in the corresponding SCV score, from 35.91 in 2006/07 to 35.30 in 2015/16 ($p < .05$). Over the same period, risk-adjusted, 30-day emergency readmission rates following discharge from an emergency (i.e. unplanned) indexed admission increased by 1.27% ($p < .001$), from 11.49% in 2006/07 to 12.76% in 2015/16. However, similar to the elective case, the SCV score decreased by .61, from 8.41 in 2006/07 to 7.90 in 2015/16 ($p < .01$).

I then examined changes in risk-adjusted, 30-day emergency readmission rates for nine clinical subgroups. For elective procedures, I found reductions in patients undergoing total hip and knee replacement (-1.29%; $p < .001$). Small decreases, or rather constant risk-adjusted, 30-day emergency readmission rates are seen for patients with an indexed admission for acute myocardial infarction (-0.04; $p = .49$), heart failure (+0.15%; $p < .05$), COPD (+0.41%; $p < .05$) and stroke (+0.62; $p < .05$). For the other four conditions covered in this chapter, I found increases in the risk-adjusted, 30-day emergency readmission rate: cholecystectomy (+1.86; $p < .001$), hysterectomy (+2.54%; $p < .001$), pneumonia (+2.72%; $p < .001$), and substantially large increases for patients with an indexed admission recorded for diabetes (+7.09%; $p < .001$).

Table 4.

Descriptive statistics of crude, 30-day readmission rates and SCV for selected patient subgroups

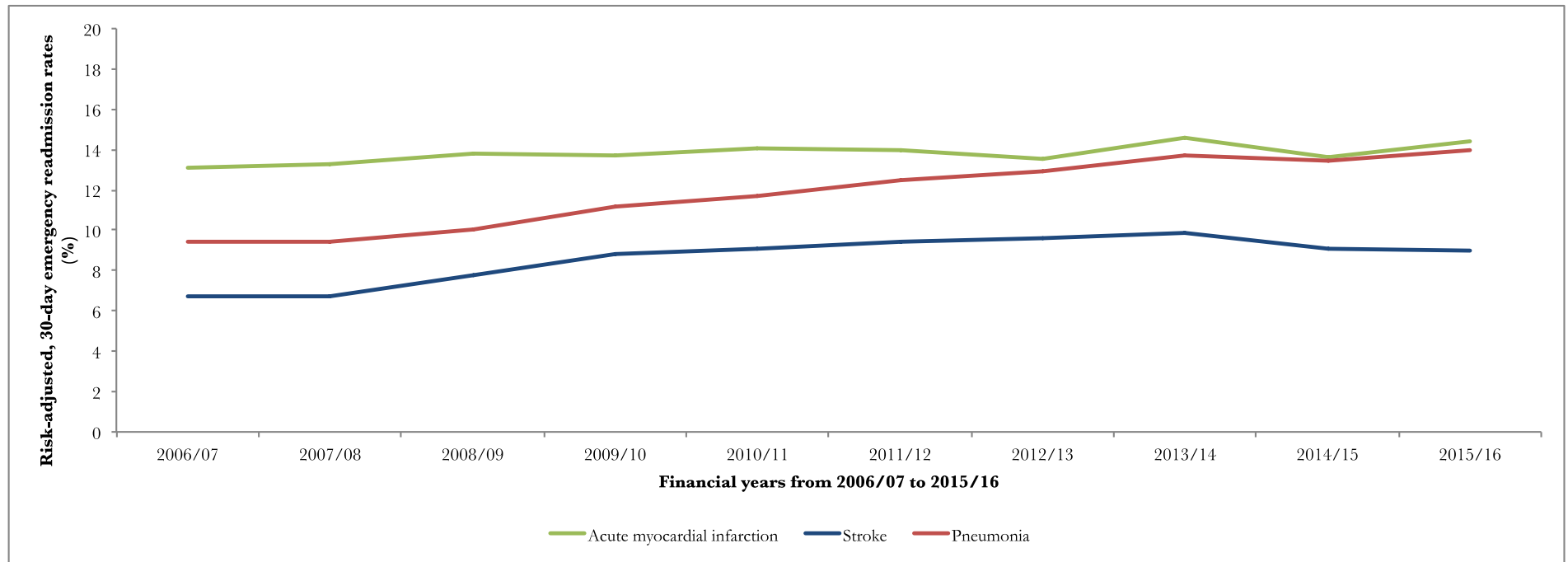
Type of indexed admission	FY 2006/07			FY 2015/16		
	No of indexed admissions	Mean readmission rate (S.D.)	SCV	No of indexed admissions	Mean readmission rate (S.D.)	SCV
All	5 204 263	6.50 (0.95)	15.60	6 219 153	6.73 (0.93)	14.58
Emergency	2 146 898	11.70 (1.07)	8.41	2 505 047	12.68 (0.97)	7.90
Elective	3 057 365	2.85 (0.46)	35.91	3 718 858	2.72 (0.39)	35.30
Acute myocardial infarction	43 416	15.07 (2.70)	6.74	39 037	15.32 (3.32)	6.37
Stroke	34 835	9.88 (2.45)	9.43	45 601	10.45 (2.07)	9.37
Pneumonia	46 224	13.73 (2.60)	7.14	106 554	15.76 (2.03)	6.48
COPD	97 306	16.54 (2.06)	6.15	103 871	16.91 (2.37)	5.97
Heart failure	32 051	17.47 (3.12)	5.76	38 349	17.77 (3.22)	5.60
Diabetes	30 280	9.56 (4.48)	9.61	25 574	13.58 (3.45)	8.67
Hip and knee replacement	59 267	7.56 (2.11)	13.94	64 155	7.06 (2.15)	13.48
Cholecystectomy	37 627	6.34 (1.88)	14.17	44 488	7.18 (1.92)	14.70
Hysterectomy	18 355	7.09 (2.85)	12.30	13 897	7.59 (3.30)	14.85

Note. The table depicts crude 30-day emergency readmission rates; S.D: Standard Deviation; COPD: Chronic obstructive pulmonary disease

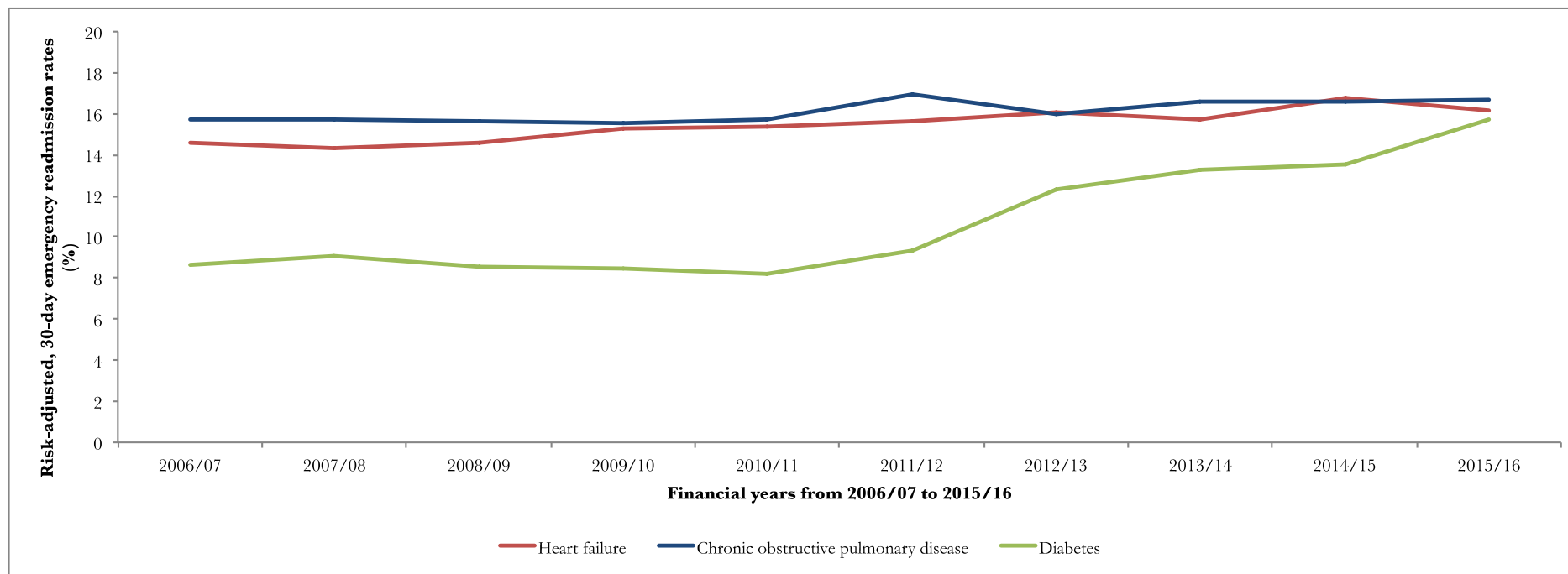
Except for emergency readmission rates for patients with an indexed admission for cholecystectomy and hysterectomy, the SCV score for all other conditions decreased. This suggests lower levels of unobservable variation in quality (*i.e.* measured through readmission rates) across England. However, depending on the condition, in this analysis I found either medium or high levels of variation, indicated by the SCV score. The lowest SCV scores were observed for patients with heart failure (5.60) and COPD (5.97). Trends in risk-adjusted, 30-day emergency readmission rates and the SCV score for all clinical subgroups are depicted visually in Figure 3.

Last, I also performed sensitivity analyses around the time-window used to capture emergency readmissions, thus looking at emergency readmissions that occurred within 7 days, or 90 days of discharge. I found a slight increase in 7-day emergency readmission rates, from 3.20% in 2006/07 to 3.37% in 2015/16, but a slight decrease in 90-day emergency readmission rates, from 9.99% in 2006/07 to 9.78% in 2015/16. Despite differences in readmission trends, the SCV score reduced for both patients readmitted within 7-days (-1.84) and 90-days (-0.57). An overview of changes is presented in Table 5.

a)



b)



c)

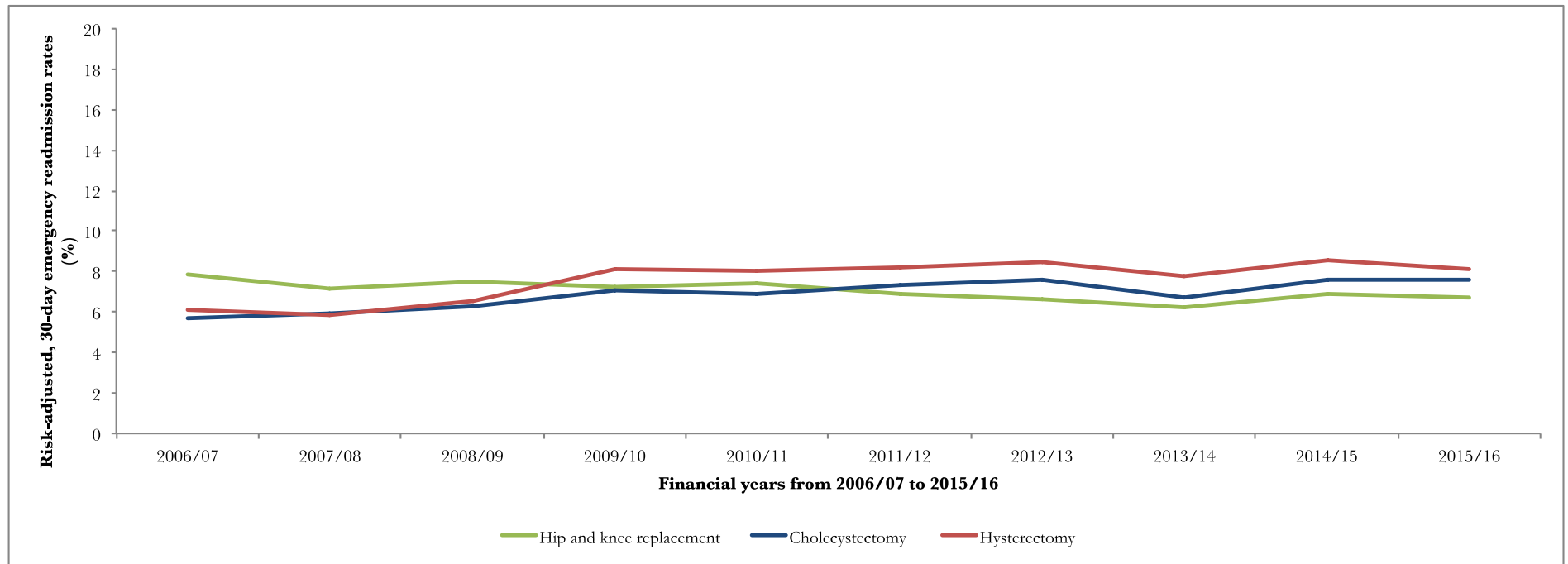


Figure 3. Trends in risk-adjusted, 30-day emergency readmission rates for a) indexed acute conditions, b) indexed chronic conditions, and c) surgical interventions, from 2006/07 to 2015/16.

Table 5.

Sensitivity analysis for 7-day and 90-day emergency readmission rates

	FY 2006/07			FY 2015/16		
	No of indexed admissions	Mean readmission rate (S.D.)	SCV	No of indexed admissions	Mean readmission rate (S.D.)	SCV
7-day emergency readmission rate	5 728 882	3.20 (.56)	31.11	7 123 792	3.37 (.58)	29.27
30-day emergency readmission rate	5 204 263	6.50 (.95)	15.60	6 219 153	6.73 (.93)	14.58
90-day emergency readmission rate	4 597 361	9.99 (1.33)	10.42	5 088 164	9.78 (1.22)	9.85

Note. Emergency readmission rates are for any indexed admission; Crude readmission rates weighted by the number of indexed admissions per Trust; SCV: Systematic Component of Variation.

3.4 Discussion

The introduction of this chapter alluded to the importance of emergency readmission rates as a metric of assessing quality of care in the English NHS; not only are readmission rates a widely used metric within the healthcare system, but also local and national-level health policies in England specifically target readmission rates, such as the national-level policy of imposing financial penalties on hospitals with excessive readmission rates, as a way to improve care quality (Department of Health, 2010). However, despite this enhanced focus, surprisingly little is known about whether such policies have in fact impacted quality of health care provided by the NHS, including what the trajectory of readmission rates over the last decade looks like. To fill this vital gap in research, I investigated emergency readmission rates for all non-specialist English NHS Trusts between the period of 2006/07 and 2015/16. The results reveal that for any indexed admission, there was a slight increase in risk-adjusted, 30-day emergency readmission rates post discharge from 6.56% in 2006/07 to 6.76% in 2012/13, following which readmission rates decreased to 6.64% in 2015/16. Simultaneously, the SCV-measured degree of variation decreased from 15.60 to 14.54 between 2006/07 and 2015/16.

When results were separated based on the diagnosed clinical condition and type of admission, a heterogeneous trend was found, where readmission rates had decreased for some groups of patients, but increased for other groups. In the context of type of admission, for patients who underwent any elective surgery, results highlighted that there was a slight decrease in the readmission rates; perhaps reflecting an effect of government initiatives such as the Commissioning for Quality and Innovation scheme in the 2008 NHS Stage Review, that specifically targeted improvement of metrics like infection rates (UK Department of Health, 2008). However, for patients who had emergency admissions, the opposite was found, *i.e.* emergency readmissions increased over the ten-year period.

In the context of the type of clinical disorder, disaggregation showed that readmission rates for patients who had initially been admitted for heart failure, acute myocardial infarction, stroke and COPD had remained constant, decreased for patients who had been initially admitted for hip- or knee replacement procedures, and increased for those who had been initially admitted for diabetes, pneumonia, cholecystectomy and hysterectomy. With respect to the last group, the largest increase in risk-adjusted, emergency 30-day readmission rates was seen for patients with diabetes. This could be due to several reasons; for instance, there is a possibility that coding practices related to diabetes has improved over the observation period. Second, readmission rates in this population have been previously linked to side effects of diabetic drugs (Agency, 2016). A third explanation is that diabetes-related death or mortality has seen a significant decrease over the last years, but at the same time, the incidence of diabetes itself has increased with the parallel increase in the population of socio-economically deprived individuals (Fleetcroft *et al.*, 2017).

Some key differences exist between the findings in this chapter and previous literature on readmission rates for different groups of clinical patients. For instance, I found a 30-day readmission rate of 17.0% in 2015/16 for COPD, in comparison to a previous study that reported a readmission rate of around 10.2% for all patients registered with a general practice in London between 2006 and 2010 (Harries *et al.*, 2017), and another study by the Royal College of Physicians reported an even higher rate 31% to 34% between 2001 and 2010, however, for readmissions that occurred 90 days after discharge (White and Harries, 2016). Similar differences exist when comparing the current findings to those from a different health care system. For example, studies conducted in the United States reveal that the readmission rates for pneumonia and acute myocardial infarction were 18.3% and 19.9%, respectively (Dharmarajan *et al.*, 2013). In contrast, I found that, for the same conditions, the readmission rates in the NHS for 2015/16 are much lower, at 16.0% for pneumonia and 15.2% for acute myocardial infarction.

However, the pattern of readmission rates found in this chapter closely match those found in a previous paper examining trends of readmission rates within the English NHS (Blunt *et al.*, 2015b), with a slight difference in the magnitude of readmission rates, *i.e.* 6.67% in my analysis versus 7.00% in theirs. There are two key reasons for this difference. First, I employed a different method of linking data from HES; I used continuous inpatient spells whereas the authors of the other paper used single spells. Second, my definition of indexed admission was different to the previous study; I considered only the first readmission, while the other study considered every readmission for the patient that occurred within 30-days of discharge.

Few research studies in the past have assessed trends in readmission rates. Two studies examined readmission rates in the United States as a measure of quality of care; one did so for different types of hospitals (Salerno *et al.*, 2017), while a second looked at readmission rates related to surgeries and for selected subgroups of patients (Tsai *et al.*, 2013). Other studies have examined quality of healthcare provided at singular pathway points within the healthcare system, such as the exploration of care quality differences between hospitals by using mortality rates as a metric (Goodacre, Campbell and Carter, 2015). Within the English context, one study that examined readmission rates did so only up to the period of May 2010, but did not separate the analysis for different types of clinical conditions (Blunt *et al.*, 2015b). Through this chapter, I have built, and importantly expanded on previous literature, by first providing a comprehensive and updated overview of the changes in risk-adjusted, 30-day emergency readmission rates over a ten-year period (until February 2016), and second, by providing a more meaningful analysis of readmission rates separately for nine clinical conditions. Given the enhanced focus and increased efforts on part of the government to reduce readmission rates since *Equity and Excellence* was published in April 2010, this updated overview provides a timely description of the readmission metric. However, this chapter also suffers from methodological limitations, which along with its strengths, are discussed in the next section.

3.4.1 Strengths and limitations

To assess trends in readmission rates in the English NHS, the metric of risk-adjusted, 30-day emergency or unplanned readmission rates was used as an outcome measure. Being readmitted to hospital within 30 days of initial discharge from the hospital describes not only an undesirable circumstance for patients, but it also adds additional and perhaps avoidable strain on health care services. This follow-up period was also chosen due to its correlation with key indicators that reflect quality of care along the entire patient pathway, such as the initial hospital stay and post-discharge support (Phillips *et al.*, 2004; Hansen, Williams and Singer, 2011; Feltner *et al.*, 2014; Harrison *et al.*, 2014; Lee *et al.*, 2015; Rennke and Ranji, 2015). However, it is also highly possible that quality of care affects readmissions that occur after the 30 days since discharge. For instance, some studies highlight the value of using 90-day readmission rates when evaluating care quality given to older, more frail patients, once they are discharged from rehabilitation facilities (Galloway *et al.*, 2016). Other studies argue that using the 7-day readmission metric is more appropriate since it better correlates with the care quality at the initial hospital stay (Chin *et al.*, 2016).

To address such concerns, sensitivity analyses were conducted which supplemented the analysis for trends and variation in 30-day readmission with an analysis of trends and variation in 7-day and 90-day emergency readmission rates. Results showed that there were small increases and decreases in 7-day readmission rates and 90-day readmission rates, respectively. Specifically, statistically significant differences were found in emergency readmission rates across certain financial years; however, these changes were of a small magnitude, and their clinical meaningfulness depended on the distribution of incremental changes across Trusts. Overall, these results did not considerably change the interpretation of the original results. Refer to Table 3 for the SCV of both 7-day and 90-day readmission rates.

Some of the key criticisms of using emergency readmission rates as a measure of care quality are that they are not standardised to different patient groups, for example, they change based on the patient demographic or severity of condition, or that they are poorly related to other indicators of in-hospital quality (Press *et al.*, 2013; Friebe *et al.*, 2017). Quality is a multidimensional and complex aspect, and a single metric might not be sufficient to present a holistic and accurate overview of quality changes occurred over time in a healthcare system. This might be particularly relevant when a single metric like readmission rates are used to compare quality of care between different providers, for instance, when hospitals are imposed with hefty financial penalties for excessive readmission rates (Friebe and Steventon, 2016). However, in this chapter, I did not make any comparisons of quality of care across NHS hospitals, but simply assessed the longitudinal trends in readmission rates for all NHS Trusts across a ten-year period, while controlling for random variation effects.

The data used for the final analysis included all individuals treated as inpatients in English hospitals. This data was risk-adjusted at the individual-level, which accounted for systematic differences in observed characteristics of patients between Trusts. We also controlled for patient demographics such as socio-economic status. Thus, any variation in readmissions that correlated with socioeconomic status was assumed to be outside of the healthcare system's direct control. Even though controlling for socioeconomic status is standard practice when assessing health system performance in England, previous research has widely debated this stance, primarily because areas (and by extension patients) that are more economically deprived tend to receive poorer quality health care, which then possibly translates into higher readmission rates (Friebe and Steventon, 2016).

Further problems relate to the risk-adjustment of emergency readmission rates, specifically the potential for omitted variable bias. This can be caused by a lack of patient-level information that is highly predictive of a readmission, but not collected within the HES database.

An example includes the clinical severity, or acuity of the health condition (Zhou *et al.*, 2016). Because I was restricted to information made available in HES, the true likelihood of a patient having to return to hospital within 30-days may be under- or over-estimated depending on the severity of disease. To address this concern within the constraints of the available dataset, I calculated each patients' Charlson comorbidity index and entered it as a predictor into the logistic regression model to account for some degree of clinical complexity (Charlson *et al.*, 1987). I also addressed potentially improved coding practices by including interaction terms between each financial year and the respective Charlson index into the regression model.

While there are several advantages to using the SCV to measure the level of potentially 'avoidable' variation in quality of care measured through readmission rates, the SCV is not an intuitive measure of variation, and also carries significant limitations due to the reliance on available patient-level information that was entered into the logistic regression model. The key assumption is that any information entered into the prediction model sufficiently addresses all 'unavoidable' variation. However, as with the risk-adjustment of readmission rates, the information entered into the predictive model was restricted to the data available in HES, and it is likely that other unobserved factors can explain some of the variation in emergency readmission rates. For example, previously published literature has suggested increases in emergency readmission rates for patients with an indexed acute condition to be correlated with lower rates of mortality, specifically in patients with hip fractures (Laudicella, Li Donni and Smith, 2013). Decreases in mortality could for example be caused by technological advancements or improved treatment methods such as the widespread uptake of thrombolysis treatment in stroke patients, and while these patients would have previously died, it is possible that these patients remain sicker post discharge and are therefore more likely to be readmitted within 30 days. In fact, and following this mentioned assumption, increases in emergency readmissions for this patient subgroup may represent improvements in quality of care, rather than deteriorations.

Moreover, examining changes in variation over such a long time period may lead to time-varying confounding, for example in case of the establishment of Hyper Acute Stroke Units in London and Greater Manchester in 2010 (Friebe *et al.*, 2017). An in-depth evaluation of these changes is presented and discussed in chapter 6.

This chapter provides a comprehensive description of longitudinal changes in readmission rates, without directly assessing the causal impact of any one healthcare intervention introduced within this time-period. The enhanced policy focus on readmission rates through several local-level and national-level initiatives aimed at care quality improvement within the English NHS should therefore be evaluated in future research, for instance, making the initiative of GP's more accessible as a way to discourage individuals from accessing hospitals (National Audit Office, 2017), or financially penalising hospitals with excess readmission rates (Department of Health, 2010). The latter policy will be evaluated in chapter 5 of this thesis. Future research in this area can also be improved by linking together in-hospital or secondary care data with post-discharge data (where information about the care provided to the patient once discharged is available). This will allow researchers to establish causal relationships of care quality received along the patient pathway. Future research can also benefit from using more informed risk-adjusted models than currently used, for instance, including information regarding severity of the clinical condition or neurological outcomes. Finally, another source of data that can be picked apart and used is that from auditing of hospitals, which might include crucial information on care quality, and which is not currently available in HES-like data sets.

3.5 Conclusions

In this chapter, I found that between 2006/07 and 2012/13, there was a slight increase in readmission rates that followed a discharge from any indexed admission; however, post 2012/13,

results showed a slight decrease, or rather constant trend in readmission rates. Supplementing this, I also found that there was a decrease in variation of readmission rates between hospitals in the English NHS. These changes coincide with an enhanced focus on reducing readmission rates in the English NHS, perhaps alluding to the success of such local and national-level policies that sought to stabilise or stop the rising readmission rates since 2010.

It is important to highlight, however, that the observed changes in readmission rates and SCV were modest, and had high variation when separated for clinical condition. This may be because for long-term clinical conditions, decreasing readmission rates might represent the quality of care provided to patients outside of the hospital setting, such as in the primary care setting. However, for acute or short-term conditions like pneumonia, an increase in readmission rates might be indicative of aspects that slip through the scope of the readmission rate metric, for instance, a higher likelihood of patients' surviving the initial indexed admission. Finally, it may also be that several factors that could not be accounted or controlled for in my analysis may in fact explain the changes observed in readmission rates.

This chapter highlights the importance of understanding the longitudinal changes in *variation* of healthcare quality. Without this understanding, targeted policies and initiatives might not be as fruitful as they should be. The work presented in this chapter can be seen as starting point for further analyses in this thesis. While findings from this chapter are important as a stock-take of changes occurred overall, it offers no causal link between policies implemented to reduce readmission rates and actual changes in readmission rates. The next chapters will build upon these findings, and explore causal relationships between a national-level policy aimed at improving quality of care in the English NHS in chapter 5, and a local-level policy with the same aim to be evaluated in chapter 6. The next chapter is going to validate the usefulness of readmission rates as a measure for quality of care, specifically their association with aspects of care quality from the patient perspective.

Chapter 4 The relationship between readmission rates and changes in patient-reported outcome measures

4.1 Preamble to chapter 4

Healthcare systems globally have implemented policies aimed at reducing readmissions, including financially penalising hospitals with high readmission rates in the United States (US) and England. The penalties have been controversial, and there have been concerns that such a focus on readmissions might distract from other efforts to improve care, or might inappropriately displace activity from inpatient to other settings. What is needed is information regarding the wider impact of readmission reduction initiatives on patient-reported health and wellbeing. These measures can capture the effect of ‘unintended consequences’ and align with the aims of any healthcare system.

This chapter uses data from the NHS in England, which, unlike other global healthcare systems, has been gathering patient-reported outcome measures (PROMs) for certain elective surgeries since 2009. It studies a period marked by a sustained, national focus on reducing readmission rates, and two common elective surgeries. Hip and knee replacements are associated with substantial 30-day readmission rates (8.5% and 5.5%, respectively) and are relevant internationally, since they have recently been included in the Hospital Readmission Reduction Programme (i.e. a programme that saw the introduction of financial penalties for hospitals with high readmission rates; HRRP) in the US. The contribution of this chapter is to test the association between changes in risk-adjusted, 30-day readmission rates and changes in health status following those surgeries across three financial years.

A research paper derived from this chapter has been published in *Medical Care* (Friebel *et al.*, 2017), under the terms of the Creative Commons Attribution License, which permits any use, distribution and reproduction in any medium, provided the original author(s) and the source are credited. Rocco Friebel had the idea for this chapter, conducted the data linkage between the PROMs database and the Hospital Episode Statistics (HES) database, performed the analysis and produced the first draft version of the manuscript. The work produced in this chapter contains feedback from Dr Kumar Dharmarajan, Prof Harlan M. Krumholz and Dr Adam Steventon who also acted as co-authors on the published paper. I would like to thank them for their invaluable discussions and comments on a previous version of this chapter. I would also like to thank two unnamed peer-reviewers for providing feedback that ultimately strengthened the derived publication and work reproduced in this chapter.

4.2 Introduction

In 2011 and 2012, England and the US respectively, introduced healthcare policies that would financially penalise hospitals with high readmission rates (Kristensen, Bech and Quentin, 2015). England did so as part of a larger and more significant reform policy in a bid to reduce unplanned and avoidable readmissions (Department of Health, 2011). In the first year of the policy's introduction, reimbursement of hospital services depended on the type of admission. If the initial or indexed admission was a planned one, for instance for elective surgeries, hospitals did not receive any compensation for emergency readmissions that took place within 30 days of the patient being discharged. However, if the original admission was unplanned, for instance via emergency departments, NHS hospitals providing care to patients received reimbursement up to a

threshold that was calculated to include the costs related to a readmission rate that would probably occur even with the highest standard of care quality. However, post April 2012, this threshold was generalised to all types of admissions, both planned and unplanned, and the financial resources accumulated from incurred penalties was redistributed to fund rehabilitation services for patients once discharged from hospital.

On the other hand, the financial penalties scheme in the US was introduced under the HRRP, and was initially intended for the clinical conditions of acute myocardial infarction, heart failure and pneumonia. However, in the 2015 financial year, hip and knee replacements and obstructive pulmonary disease were also included under HRRP. The HRRP has perhaps been successful (Joynt *et al.*, 2016), as evidenced by a substantial drop in readmission rates for the five clinical conditions, from 21.5% in 2007 to 17.8% in 2015 (Barrett *et al.*, 2015; Zuckerman *et al.*, 2016).

As outlined in previous chapters, readmission rates have been a key focus for healthcare systems due to their correlation with different aspects along the entire patient pathway (Ashton *et al.*, 1997; Hansen, Williams and Singer, 2011, Feltner *et al.*, 2014; Rennke and Ranji, 2015, Harrison *et al.*, 2014; Lee *et al.*, 2015). On the one hand this focus has allowed readmission rates as a measure of care quality to amass a sound evidence base. On the other hand, what continues to remain unclear is the relationship between readmission rates and other critical aspects of healthcare quality, and more importantly, how readmission rates reflect the patients' own sense of health and well-being (Hostetter and Klein, 2011). While healthcare systems might collect patient-filled reports, the lack of a systematic and standardised approach to collecting such data has disallowed an answer to this question. However, in this chapter I will attempt to answer this question by using a new dataset available through NHS Digital, which contains data from 2009 for 270,000 patients admitted to NHS hospitals for hip and knee replacement

surgeries, and all of whom have information on self-reported patient-reported outcome measures (PROMs) (Digital, 2017), which are further defined and explained in section 4.3.3.

The focus on hip and knee replacements is twofold. First, both hip and knee replacements are standard elective surgeries that are aimed at improving patients' functional outcomes. Thus, the patient's subjective experience of whether an improvement in their quality of life has occurred, or not, can be measured more accurately through PROMs. Second, both these clinical conditions have high 30-day readmission rates, with 8.5% for hip replacements and 5.5% for knee replacements (Huddleston *et al.*, 2009; Cram *et al.*, 2011), making them relevant to the English policy focus on readmission rates. In fact, several initiatives have been undertaken by the English government in an attempt to reduce readmission rates for these clinical conditions. These include telephone helplines led and operated by nurses, that provide healthcare advice relevant for post-discharge care (Northumbria Healthcare NHS Foundation Trust, 2012); 'enhanced recovery programmes' that consist of pre-operative education, new anaesthetic techniques, and postoperative rehabilitation plans (Wright, Cullinger and Bacarese-hamilton, 2015); and Orthopaedic outreach services that provide follow-up care outside of the hospital setting (Guy's and St Thomas' NHS Foundation Trust, 2013).

Each of the above stated interventions might have had an impact on readmission rates, for example, by improving the patients' ability to self-care (*e.g.* by learning how to manage their own wounds, which includes the application of new dressings), and thereby preventing their need to be readmitted. The interventions could have also directly impacted health outcomes reported by the patient, such as their experience of pain or improvement in their mobility by exercise management. While previous research has

individually evaluated the impact of some of the interventions (for *e.g.*, see Alnaib *et al.*, 2015), little research has assessed whether a reduction in readmission rates at the system-level is associated with improvements in PROMs. This association demands attention due to valid concerns raised regarding the possible unintended negative consequences on aspects of healthcare quality due to the imposition of financial penalties on hospitals with high readmission rates (Naylor *et al.*, 2012; Gu *et al.*, 2014; Mason, 2014; Carey and Lin, 2015). For example, previous research has highlighted that financial penalties may cause post-discharge follow-up care to be shifted from inpatient to out-of-hospital settings in order to avoid being classified as a readmission, and this in turn might have implications for the delivery of high quality care (Figuerola, Wang and Jha, 2016). Additionally, evidence has also emerged suggesting that financial penalties disproportionately impact some hospital groups over others, for instance, hospitals in low socio-economic areas (Bernheim *et al.*, 2016; Zuckerman *et al.*, 2016).

Indeed, if focusing on reducing readmission rates is having the opposite effect to what was intended, *i.e.* having negative impacts on some patient outcomes and thereby on quality of care, then a responsibility rises on part of the government for corrective action and the need to amend local and national-level policy (Friebel and Steventon, 2016). On the other hand, if in fact there is no association between readmission rates and PROMs, then this lack of association might reflect that the incentives and motivations to lower readmission rates cannot be relied on to improve these specific aspects of care. Moreover, this may also show that other more targeted policies, in addition to financial penalties, might be more impactful in addressing and improving PROMs.

In this chapter, I will use PROMs data from the English NHS to investigate whether there is an association between readmission rates and PROMs at the institutional-level, *i.e.* whether hospitals that decreased readmission rates over time also

showed improvements in patient-reported health gains post-surgery over time. To my knowledge, this is the first study that is attempting to understand this relationship at the hospital-level.

4.3 Methods

4.3.1 Study sample

The study period of this chapter starts with the publication of the government white paper *Equity and Excellence* in April 2010, which saw the introduction of a number of readmission reduction policies in England (Department of Health Payment by Results Team, 2010), and ends with a major restructuring of the NHS in 2013. Similar to chapter 3, the level of the analysis is at the NHS Trust-level. I included any Trust that performed hip and knee surgeries during the observation period, with no lower limit of the number of surgeries performed per year. While NHS Trusts commonly contain several hospital sites, the average number of Orthopaedic units is three according to the National Joint Registry (2017).

Patients who underwent hip and knee replacement surgery in England, which included primary and revision surgeries, were identified based on their records in the HES database. The selection of patients into the study sample was guided by the recorded procedure codes (i.e. OPCS-4 codes), using the official list of codes published by The Health and Social Care Information Centre (2015). Table 6 depicts the list of procedure codes used for the identification of patients in this chapter. Other inclusion criteria included the patient age of 18 years or older and with a record for hip and knee

replacement between 1st April 2010 and 28th February 2013. I excluded any patient receiving surgery in March 2013, to allow a sufficient follow-up period for the calculation of 30-day readmission rates given the limitations of the dataset available. Moreover, I excluded any patient with missing information for key variables used for the risk-adjustment of readmission rates. For patients experiencing multiple admissions during the observation period, I counted each admission as an indexed admission provided it was more than 30 days apart from the preceding admission.

Table 6.

ICD-10 codes and OPCS-4 codes for (i) hip replacements and (ii) knee replacements

(i)			
Procedure	Definitions	Combination & sites	Exclusions
Hip surgery			
Total hip replacement (primary)	W37.1, W37.8, W37.9, W38.1, W38.8, W38.9, W39.8, W39.9	N/A	
Total prosthetic replacement of the head of the femur (primary)	W46.1, W46.8, W46.9, W47.1, W47.8, W47.9, W48.1, W48.8, W48.9	N/A	
Hybrid prosthetic hip replacement (primary)	W93.1, W93.8, W93.9, W94.1, W94.8, W94.9, W95.1, W95.8, W95.9	N/A	
Other hip replacement (primary)	W52.1, W52.8, W52.9, W53.1, W53.8, W53.9, W54.1, W54.8, W54.9	Z76.1 ("Head of femur"), Z75.6 ("Acetabulum"), or Z84.3 ("Hip joint")	
Total hip replacement (revision)	W37.0, W37.2, W37.3, W37.4, W38.9, W38.2, W38.3, W38.4, W39.0, W39.2, W39.3, W39.4, W39.5, W39.6	N/A	
Total prosthetic replacement of the head of the femur (revision)	W46.0, W46.2, W46.3, W47.0, W47.2, W47.3, W48.0, W48.2, W48.3, W48.4, W48.5	N/A	
Hybrid prosthetic hip replacement (revision)	W93.0, W93.2, W93.3, W94.0, W94.2, W94.3, W95.0, W95.2, W95.3, W95.4	N/A	
Other hip replacements (revision)	W52.0, W52.2, W52.3, W53.0, W53.2, W53.3, W54.0, W54.2, W54.3, W54.4	Z76.1 ("Head of femur"), Z75.6 ("Acetabulum"), or Z84.3 ("Hip joint")	
Resurfacing arthroplasty of joint (primary)	W58.1	Z76.1 ("Head of femur"), Z75.6 ("Acetabulum"), or Z84.3 ("Hip joint")	
Resurfacing arthroplasty of joint (revision)	W58.2	Z76.1 ("Head of femur"), Z75.6 ("Acetabulum"), or Z84.3 ("Hip joint")	

Z94.1 ("bilateral operation") or where a pair of unilateral hip replacements take place in the same spell accompanied by both Z94.2 ("Right-sided") & Z94.3 ("Left-sided") (applicable to all procedures)

(ii)			
Procedure	Definitions	Combination & sites	Exclusions
		<u>Knee surgery</u>	
Total knee replacement (primary)	W40.1, W40.8, W40.9, W41.1, W41.8, W41.9, W42.1, W42.8, W42.9	N/A	
Unicondylar/ Unicompartmental knee operations (primary)	W52.1, W52.8, W52.9, W53.1, W53.8, W53.9, W54.1, W54.8, W54.9	Z76.5 (“lower end of femur NEC”), Z77.1 (“condyle of tibia”), Z77.4 (“upper end of tibia” NEC), Z84.4 (“patellofemoral joint”), Z84.5 (“tibiofemoral joint”), or Z84.6 (“knee joint”)	
Hybrid prosthetic knee replacements (primary)	O18.1, O18.8, O18.9	N/A	
Total knee replacements (revision)	W40.0, W40.2, W40.3, W40.4, W41.0, W41.2, W41.3, W41.4, W42.0, W42.2, W42.3, W42.4, W42.5, W42.6	N/A	Z94.1 (“bilateral operation”) or where a pair of unilateral hip replacements take place in the same spell accompanied by both Z94.2 (“Right-sided”) & Z94.3 (“Left-sided”) (applicable to all procedures)
Unicondylar/ Unicompartmental knee operations (revisions)	W52.0, W52.2, W52.3, W53.0, W53.2, W53.3, W54.0, W54.2, W54.3, W54.4	Z76.5 (“lower end of femur NEC”), Z77.1 (“condyle of tibia”), Z77.4 (“upper end of tibia” NEC), Z84.4 (“patellofemoral joint”), Z84.5 (“tibiofemoral joint”), or Z84.6 (“knee joint”)	
Hybrid prosthetic knee replacements (revision)	O18.0, O18.2, O18.3, O18.4	N/A	

4.3.2 Readmission rates

I identified hospital readmissions at the patient-level, following the official strategy used by policymakers in England (defined in Chapter 1). The risk-adjustment process of readmission rates followed the method used in chapter 3. In calculating the risk-adjusted, 30-day readmission rate for each Trust and financial year, I aligned the methodology with the one used for the risk-adjustment of PROMs. Thus, I multiplied the ratio of observed readmission rate and predicted readmission rate at each Trust, by the average readmission rate observed across all trusts in the respective financial year.

4.3.3 Patient-reported outcome measures

Distinctive to most other healthcare systems, the NHS has introduced the systematic collection of information on PROMs for a number of surgical interventions since 2009. The introduction of PROMs is thought of as a tool to encourage reporting of variation in care between providers in a more transparent manner, but also to promote increases in efficiency (Department of Health, 2010). The current programme of reporting PROMs covers hip and knee replacement, hernia repair, and varicose veins treatment (Devlin and Appleby, 2010). To collect PROMs, patients are requested to complete two rounds of questionnaires, including at the pre-operative assessment or on admission. Any patient who participated in the first round receives a post-operative survey via post. The second questionnaire is usually sent out approximately six months after the procedure, and also includes one reminder for patients not responding to the first request. In the following sections of this chapter, patients who were not responding to questionnaires will be referred to as non-responders.

The information collected on changes in health gain following hip and knee replacement and stored in the PROMs dataset are captured in four instruments. These

include the general EuroQuol five dimensions questionnaire (EQ-5D) and EuroQuol visual analogue scales (EQ-VAS), but also procedure-specific instruments like the Oxford Hip Score and Oxford Knee Score.

The EQ-5D instrument, a general measure of quality of life, entails five dimensions that capture different aspects of a patient's quality of life. This includes the ability to self-care, levels of pain or discomfort, levels of anxiety/depression, activity status, and mobility. The answers stated in the questionnaire are then converted into specific quality of life scores, using utilities derived from trade-offs within a representative population (UK). These can range from -0.59 (worse than death), through 0.00 (dead) to 1.00 (perfect health).

On the other hand, the EQ-VAS instrument measures subjective health status on a single graphical scale, ranging from 0 to 100.

Finally, the Oxford Hip and Knee Scores measure disease-specific procedures (Dawson *et al.*, 1996), and are tailored in a way that they capture specific functionality problems within the hip and knee replacement population. This includes aspects such as limitations in functional status, such as limping due to the pain caused by the hip or knee. In total, the Oxford Hip and Knee Scores contain 12 items across four dimensions, with the aggregated scores ranging from 0 to 48. In this instance, 0 refers to severe symptoms and disability due to the hip or knee, whereas 48 represent no problem at all.

According to Browne *et al.* (2010), minimum changes in scores are required to be clinically meaningful. The study suggested minimal increases in scores that are equal to 0.14 for EQ-5D, 8.4 for the Oxford Hip Score, and 3.8 for the Oxford Knee Score. However, because the analysis in this chapter is conducted at the Trust-level, reported changes of clinical significance may not be appropriate to judge changes in whole populations.

4.3.4 Risk-adjustment of patient-reported outcome measures

The PROMs data used for this chapter was provided by NHS Digital (formerly the Health & Social Care Information Centre) and made public for each Trust and financial year (Health & Social Care Information Centre, 2015). The reported data present the average changes in health gains amongst patients who returned both the pre-operative and post-operative questionnaires for each Trust, and risk-adjusted for patient characteristics. The risk-adjustment process followed a similar methodology as the one used for readmission rates, yet instead of a logistic regression model, ordinary least squares regression (OLS) models were applied to the post-questionnaire score. In the OLS models, the following variables were entered as controls (Coles, 2010): patient age, gender, self-reported comorbidities, socioeconomic deprivation score, the patients' self-reported health status that was recorded in the pre-operative questionnaire, destination of discharge, length of hospital stay, and timing of the questionnaire completion.

Similar to the risk-adjustment of readmission rates, a ratio of the observed post-operative score and the predicted post-operative score was calculated for each Trust and financial year, which indicates whether the Trusts provided care that is above or below what would have been expected given the type of patients treated in that financial year. Next, the average post-operative score observed across all providers in a given financial year was multiplied by the estimated ratio of observed and expected health gain. In a final step to calculate the risk-adjusted health gain for a given Trust, the national average pre-operative PROMs score was subtracted from the Trust-specific risk-adjusted post-operative PROMs score. As previously mentioned, NHS Digital provided the risk-adjusted measure of health gain for this analysis.

Both the information on risk-adjusted 30-day readmission rates that was extracted from the HES database, and the information on risk-adjusted changes in health

gain provided by NHS Digital were then linked to create one dataset for each Trust and three financial years (2010/2011, 2011/2012, and 2012/2013). To be used later in the statistical analysis, I also linked information on response rates provided by NHS Digital for each Trust.

4.3.5 Statistical analysis

The analysis conducted for this chapter was based at the Trust-level, and performed separately for hip replacement and knee replacement, and for the three corresponding PROMs. Panel data models were employed (Wooldridge, 2002) to harvest the information provided across several Trusts as well as time points. The analyses allow for no causal inferences, but in effect, I examined whether changes in risk-adjusted, 30-day emergency readmission rates across three financial years were associated with changes in risk-adjusted health gains in the same Trust and over the same time period.

The panel data approach used in this chapter has some clear advantages. For example, it deals with potential confounding due to differences in the characteristics of Trusts, assuming that the relationship between these characteristics and the outcome is constant across the three financial years. Importantly, these characteristics can be of an observed and unobserved nature. To model these relationships, I estimated panel data models with OLS regression estimators. I entered the respective risk-adjusted health gain as a dependent variable, and entered the risk-adjusted readmission rate as an explanatory variable. No additional patient-case mix information was required for this analysis, as the risk-adjusted readmission rates already capture those aspects that might lead to systematic variation.

To determine whether Trusts should be entered as fixed or random effects in the panel data model, I performed the Hausman model specification test. In the analysis, the model fit is presented through *R-squared* statistics.

One specific concern relates to the variation in response rate by Trust, and I therefore followed several approaches to dealing with non-responses in the PROMs data. At the initial stage, I analysed regression models without accounting for variation in the response rate. Then, I entered time-varying, response rates for each Trust as an additional explanatory variable into the regression model. In the final model specification, I restricted the analysis to Trusts with a minimum response rate of 60.0%. Moreover, I also explored the impact of mortality rates on the changes in health gain, by entering trust specific mortality rates as an additional explanatory variable. Mortality rates were calculated from the HES data and captured in-hospital mortality that occurred within 6 months of discharge following the initial surgery.

4.3.5 Approach to missing data and sensitivity analysis

There are several reasons that could lead to missing data in the linked dataset. These include when either PROMs data were not reported in a specific year, or because the Trust may have not been in existence for the entire observation period, for instance, such cases might occur during periods of Trust mergers. As a minimum requirement, I selected Trusts that reported PROMs data for a minimum of two financial years, out of three financial years. Therefore, the panel data analysis was based on an unbalanced panel (*i.e.* containing missing values for some Trusts in some financial years). I performed additional sensitivity analysis around missing values, by constructing a strictly balanced panel that was limited to Trusts with full records for the whole observation period.

4.4 Results

4.4.1 Index discharges

Across the entire observation period (*i.e.* from April 2010 to February 2013), I identified 158 Trusts that performed hip replacement surgery and 158 Trusts that performed knee replacement surgery. For knee replacements, a total of 26 Trusts did not report PROMs data for at least two out of three financial years, whereas for hip replacements it was 33 Trusts. Subsequently after deleting these Trusts, the study sample included 132 Trusts for hip replacements and 125 Trusts for knee replacements.

Following the inclusion criteria for patients outlined in the methods section, I excluded a small number of patients, which resulted from missing data in the HES record fields that were used for risk-adjustment of the respective readmission rates. I excluded 6,589 hip replacement patients and 7,256 knee replacement patients. The final study sample of discharged patients included 135,066 following hip replacement and 138,042 following knee replacement.

On average, each Trust performed 347 procedures in a given financial year, ranging from 70 to 1174 procedures. For knee replacements this yearly average was at 371 procedures, and ranging from 62 to 1148 procedures. The characteristics of both patient groups remained relatively constant across the study period – summary statistics are presented in Table 7. This includes the average patient age, the gender ratios and ethnicity groups. However, the average length of stay for both patient groups decreased. For hip replacement, the average length of stay was 6.05 days in 2010, but decreased to 5.39 days in 2013. Similarly, for knee replacements, the average length of stay was 6.05 days in 2010, but decreased to 5.38 days in 2013.

From the PROMs data set, I found that 71,168 hip replacement patients returned both pre-operative and post-operative PROMs questionnaires across the three financial years, whilst 70,329 knee replacement patients returned both questionnaires over the same period. This resulted in an average response rate of 52.7% and 50.9%, respectively. Importantly, the response rates varied widely amongst Trusts. For hip replacements, the response rate ranged from 12.1% to 84.9%, whereas for knee replacements the response rate varied from 8.6% to 100.0%. The mean response rates increased slightly across financial years. For hip replacements, it was 50.1%, 51.7%, and 53.5% in 2010/2011, 2011/2012, and 2012/2013, respectively. For knee replacements, response rates were at 47.8%, 52.5%, and 57.1% in 2010/2011, 2011/2012, and 2012/2013, respectively. Mortality rates were found to be low, reflecting the relatively low risk carried by both surgical interventions. Between April 2010 and February 2013, I estimated that .99% of hip replacement patients died in-hospital, with an equivalent figure of .88% for knee replacement patients. However, the presented mortality rates only refer to mortality at the in-hospital stay over a six-month period, but the actual mortality rate might be higher considering that some patient are likely to die outside the hospital. This was not captured in the available HES dataset.

Table 7.

Summary statistics of the study sample for each procedure and three financial years

Variables	Hip Replacement			Knee Replacement		
	FY 2010/11 Mean (SD)	FY 2011/12 Mean (SD)	FY 2012/13 Mean (SD)	FY 2010/11 Mean (SD)	FY 2011/12 Mean (SD)	FY 2012/13 Mean (SD)
No. operations	350.65 (184.09)	361.66 (192.12)	329.67 (178.86)	384.18 (207.38)	381.51 (200.15)	347.56 (186.29)
Patient age (y)	68.15 (1.97)	68.10 (1.97)	68.12 (2.01)	67.08 (2.06)	67.20 (2.17)	67.20 (2.24)
Female (%)	60.66 (4.06)	60.65 (3.35)	60.37 (3.77)	57.67 (4.36)	58.24 (3.63)	57.84 (3.93)
White (%)	96.27 (6.31)	96.17 (6.80)	95.71 (7.65)	95.53 (7.08)	95.18 (7.48)	95.35 (7.63)
Black (%)	.90 (2.52)	.87 (2.32)	1.08 (3.07)	1.20 (3.46)	1.29 (3.76)	1.14 (3.11)
Asian (%)	.68 (1.18)	.58 (.83)	.63 (.98)	1.20 (1.97)	1.10 (1.64)	1.02 (1.50)
Living in rural areas (%)	13.40 (11.37)	13.68 (11.66)	13.33 (11.14)	12.61 (10.75)	12.99 (11.23)	12.86 (10.62)
Length of hospital stay (d)	6.05 (.95)	5.58 (1.14)	5.39 (1.00)	6.05 (1.15)	5.60 (1.22)	5.38 (1.09)
No. admissions/least SED	292.75 (156.41)	316.29 (164.88)	270.33 (145.55)	335.90 (205.80)	335.20 (191.47)	298.41 (169.54)
No. admissions/med. SED	372.41 (192.67)	389.13 (180.59)	361.04 (180.63)	412.95 (217.93)	409.62 (200.65)	381.17 (194.37)
No. admissions/most SED	389.27 (191.42)	375.53 (222.47)	359.64 (196.46)	405.58 (194.19)	394.70 (204.72)	366.66 (188.88)
Charlson index	.28 (.07)	.29 (.08)	.33 (.07)	.27 (.06)	.27 (.06)	.33 (.06)
30-day adj.readmission rate	6.51 (2.37)	5.97 (2.07)	4.92 (1.74)	6.26 (2.24)	6.16 (2.00)	4.87 (1.62)
Change in EQ-5D* (Δ)	.39 (.03)	.41 (.03)	.42 (.03)	.29 (.03)	.30 (.03)	.31 (.03)
Change in EQ-VAS* (Δ)	8.66 (1.99)	9.66 (1.64)	11.02 (1.83)	2.87 (1.73)	4.09 (1.62)	4.90 (1.44)
Change in OKS* (Δ)	19.34 (1.28)	19.78 (1.30)	20.61 (1.23)	-	-	-
Change in OHS* (Δ)	-	-	-	14.57 (1.30)	14.86 (1.18)	15.59 (1.19)
No. NHS Trusts	127	130	132	123	125	124

Note. ¹Summary statistics are calculated across Trusts and procedure separately; ²FY: financial year; SED: Socioeconomically deprived; ³med: Medium ⁴EQ-5D: EuroQuol five dimensions questionnaire; ⁵EQ-VAS: EuroQual visual analogous scale; ⁶NHS: National Health Service; *risk-adjusted

4.4.2 Trends in readmission rates and health gain

Risk-adjusted, 30-day readmission rates for both procedures decreased over the observation period. In case of hip replacement, it decreased by 1.6%, from 6.5% in 2010 to 4.9% in 2013. Similarly, risk-adjusted readmission rates decreased by 1.5% for knee replacements, from 6.3% in 2010 to 4.9% in 2013. Trends in risk-adjusted readmission rates for each financial year are depicted in Figure 4. In addition, I found that not all Trusts managed to reduce their readmission rates over the observation period. Specifically, for hip replacements 84.1% of Trusts reduced their readmission rates, whilst for knee replacements only 75.8% saw reductions in the readmission rate. This can also be seen in the distribution of readmission rate changes illustrated in Figure 5.

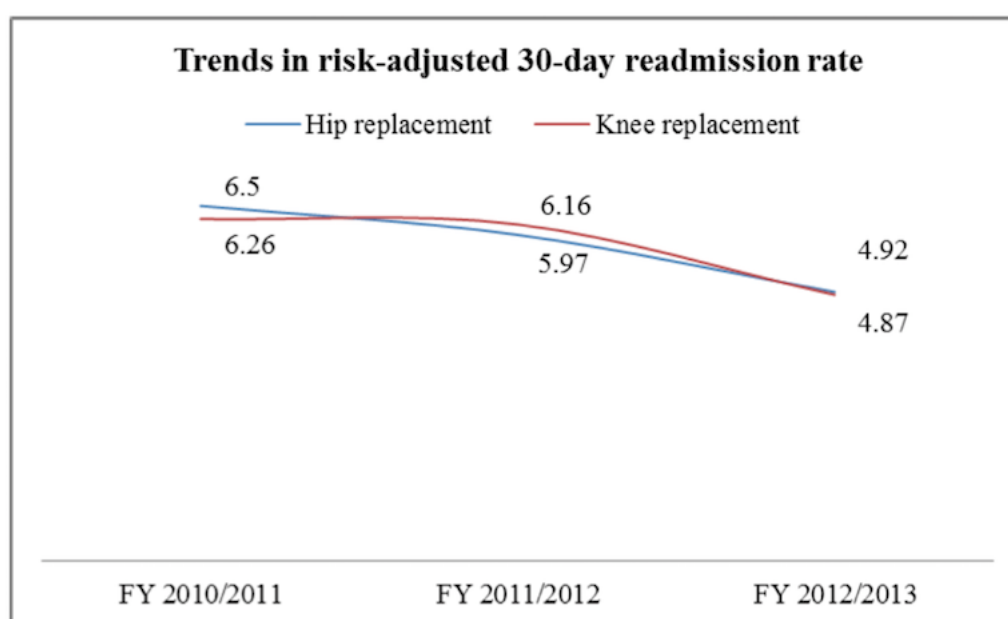


Figure 4. Trends in risk-adjusted, 30-day emergency readmission rates following hip and knee replacements.

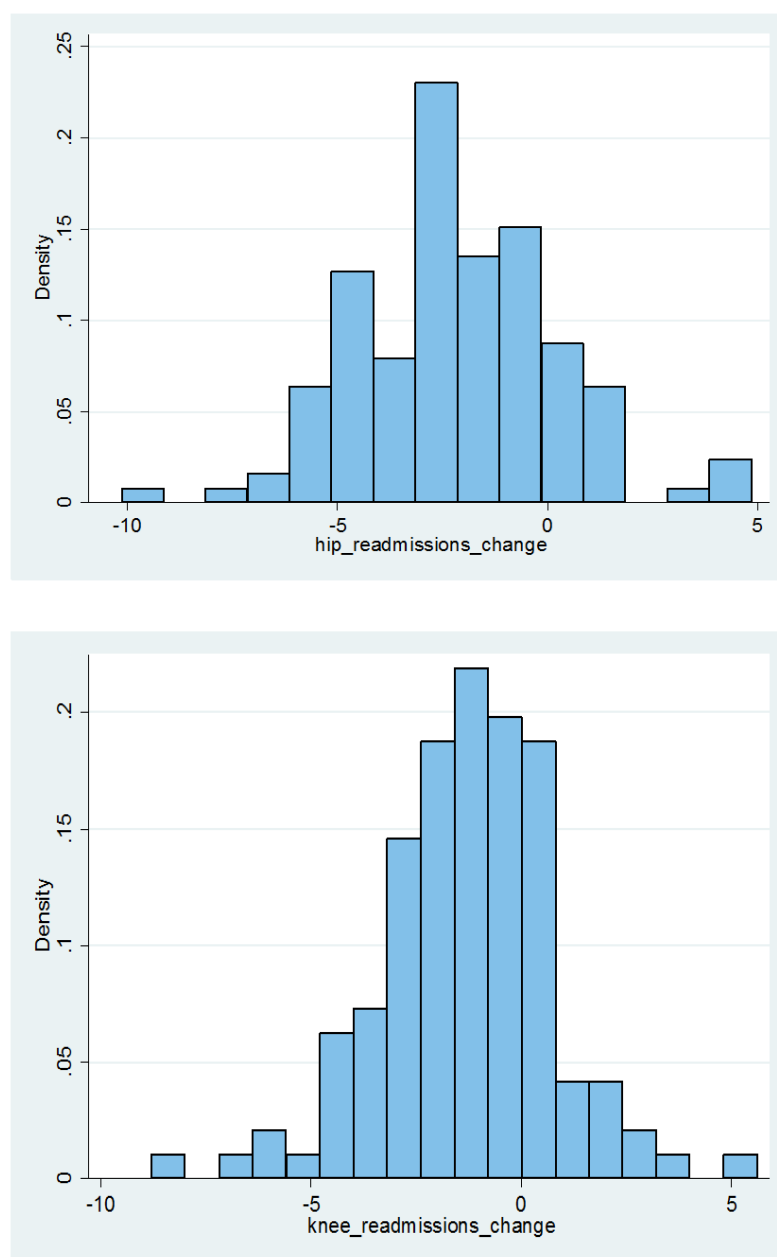


Figure 5. Variation in change of risk-adjusted, 30-day readmission rate by trust

Figure note. Variation in change was calculated by subtracting the value of the variable in 2012/13 from the value of the variable in 2010/11.

The quality of life reported by patients after six months following the procedures tended to be higher than before surgery, and with marked increases across the observation period. Trends in health gain over time are depicted in Figure 6.

I find that the risk-adjusted health gain following hip replacement and measured through EQ-5D increased by .03, from 0.39 in 2010/11 to .42 in 2012/13. Similar increases were observed for knee replacement patients, with increases in EQ-5D by .02, from .29 to .31, over the same period. I observed larger changes for health gains measured through EQ-VAS and the Oxford Hip Score, specifically an increase by 2.36, from 8.66 in 2010/11 to 11.02 in 2012/13, and an increase by 1.27, from 19.34 in 2010/11 to 20.61 in 2012/13, respectively. A similar trend of increased health gain was observed in knee replacement patients. Risk-adjusted health gain in the EQ-VAS scale increased by 2.03, from 2.87 in 2010/11 to 4.90 in 2012/13, whereas increases in the Oxford Knee Score were of slightly smaller magnitude, increasing by 1.02, from 14.57 in 2010/11 to 15.59 in 2012/13. As illustrated in Figure 7, 83.8% and 81.4% of Trusts reported improvements in health gains following hip replacement and knee replacement, respectively.

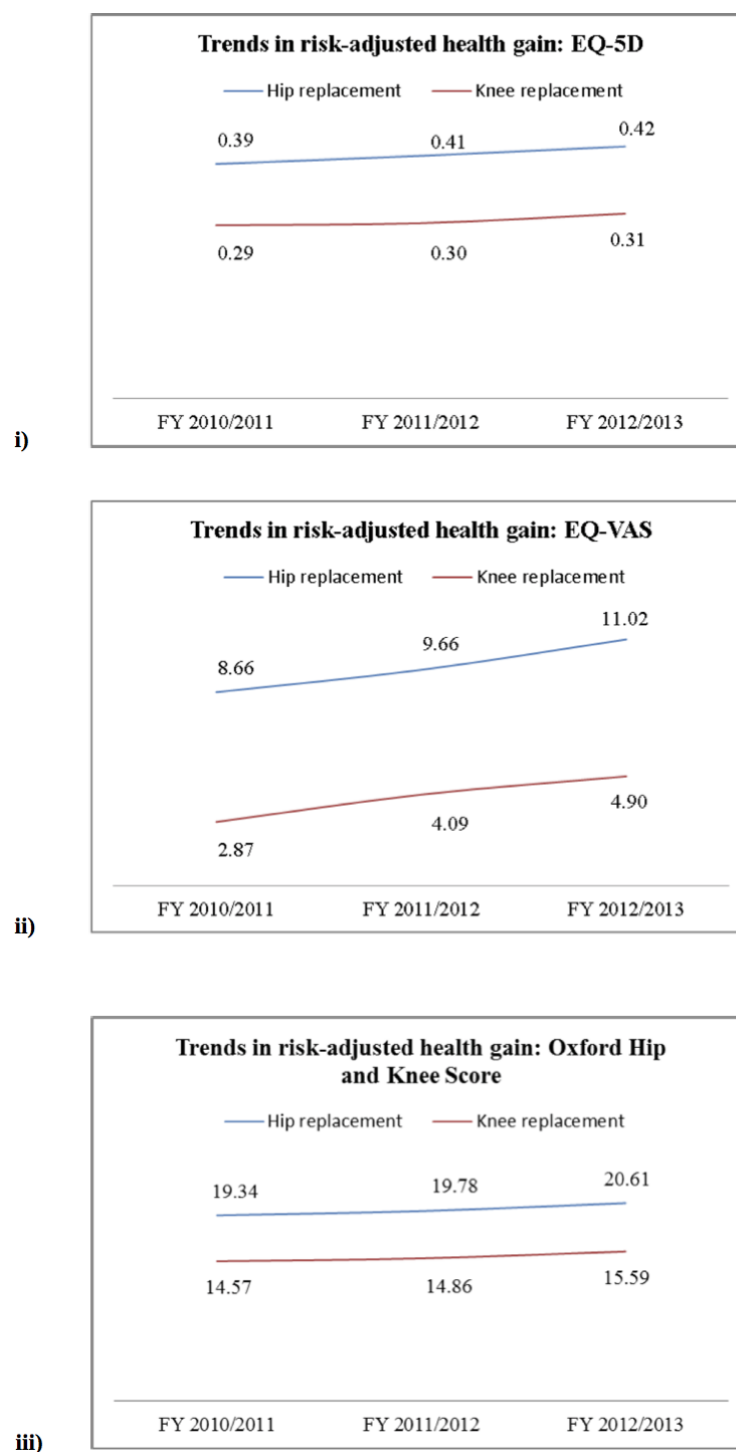
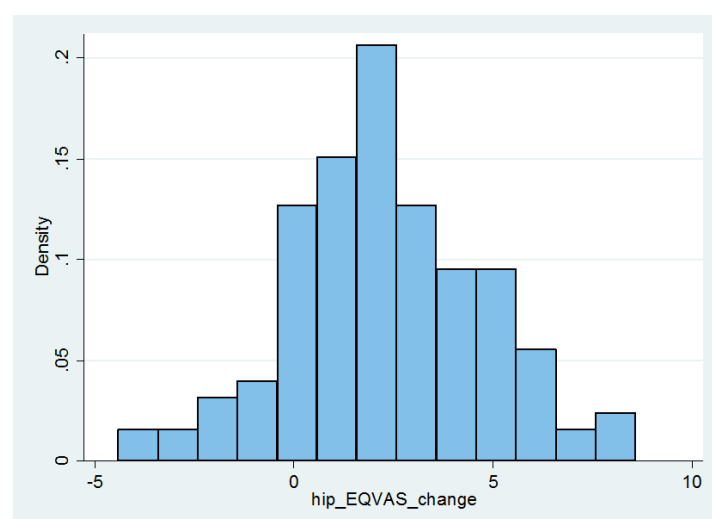
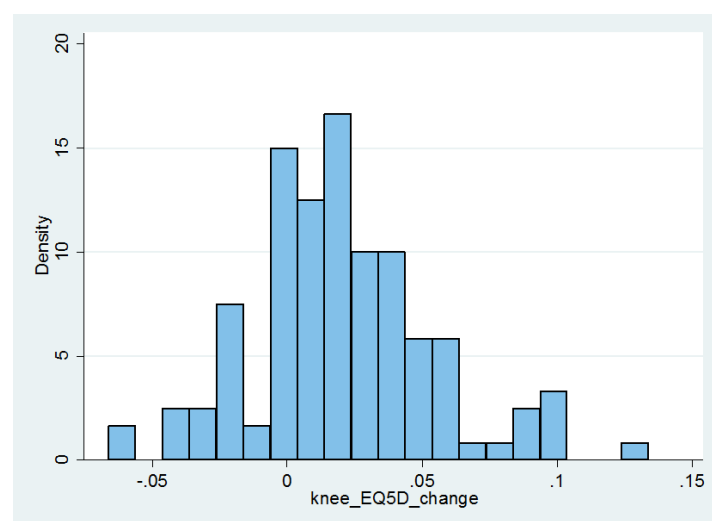
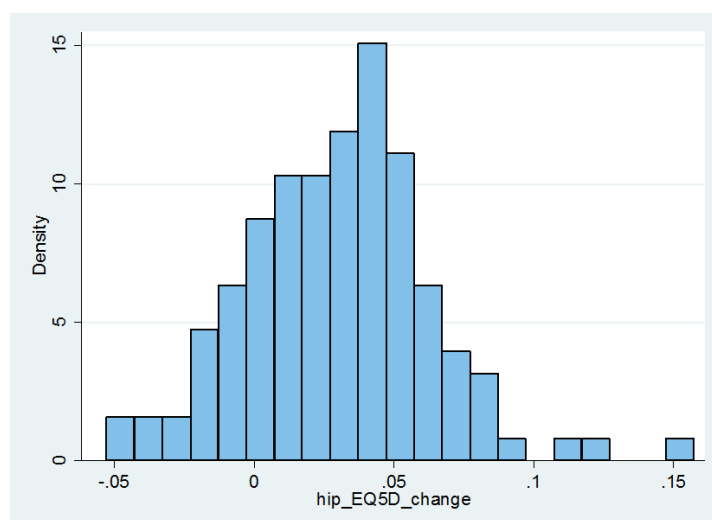


Figure 6. Trends in patient-reported outcome measures (average EQ-5D; EQ-VAS; Oxford Hip and Knee Score across all Trusts). EQ-5D indicates EuroQuol five dimensions questionnaire; EQ-VAS, EuroQuol visual analogue scales; FY, financial year.



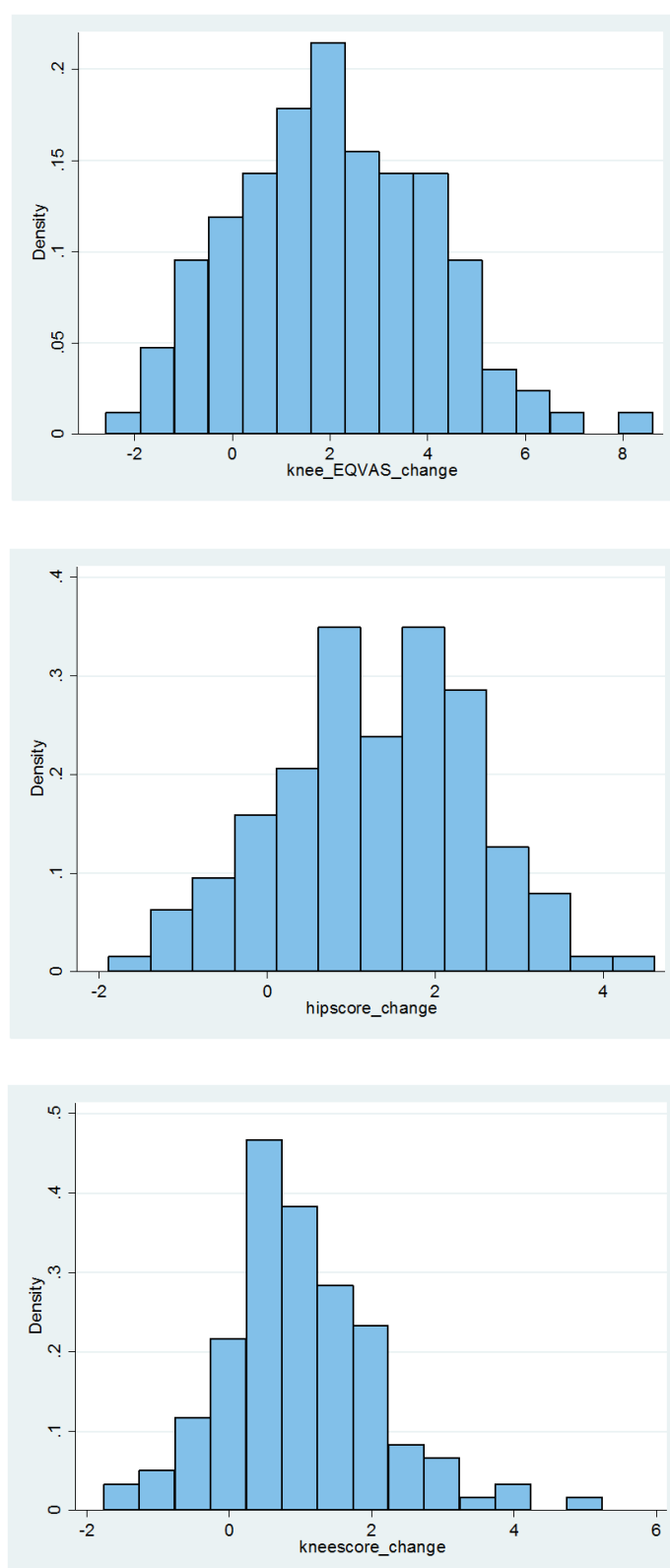


Figure 7. Variation in change of health gains (EQ-5D, EQ-VAS, Oxford Hip Score and Oxford Knee Score) by Trust

Figure note. Variation in change was calculated by subtracting the value of the variable in 2012/13 from the value of the variable in 2010/11.

4.4.3 Panel data models

The outcome of Hausman model specification test is presented in Table 8, and as a result I preferred random effects for all knee replacement models. On the other hand, while I preferred random effects for the Oxford Hip Scores in hip replacement models, I chose fixed effects when modelling associations for EQ-5D and EQ-VAS for this patient group.

The results of the panel data analysis showed that reductions in risk-adjusted readmission rates were associated with improvements in health gain for both hip and knee replacement patients, but also across all measures of health gain. For instance in hip replacement patients, an absolute 1% decline in the risk-adjusted readmission rate was associated with a .004 (95% Confidence Interval or CI, .002–.006) unit increase in health gain measured by the EQ-5D instrument, whereas in knee replacement patients the same absolute 1% decrease was associated with a .003 (95% CI, .001–.004) increase in health gain measured by the EQ-5D instrument. The magnitude of the association seemed greater for all other measures of health gain, with the regression output depicted in Table 9.

Table 8.

Hausman model specification test for hip and knee replacements

	Hip Replacement			Knee Replacement		
	EQ-5D	EQ-VAS	Oxford Hip Score	EQ-5D	EQ-VAS	Oxford Knee Score
Prob > Chi-squared	.01	.01	.27	.69	.23	.63
Decision	fixed	fixed	random	random	random	random

Note. ¹To test the preferred effect for the two treatment group panel data model; ² If Prob>chi2 is significant (*i.e.* < .05) then the preferred model uses fixed effects.

Table 9.

Unbalanced panel data analysis for the association between changes in readmission rates and PROMs

Variable	EQ-5D	EQ-VAS	Oxford Hip Score	Oxford Knee Score
30-day readmission rate following hip replacement	.004***	.39***	.21***	-
Coefficient (95% CI)	(.002 to .006)	(.26 to .52)	(.15 to .27)	-
Average number of Trusts per year	130	130	130	
30-day readmission rate following hip replacement	.003***	.21***	-	.14***
Coefficient (95% CI)	(.001 to .004)	(.12 to .30)	-	(.09 to .20)
Average number of Trusts per year	124	124	124	124

Note. *** Variable has robust impact on dependent variable at 1% significance level; ** Variable has robust impact on dependent variable at 5% significance level; *Variable has robust impact on dependent variable at 10% significance level; The Hausman test was used to determine the preferred model effect; Direction of coefficients has been inverted to represent effect of a 1% reduction in the readmission rate on the dependent variable; The R² statistics were 11.0%, 12.0%, and 10.0% for hip replacement, and 6.0%, 6.0%, and 8.0% for knee replacement; CI indicates confidence interval; EQ-5D indicates EuroQuol five dimensions questionnaire; EQ-VAS indicates EuroQuol visual analogue scales.

4.4.4 Sensitivity analyses

As a first sensitivity analysis, I entered time varying response rates as an additional explanatory variable into the regression model. I found no substantial differences in comparison with the findings from the main model. In fact, the p-values of the coefficient for response rates indicated no significant relationship between the response rates, or any of the dependent variables. Regression output is presented in Table 10.

As a second sensitivity analysis, I restricted the sample to Trusts with a minimum response rate of 60%, which included 53 Trusts for hip replacements and 61 Trusts for knee replacement. I found that restricting the sample led to a reduction in coefficient sizes for EQ-VAS and Oxford Hip Score in comparison with the main model. Despite this decrease, all associations between risk-adjusted, readmission rates and PROMs measures remained statistically significant. Regression output is presented in Table 11.

As a third sensitivity analysis, I restricted the sample to Trusts with complete data for the entire study period. Thus, I only focussed on Trusts with full records on PROMs for three consecutive financial years. Regression output is presented in Table 12. The output of the sensitivity analysis showed that EQ-VAS coefficient for hip and knee replacements increased slightly, but there were no changes to any of the other PROMs metrics.

As a final sensitivity analysis, I entered the six-month mortality rate into the regression model. Regression output is presented in Table 13. I found no significant association between mortality and any of the health gains entered into the model as dependent variables.

Table 10.

Unbalanced panel data analysis for association between readmission rates and PROMs with adjustment for response rate

Variable	EQ-5D	EQ-VAS	Oxford Hip Score	Oxford Knee Score
30-day readmission rate following hip replacement	.004***	.38***	.20***	-
Coefficient (95% CI)	(.003 to .006)	(.25 to .51)	(.15 to .26)	-
Response Rate	-.000	-.001	-.002	
Coefficient (95% CI)	(-.000 to .000)	(-.019 to .041)	(-.008 to .013)	
30-day readmission rate following knee replacement	.003***	.21***	-	.13***
Coefficient (95% CI)	(.001 to .004)	(.12 to .30)	-	(.09 to .19)
Response Rate	-.000	-.001	-	-.006
Coefficient (95% CI)	(-.000 to .000)	(-.017 to .003)		(-.145 to .000)

Note: *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%; The Hausman test was used to determine the preferred model effect; Direction of coefficients has been inverted to represent effect of a 1% reduction in the independent on the dependent variable.

Table 11.

Unbalanced panel data analysis for associations between readmission rates and PROMs while restricting sample to Trusts with minimum response rates of 60%

Variable	EQ-5D	EQ-VAS	Oxford Hip Score	Oxford Knee Score
30-day readmission rate following hip replacement	.004***	.35***	.16***	-
Coefficient (95% CI)	(.003 to .008)	(.11 to .60)	(.05 to .27)	-
Average no. of Trusts per year	53	53	53	-
30-day readmission rate following knee replacement	.003***	.30***	-	.14***
Coefficient (95% CI)	(.001 to .006)	(.11 to .50)	-	(.05 to .24)
Average no. of Trusts per year	61	61	-	61

Note: *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%; The Hausman test was used to determine the preferred model effect; Direction of coefficients has been inverted to represent effect of a 1% reduction in the readmission rate on the dependent variable.

Table 12

Strictly balanced and unbalanced panel data model for association between readmission rates and PROMs

Variable	EQ-5D	EQ-VAS	Oxford Hip Score	Oxford Knee Score
<u>Strictly balanced panel</u>				
30-day readmission rate following hip replacement	.004***	.38***	.21***	-
Coefficient (95% CI)	(.003 to .006)	(.25 to .51)	(.15 to .27)	-
Average no. of Trusts per year	125	125	125	-
30-day readmission rate following knee replacement	.003***	.26***	-	.15***
Coefficient (95% CI)	(.001 to .005)	(.14 to .38)	-	(.09 to .21)
Average no. of Trusts per year	120	120	-	120
<u>Unbalanced panel</u>				
30-day readmission rate following hip replacement	.004***	.39***	.21***	-
Coefficient (95% CI)	(.002 to .006)	(.26 to .52)	(.15 to .27)	-
Average no. of Trusts per year	130	130	130	-
30-day readmission rate following knee replacement	.003***	.21***	-	.14***
Coefficient (95% CI)	(.001 to .004)	(.12 to .30)	-	(.09 to .20)
Average no. of Trusts per year	124	124	-	124

Note: *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%; The Hausman test was used to determine the preferred model effect; Direction of coefficients has been inverted to represent effect of a 1% reduction in the readmission rate on the dependent variable.

Table 13.

Unbalanced panel data analysis for association between readmission rate and PROMs with adjustment for response rate and 6-month mortality rate

Variable	EQ-5D	EQ-VAS	Oxford Hip Score	Oxford Knee Score
30-day readmission rate following hip replacement	.004***	.38***	.21***	-
Coefficient (95% CI)	(.002 to .006)	(-.08 to .57)	(.15 to .27)	-
Response Rate following hip replacement	.00	-.00	-.003	-
Coefficient (95% CI)	(-.00 to .00)	(-.03 to .02)	(-.01 to .00)	-
6-month mortality rate following hip replacement	.002	.22	.14	-
Coefficient (95% CI)	(-.003 to .008)	(-.17 to .62)	(-.04 to .34)	-
30-day readmission rate following knee replacement	.002***	.15***	-	.13***
Coefficient (95% CI)	(-.000 to .004)	(-.03 to .27)	-	(-.07 to .19)
Response Rate following knee replacement	-.00	-.04***	-	.005
Coefficient (95% CI)	(-.00 to .00)	(-.006 to .02)	-	(-.001 to .013)
6-month mortality rate following hip replacements	-.23	-27.29*	-	-13.63*
Coefficient (95% CI)	(-.70 to .24)	(-58.85 to 4.26)	-	(-29.39 to 2.11)

Note: *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%; The Hausman test was used to determine the preferred model effect; Direction of coefficients has been inverted to represent effect of a 1% reduction in the independent on the dependent variable.

4.5 Discussion

In this chapter, I investigated a time period in the English NHS (2010-2013) that saw an enhanced policy focus to reduce readmission rates. In my analysis, I found that risk-adjusted, readmission rates decreased from 6.5% to 4.9% for hip replacement patients, and from 6.2% to 4.9% for patients admitted for knee replacements. Importantly, results also revealed that there was an association between readmission rates and PROMs. Specifically, I found that in hospitals where the greatest reduction in emergency readmissions was observed, the treated patients tended to report greater improvements in risk-adjusted, patient-reported health gains.

With respect to hip replacements, the analysis showed that with each absolute percentage decrease in readmission rates, there was a .004 increase in health gain as measured by the EQ-5D, and a .21 improvement in procedure-specific quality of life, both of which were above what would have been expected. A similar trend was found with respect to knee replacements, *i.e.* with each absolute percentage decrease in risk-adjusted readmission rates, improvements of .003 on the EQ-5D and of .14 on the quality of life metric were found. Both sets of associations were modest, and did not reach levels of clinical significance suggested in previous studies (*i.e.* .14 for EQ-5D, 8.4 for Oxford Hip Score, and 3.8 for Oxford Knee Score) (Browne *et al.*, 2010). However, at the ground level, the significance of such improvements for patients themselves will depend on the distribution of the incremental health-gains across the specific patient population. Notably, I did not find evidence to suggest that there was a negative link between risk-adjusted hospital readmissions and PROMs; that an increase in readmissions was associated with poorer patient gains, but rather I found evidence for a modest positive relationship.

Previous research in this field has investigated the relationship between hospital readmission rates and measures of quality of care such as an atmosphere of patient safety during the initial hospital stay (Hansen, Williams and Singer, 2011), as well as the discharge process and

coordination once a patient transitions from hospital to the community setting (Feltner *et al.*, 2014). One previous study has explored the links between readmission rates and PROMs related to hip and knee replacements; however, in that study, self-reported six-month readmission rates were chosen as the metric (Grosse *et al.*, 2012). This chapter expands on this field of research, and uses a methodology different from the one used in Grosse *et al.*'s (2012) paper, thereby making a novel contribution to this field.

4.5.1 Strength and limitations

In this chapter, I examined the relationship between risk-adjusted, 30-day readmission rates with health gain measured at six months after surgery, to assess whether readmission reductions are linked to 'spill-over' effects for patient health in the longer term. While patient outcomes may continue to improve six months after the interventions (Browne *et al.*, 2007), and with longer follow-up periods for the assessment of patient outcomes being used in other joint registries (Rolfson *et al.*, 2016), the decision to opt for a six months follow-up period in the English PROMs programme was based on a pilot study that suggested six months to be the earliest point for assessment of surgical benefits (Grosse *et al.*, 2012).

One concern in this analysis was that the readmission metric captured every patient discharged following surgery and with complete patient records on key variables used for risk-adjustment, whereas the used measure of health gain was limited to patients responding voluntarily to the PROMs pre-operational and post-operational questionnaires. This might lead to particular problems for this study, specifically when responders to PROMs questionnaires are systematically different from those not responding, and thus were not represented in the dataset. This includes systematic variation in pre-operative health conditions (*i.e.* responders tend to have fewer pre-operative health conditions compared with non-responders) (Hutchings *et al.*, 2013), differences in literacy levels (*i.e.* responders tend to be more literate compared to their non-

responding counter parts) (Jahagirdar *et al.*, 2013), and also differences in cognitive abilities (*i.e.* responders tend to have lower levels of impairment such as dementia compared with non-responders) (Gibbons *et al.*, 2016). I addressed this potential threat to the validity of the analysis, by controlling for the time varying, Trust-level response rates in the estimated panel data model. The results did not materially change from the main model specification, and nor did they change when I controlled for the six-month mortality rates. I performed sensitivity analyses by restricting the sample of Trusts to those reporting a minimum response rate of 60%, resulting in marginal changes in the coefficient sizes in comparison to the main model specification. However, restricting the sample resulted in a significantly smaller sample size, with potential limitations for the generalizability of findings.

The method of analysis employed in this chapter aimed at assessing a wider set of initiatives reflective of routine practice in the NHS, while previous studies have evaluated the impact of specific interventions, including the introduction of a telephone helpline to provide nurse-led guidance for recently discharged patients (Guy's and St Thomas' NHS Foundation Trust, 2013). The employed study design was of non-experimental nature and allowed a comparison of trends in risk-adjusted, readmission rates over three financial years, with trends in risk-adjusted health gain over three financial years.

Unlike many other healthcare systems, the NHS has been collecting PROMs data for over 270,000 patients before and after hip and knee replacement surgery since 2009, leading to significant benefits for the analysis presented in this chapter. By using risk-adjusted measures of both readmission rates and PROMs, I was able to account for systematic differences in observable, and importantly recorded, patient case-mix between Trusts. I adopted a panel data study design, which minimized confounding due to observable or unobservable differences between Trusts, provided they remained constant across the observation period. However, just like in any other observational study, it is impossible to assume that the observed association

between readmission rates and PROMs may not be explained by other factors. For example, the findings presented in this chapter are likely to be affected by changes in case-mix over time and between providers, which are not fully captured in the data used for the risk-adjustment process. Moreover, the analysis may be impacted by time-varying confounding, including the set up of specialist Orthopaedic Units, such as the one opened in The Mid Yorkshire Hospitals NHS Trust in 2013 (The Mid Yorkshire Hospital NHS Trust, 2013).

It is important to therefore highlight that further research is needed to examine the underlying mechanisms of the results found in this chapter, particularly to assess whether the findings are the result of interventions aimed specifically at reducing readmission rates and thereby improving the patients' health gain (*i.e.* through improved discharge processes for surgical patients), or alternatively whether the findings reflect efforts aimed at improving both metrics at the same time (*i.e.* through specific rehabilitation programmes targeting patients at the pre-operation stage) (Ibrahim *et al.*, 2013). I would recommend that these studies would profit from more timely collected PROMs data, which in turn will allow testing for deviances in patient health closer to the occurrence of the readmission. While this study focussed on hip and knee replacement patients for several reasons discussed in an earlier section, future work should explore other patient groups (*e.g.* medical as well as surgical admissions) to understand whether these findings are generalizable to different settings, but also other healthcare systems. Ideally, future research would use linked PROMs-HES data at an individual level.

4.6 Conclusion

Reductions in risk-adjusted, 30-day readmission rates in patients discharged from English Trusts following hip or knee replacement surgery were complemented by small rises in patient-reported health gains measured through four PROMs metrics. These findings carry some

significance, since they suggest that the post-2010 enhanced policy focus on reducing readmission rates in the NHS has not resulted in unintended consequences for patients. This fear had been expressed in previous studies. Moreover, one explanation for this weak link between readmissions and PROMs is that both types of metrics measure different dimensions of quality of care. And while improvements in each metric represent substantial benefits for patients, these might materialise through different channels or mechanisms.

The finding of this chapter also highlights the requirement for the collection of PROMs data across the healthcare system (Rolfson *et al.*, 2016), preferably in a more systematic way. Subsequently, this could lead to studying health gains more directly than is currently the case, with this chapter illustrating one example of how linkages between rich databases can lead to insights into the quality of care provided in healthcare systems.

The work presented in this chapter provides a significant contribution to the objectives of the thesis. I was able to suggest some correlation between readmission rates and other measures for quality of care and make a significant contribution to the debate about whether an enhanced policy focus on readmission rates may lead to unintended consequences. Using a linked dataset on a relatively large number of patients, I was able to complement the commonly used readmission metric, which is usually derived from administrative health data, with the patient perspective - specifically, the self-reported quality of life for patients undergoing treatment for hip and knee replacement in the NHS. However, the methodology used in this chapter allows for no inference regarding causal relationships between the enhanced policy focus on readmission rates and changes in readmission rates, with the next chapter providing the first causal assessment of the financial penalty policy introduced following the 2010 government white paper, *Equity and Excellence*.

Chapter 5 Do financial penalties reduce readmission rates? A continuous treatment effect evaluation

5.1 Preamble to chapter 5

Financial penalties for hospitals with excess readmission rates have been introduced in the United States (US) under the Hospital Readmission Reduction Program (HRRP), and in the English National Health Service (NHS) following the government white paper *Equity and Excellence: Liberating the NHS*. Previous research attempting to evaluate the impact of these policies have relied on before-and-after study designs, or conducted interviews, both with significant methodological limitations. As discussed earlier in this thesis, large uncertainty exists around the impact of financial penalties, particularly around possible negative consequences for patients, or provider groups.

This chapter exploits the endogeneity that arises by setting financial penalty thresholds in the English NHS. I apply the Generalised Propensity Score (GPS) methodology proposed for continuous treatment effects and estimate dose-response functions that relate varying levels of financial penalties to risk-adjusted, 30-day readmission rates.

Work from this chapter has been presented at several conferences and workshops, including at the International Health Economics conference in Boston (2017), the IRDES workshop in Paris (2017), the conference of the American Health Economics Association in Philadelphia (2016) as well as at seminars at The Health

Foundation and Imperial College London. I would like to acknowledge the contribution of Dr Adam Steventon, who acted as a co-author on this paper.

5.2 Introduction

To improve the quality of healthcare, policy-makers in countries such as England and US have incorporated financial penalties for excess hospital readmission rates into their payment systems (Kristensen *et al.*, 2015). The focus on readmission rates has arisen because they correlate with the quality and safety of care at various points across the patient pathway, while being measurable within existing administrative data sets. Specifically, readmission rates have been linked to the quality of care at the initial hospital stay (Hansen, Williams and Singer, 2011), transitional care services (Feltner *et al.*, 2014; Lee *et al.*, 2015; Rennke and Ranji, 2015), and post discharge support (Phillips *et al.*, 2004; Harrison *et al.*, 2014). Hospital readmissions may also increase the risk of experiencing an adverse event due to the additional time spent in hospital (Hauck and Zhao, 2011), and are costly to the payer (Friedman and Basu, 2004).

Financial penalties may incentivise hospitals to work collaboratively with other organisations to develop approaches to reduce readmission rates. Studies have shown that 30% (range 5% to 79%) of all hospital readmissions are potentially preventable (Van Walraven *et al.*, 2011; Blunt *et al.*, 2015b), and that readmissions are amenable to changes to the delivery of hospital care, such as the introduction of enhanced education for high-risk patients (Sharon, Edwards and Lashbrook, 2011), dedicated transitional care units (Rennke and Ranji, 2015), or follow-up care provision (Kripalani *et al.*, 2014). The financial penalties might also incentivise hospitals to work more closely with primary care

and community health organisations to improve post-discharge care. In a questionnaire study, 65.8% of hospital leaders reported that the introduction of financial penalties for Medicare in the US led to a great impact on efforts amongst hospital teams to reduce readmissions (Joynt *et al.*, 2016).

Even though financial penalties for excess readmissions are common internationally, no robust evaluation exists regarding the effectiveness of these policies. Policy-makers had to rely on before-and-after comparisons, such as the study conducted for the HRRP in the US (Zuckerman *et al.*, 2016), which found a 3.7% reduction in readmission rates for patients admitted for acute myocardial infarction, heart failure, and pneumonia between 2007 and 2015. Before-and-after studies assume that changes in the level (or gradient) of the outcome that exist contemporaneously with the date of the policy implementation can be attributed to the policy, yet this assumption is often implausible given secular trends and other changes occurring in the healthcare system (Portela *et al.*, 2015). From a methodological perspective, the challenge inherent in evaluating financial penalties is that those policies are typically introduced across whole healthcare systems at a single point in time. While such an approach to implementation is necessary when introducing financial penalties to ensure a fair playing field between hospitals (Carey and Lin, 2016), it also means that there is no contemporaneous collection of untreated hospitals with which to compare the outcomes of treated hospitals. Although methods have been developed that use historical control groups, contemporaneous controls are important because there is a recurrent concern of biased outcomes due to unaccounted differences in risk of receiving a treatment (Goodacre, 2015), particularly if the likelihood of receiving larger or smaller financial penalties is based on the relationship between hospital characteristics and the readmission rate.

As a result of these problems, it is rarely possible to estimate an average treatment effect of financial penalties using the techniques that have been developed for binary treatment settings, such as by matching untreated units to treatment units on the basis of their estimated propensity scores (Rosenbaum and Rubin, 1983). Yet, while it is not possible to produce a credible estimate of the average treatment effect, in some settings, it is possible to estimate a dose-response function that relates the level of the financial penalty received to the expected outcomes (Wong and Lachenbruch, 1996). With regards to readmission penalties, such a dose-response curve would be valuable to inform decisions about the magnitude of financial penalties to levy on hospitals, given that the decision to introduce a penalty has already been made. The magnitude of the penalty is likely to influence outcomes, especially since there have been concerns about unintended consequences from hospital readmission penalties that could plausibly depend on the penalty-level imposed (Friebel and Steventon, 2016). One hypothesis is that the dose-response curve will follow a ‘u-shape’ because, for example, too large financial penalty rates could cause funding shortages within hospitals, thus hampering efforts to improve the quality of care and subsequently leading to an increase in future readmission rates. Meanwhile, too small financial penalties could be ineffective in motivating any change that can reduce readmission rates below the current level.

In this chapter, I exploit a feature of the way in which financial penalties for hospitals with high readmission rates were introduced in England, which resulted in endogenous variation in the level of the financial penalties between administrative areas (Department of Health, 2010). This feature means I estimate average dose-response curves regarding the relationship between levels of the financial penalty and subsequent risk-adjusted, 30-day readmission rates following indexed emergency and elective admissions. My approach uses GPS methods, which have been developed to overcome

bias resulting from observed confounders in continuous treatment settings (Hirano and Imbens, 2004). This method is based on the key assumption of weak unconfoundedness. Thus, for any level of financial penalty, the readmission rate that would be experienced by a given administrative area is independent of the financial penalty assigned, conditional on the observed baseline covariates. Much like in the binary treatment case, some diagnostic tests are possible in relation to the observed covariates, based on the balancing property (*i.e.* improved association between observed covariates and the treatment groups). If these assumptions are satisfied, I can estimate unbiased relationships between levels of financial penalty and risk-adjusted, 30-day readmission rates.

5.3 Setting financial penalty threshold

The financial penalty policy introduced in England in 2010 has been discussed in Chapter 1 of this thesis (see Section 1.7). Below is described how the penalties were determined at the payer-level.

Clinical reviews were undertaken for each Trust individually and served two key purposes. First, to encourage dialogue between commissioners (*i.e.* payers of healthcare services in England called Primary Care Trusts, or PCTs that were in place until March 2013) and the providers involved in the patients' care pathway, and second, to agree on a threshold above which readmissions would not be reimbursed. This threshold was based on an agreement between Trusts and PCTs regarding the rate of readmissions that were avoidable, and thus varied across Trusts depending on the outcome of a local review.

The clinical review process was led by a clinician who was not employed by the Trust, often a GP or public health physician and included other parties such as representatives from the PCT, clinical staff from the Trust, local GPs, representatives from social care services and ambulance services, and pharmacists. This team retrospectively reviewed clinical case notes of all patients readmitted within a predefined period (*e.g.* one week). Following a standardised check-list, for each readmission, the team had to ultimately reach a decision regarding whether they were avoidable through interventions by primary care services, hospital services, social care services or community care services, and outline interventions that could have prevented the readmission. To inform the decision-making process, along with the case notes, the review team was also provided with a synopsis of administrative secondary care records, containing information on all patients with a readmission occurred within the previous financial year. The clinical review had to be completed within the first quarter of the financial year (*i.e.* by 30 June 2012), with the threshold being applied to all emergency readmissions for the remainder of the financial year (*i.e.* until 30 March 2013).

While the penalties covered patients with an indexed admission to any NHS hospital in England, some admissions were excluded, as were some readmissions. Admissions or readmissions related to maternity or childbirth, cancer, chemotherapy, radiotherapy, organ transplant, renal dialysis were excluded, as were those classified as cross-border activity between England and Wales or Scotland. The policy also excluded all readmissions without a national tariff (*i.e.* the national tariff is a set monetary value for the reimbursement of healthcare services, and is determined annually), readmissions following a self-discharge against clinical advice, readmissions for patients below four years of age, readmissions caused by a transportation accident, and readmissions that were emergency transfers from the inpatient department of another Trust (Department

of Health, 2012). The penalty was levied against the Trust associated with the initial admission.

In their annual financial accounts for 2012/13, PCTs reported approximately £248 million in savings linked to readmission penalties. As part of the policy agreement, PCTs were instructed to reinvest penalties into post-discharge rehabilitation services (*i.e.* those which fall to community services and local authority-funded social care), which are not always within the direct control of the discharging hospital. Areas of reinvestment had to be guided by recommendations determined in the clinical review. For example, in the financial year 2012/13, reinvestments were made into ‘re-ablement’ services, *i.e.* services that help patients to regain physical strength and confidence required for performing every-day activities (33% of total reinvestment from savings accumulated through financial penalties), community services (26%) and intermediate care services (12%).

In this study, I estimate the dose-response curve that relates the level of the financial penalties to risk-adjusted, 30-day readmission rates in the financial year 2012/13. This analysis is based on the PCT-level, even though thresholds were agreed between different Trusts and PCTs. I focus on PCTs, because of their participation in the determination of thresholds, and their direct involvement in the enforcement of financial penalties and re-investment of savings.

The innovative contribution of this chapter is to adjust for pre-policy variation in the observed characteristics of PCTs, using the GPS and then to estimate separate dose-response functions for readmissions of patient subgroups with indexed admissions for acute myocardial infarction, pneumonia and heart failure. Provided that certain econometric assumptions are met (outlined below), the method allows for an unbiased estimation of the average dose-response function, thus providing clinicians,

commissioners and policy-makers with information on the most effective level of financial penalty to reduce risk-adjusted readmission rates in the English NHS. This is the first study globally to estimate dose-response functions for readmission penalties, and because financial penalties have been adopted widely across healthcare systems, this study could provide a framework for similar policy evaluations elsewhere.

5.4 Data

5.4.1 Financial penalties

Financial penalties were introduced from April 2011 and monitored through Financial Information Management Systems. These systems reported data on the monetary value of readmissions that were paid by PCTs to the Trusts and likewise on the monetary value of readmissions that were withheld. Moreover, from April 2012, the monetary values of readmissions were withheld and their respective areas of reinvestment were recorded in financial accounts protocols for each participating PCT to ensure transparency and for audit purposes. No such recording system was in place for financial year 2011/12.

For each PCT operating in the financial year 2012/13, I obtained information from annual accounts on the actual monetary value of all readmissions and actual monetary value of non-reimbursable readmissions, following a Freedom of Information request to the Department of Health in England. I calculated the financial penalty rate as the ratio between the value of non-reimbursed readmissions and actual monetary value of all readmissions (including those that were not reimbursed).

On average 22.5% of readmissions were not reimbursed in 2012/13, with the financial penalty ranging from 2.7% in Sefton PCT to 52.6% in the Kensington and Chelsea PCT (see Figure 8).

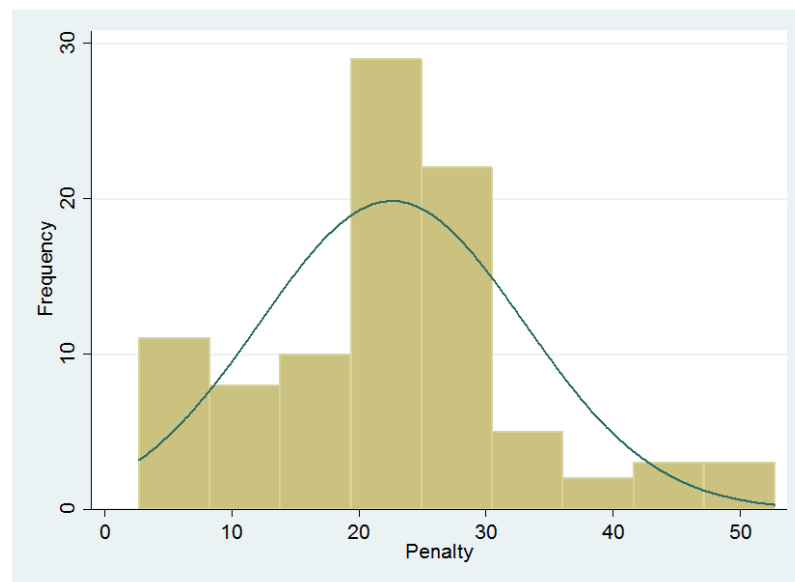


Figure 8. Distributions of financial penalties in 2012/13

5.4.2 Study sample

During the time of our study, there were 151 PCTs, of which I included 99 PCTs. I excluded administrations located on the border of England and Wales, namely Gloucestershire PCT, Herefordshire PCT, Shropshire County PCT and West Cheshire PCT (Department of Health, 2011). In those PCTs, the payment for services followed special arrangements that were outlined in the interim protocol on cross-border commissioning. I excluded a further 36 PCTs, because information was not provided on either the actual monetary value of all readmissions or actual monetary value of non-reimbursed readmissions. Finally, I excluded 16 PCTs with very high reported financial penalty (*i.e.* if the rate of non-reimbursable readmission rates exceeded 60% of total reimbursement) since these were regarded as suspect to recording errors. I chose 60% as

a cut-off point based on the distribution of financial penalties across PCTs and as it presents the mean employed financial penalty in 2012/13 plus two standard deviations. For each of the included PCTs, I identified hospital admissions using HES. I included all NHS-funded patients admitted to any hospital (NHS sector, or independent sector) between 1st April 2006 and 28th February 2013 within the selected PCTs. To reflect the criteria outlined in the policy framework for financial penalties (Department of Health, 2012), I excluded all patients who died during their initial hospital stay and any admission recorded as maternity or childbirth, cancer, chemotherapy, radiotherapy, organ transplant, renal dialysis, and also excluded patients who self-discharged against clinical advice. Although the readmission penalties excluded patients on the basis of age only if they were below four years of age, for the study I excluded patients below the age of 18 years, due to limitations in calculating the Charlson Index for this patient subgroup (see below). I did not include patients admitted during March 2013, to allow scope to identify readmissions over the subsequent 30-days within the constraints of the data set. Where a patient experienced multiple indexed admissions, I included each admission in our data set as separate observations, provided the date of discharge and date following admission was separated by more than 30 days.

5.4.3 Outcome measures

The main analysis focuses on readmissions for the financial year 2012/13 (*i.e.* readmissions occurring between 1st April 2012 to 28th February 2013), but I conduct sensitivity analysis around the policy impact on readmissions for financial years 2011/12 and 2012/13, combined. I defined readmissions as all-cause, emergency admissions to any hospital within 30 days of hospital discharge. Emergency admissions were identified based on the method of admission code recorded within the HES database. I applied exclusion criteria consistent with the policy guidelines and hence excluded all

readmissions following a transportation accident (*i.e.* identified through secondary diagnosis codes beginning with ‘V’), and any readmission associated with maternity or childbirth, cancer, chemotherapy, radiotherapy, organ transplant and renal dialysis. Due to constraints in our dataset, I was not able to implement the exclusion criteria specified in the policy guidelines for readmissions without a national tariff, but I assume that this exclusion criterion affected only a small number of admissions.

I risk-adjusted readmission rates by applying logistic regression analysis at the patient-level, adjusting for patient age on admission, gender, ethnicity, the Charlson Index (Quan *et al.*, 2011), SES (IMD, based on the small geographic areas of patient residence, with each of these areas containing on average 1,500 residents), length of stay at the indexed admission and the initial discharge destination (whether the patient was discharged to his usual place of residence, or a nursing/care home). I then calculated the risk-adjusted readmission rate for each PCT and financial year 2012/13, by first dividing the observed readmission rate by the predicted readmission rate to assess whether the PCT performed below or above what would be expected given patient case-mix. I then multiplied this ratio for each PCT and financial year 2012/13 by the average readmission rate observed at the national level in that financial year.

5.4.4 Study covariates

I aimed to identify confounders of the relationship between the financial penalty rate and PCT-level risk-adjusted, readmission rates. I note that both quantities are defined at the PCT-level, and that readmission rates had already been adjusted for some admission level factors (see previous paragraph). To identify confounders, I reviewed the literature on the determinants of readmission rates, and also considered factors that are

predictive of financial penalty rates, particularly those determined as part of the clinical review process when agreeing on penalty thresholds.

I identified multiple studies that published information on factors that can predict readmission rates. For example, Epstein *et al.* (2011) found a correlation between the number of hospitalisations to occur in regions of the US and readmission rates, and as a result, I included the number of admissions for each PCT as a covariate in our model. Due to the link between the probability of a readmission and the diagnosis at the initial hospital stay as well as their sensitivity to post-discharge support services (Langhorne *et al.*, 2007), I further included the number of admissions for selected patient subgroups, including admissions for acute myocardial infarction, stroke and pneumonia, which I identified using primary diagnosis codes. Laudicella *et al.* (2013) found an inverse correlation between survival rates and readmission rates for patients with a primary diagnosis of hip fracture to hospitals in England, motivating the inclusion of PCT-level in-hospital mortality rate as a study covariate. Finally, Kaboli *et al.* (2016) investigated the relationship between length of hospital stay and readmission rates, and found that a reduced length of stay was associated with significant reductions in readmission rates. To capture this established link and potential variation across PCTs, I calculated length of stay for indexed hospitalisations as the average time spent in hospital between admission date and discharge date for each PCT.

To determine penalisation thresholds, the clinical review teams assessed each occurring readmission based on a prescribed proforma (Department of Health, 2012). For example, readmitted patients had to be categorised into groups depending on whether the indexed discharge location was their usual place of residence or a nursery/care home. Moreover, any underlying health conditions were determined. To reflect information likely to have been available to the review teams, I obtained publicly

available data on disease prevalence at the PCT level from the Quality and Outcomes Framework (QOF; NHS Digital, 2016). Information was available from QOF for disease prevalence within each PCT for coronary heart disease, heart failure, stroke, hypertension, chronic obstructive pulmonary disease, asthma and dementia. Another potential predictor for the level of financial penalty was the quality of post-discharge support, and particularly whether the support was provided through a GP. I addressed variation in access to primary care services by including the number of GPs per PCT, obtained from QOF.

In summary, I included the following covariates, calculated separately for each PCT and financial year (*i.e.* 2006/07; 2007/08; 2008/09; 2009/10; 2010/11): number of admissions; average length of stay; proportion of admissions that resulted in discharges to the patients usual place of residence; proportion of admissions that resulted in discharges to a nursing or care home; risk-adjusted, in-hospital mortality rate; risk-adjusted, 30-day readmission rate (regardless of whether or not the indexed admission was an emergency admission); risk-adjusted 30-day readmission rate following any non-emergency admissions; number of GPs per PCT; number of hospitalisations for acute myocardial infarction, stroke and pneumonia; and, the disease prevalence within the population for coronary heart disease, heart failure, stroke, hypertension, chronic obstructive pulmonary disease, asthma and dementia. Overall, this resulted in a total of 61 covariates, which our econometric approach aimed to balance across treatment levels.

5.5 Econometric framework

The use of the GPS for continuous treatment settings was first proposed by Hirano and Imbens (2004) and further developed and applied by Bia and Mattei (2008) and Bia, Flores, Flores-Lagunes and Mattei (2014). Application examples include the impact evaluation of continuous training on wage attainment (Kluve *et al.*, 2007), and the impact evaluation of increasing transfer times to specialist neuroscience centres on health outcomes (Kreif *et al.*, 2015).

The framework postulates, for each unit i , the existence of a set of potential outcomes, $Y_i(t)$ reflecting the outcomes that would be experienced by the unit under treatment t . These potential outcomes can be considered to be random variables; for simplicity, in subsequent notation I will drop the index i where there is no risk of confusion. In the more familiar binary treatment case, $t \in \{0,1\}$, but here I allow it to be selected from an interval, $T = [t_0, t_1]$. Our main assumption is weak unconfoundedness; in other words, for any given level of the treatment, the potential outcome at that level of treatment is independent of treatment assignment, conditional on the observed baseline covariates, X .

$$Y(t) \perp T \mid X, \text{ for all } t \in T$$

Therefore, I assume that, at any given financial penalty rate, the risk-adjusted, 30-day readmission rate that would be observed for a given PCT at that level of penalty is independent of the financial penalty actually assigned to that PCT, conditional on the observed baseline covariates listed in the preceding section. Given this assumption, the GPS allows for an unbiased estimation of the average dose response function, which I define as $E[Y(t)]$.

5.5.1 Generalised Propensity Score

Following Hirano and Imbens (2004) presentation closely, in this study sample of PCTs indexed by $i = 1, \dots, N$, the GPS is defined as the conditional density of the level of the penalty rate $T_i \in [t_0, t_1]$ and PCT-level covariates X_i :

$$GPS(T, X) = f_{T|X}(t|x)$$

I first predict the observed treatment level based on covariates using OLS regression estimators. The model is specified as

$$(1) \quad T_i = \alpha + \beta_0 * X_i + \varepsilon_i$$

Here, the dependent variable T_i represents the observed penalty rate of PCT i in financial year 2012/13, and I assume it is normally distributed. The variable X_i captures confounding variables of the local population in PCT i , which I measured over the time period April 2006 to March 2011. The standard error ε_i is normally distributed with mean 0 and standard deviation σ .

In the second step, I calculate the GPS, using the formula for the density of a normally distributed random variable and based on estimates obtained from the OLS regression analysis.

$$(2) \quad \widehat{GPS}_i(t_i, X_i) = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp \left(-\frac{1}{2\hat{\sigma}^2} (t_i - \hat{\beta}_0 - \hat{\beta}_1 * X_i)^2 \right)$$

In the third step, I model the conditional expectation of the outcome Y_i given the level of financial penalty T_i and the estimated generalised propensity score $\widehat{GPS}_i$. I use a cubic approximation as the main model specification:

$$(3) \quad E[Y_i | T_i = t_i, \widehat{GPS}_i = \widehat{gps}_i] = \alpha_0 + \alpha_1 t_i + \alpha_2 t_i^2 + \alpha_3 t_i^3 + \alpha_4 \widehat{GPS}_i + \alpha_5 \widehat{GPS}_i^2 + \alpha_6 \widehat{GPS}_i^3 + \alpha_7 t_i \widehat{GPS}_i + \alpha_8 t_i^2 \widehat{GPS}_i + \alpha_5 t_i \widehat{GPS}_i^2$$

It is important to note that this function does not have any causal interpretation, since to estimate the average dose response function at $T_i = t_i$, it is necessary to take the expectation of this function over all units. Before doing so, I first consider some diagnostic tests.

5.5.2 Diagnostic tests

While the weak unconfoundedness assumption cannot be directly verified from the data, I can assess whether adjustment for the estimated GPS reduces imbalances on the observed covariates. To do so, I followed the proposed blocking approach by Hirano and Imbens (2004). The intuition of this approach is that, after adjusting for the GPS, there should be no difference in study covariates between treatment levels.

First, I divide the sample into three groups based on tertiles of the financial penalty rate: group 1 ranged from 2.7% to 14.3%; group 2 ranged from 14.5% to 28.4%; group 3 ranged from 29.1% to 52.6%. These three groups had a median penalty rate of 11.0%, 22.9% and 33.72%, respectively. Then, I predict the distribution of the GPS at the median penalty rate of each group, which I separate into five blocks based on quintiles of the respective GPS distribution. For group 1, I calculate the difference in means of each covariate between PCTs in block 1, compared to PCTs belonging to block 1 in group 2 and group 3. In total, I calculate five differences in means for group 1 (for each of the five blocks) and weight it by the number of PCTs in each group. Group 2 and group 3 are dealt with in the same way. I anticipate that adjustment of the GPS reduces the t-statistics for each difference in covariate mean within one group compared to covariate means of the respective other two groups. A t-statistic below 1.96 is considered to represent adequate balance. To achieve the best possible balance given

available covariates, I iteratively refined the specification of the GPS until achieving best possible balance.

After the balancing step, I also test the overlap for common support in a method proposed by Kluve et al. (2007). Again, I divide PCTs into tertiles based on the distribution of the financial penalty and then evaluate the GPS at the median level of financial penalty for each subgroup. I plot the distribution of the estimated GPS for group 1 against the median distribution of GPS for the rest of the sample. This method allows for a visual assessment of overlap between distributions, similar to the case of using propensity scores in binary treatments. The same approach was followed for group 2 and group 3.

5.5.3 Estimating the relationship between treatment levels and financial penalties

I amended the specification of the GPS iteratively until I had obtained adequate balancing statistics and overlap (Ho *et al.*, 2007), and then proceeded to estimate the average dose-response function for the relationship between the financial penalty rate and risk-adjusted, 30-day readmission rate following emergency admissions and non-emergency admissions combined. To estimate the dose-response curve at a given penalty rate t , I calculate the outcome expected for each PCT given that treatment level according to equation (3), and then averaged over all PCTs. Thus, I estimated the following equation:

$$(4) \quad \mu(t) = E[\hat{Y}(t)] = \frac{1}{N} \sum_{i=1}^N (\hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 t^3 + \hat{\alpha}_4 \widehat{gps}(t, X_i) + \hat{\alpha}_5 \widehat{gps}(t, X_i)^2 + \hat{\alpha}_6 \widehat{gps}(t, X_i)^3 + \hat{\alpha}_7 t \widehat{gps}(t, X_i) + \hat{\alpha}_8 t^2 \widehat{gps}(t, X_i) + \hat{\alpha}_9 t \widehat{gps}(t, X_i)^2)$$

I estimated the dose response curve for each 1.0% level of t that lies between 0% and 53%, to cover the full range of financial penalties observed for the included PCTs in financial year 2012/13. I estimated 95% CIs for each point in the dose response curve by

producing 2000 bootstrapped samples, refitting the GPS on each sample. CIs were estimated using standard errors and assuming normal distribution of each treatment level effect.

5.4.5 Subgroup and sensitivity analyses

To assess the robustness of our analyses, I first perform sensitivity analysis around the model specification for the dose-response curve (as outlined in equation 3), using quadratic polynomials and quartic polynomials.

To further test whether the impact of financial penalties varied between patient subgroups, I perform sensitivity analyses, restricting our patient cohort to readmissions following an emergency versus non-emergency indexed admission, separately. In particular, this sensitivity analysis was informed by the initial policy decision to introduce two separate non-payment frameworks for risk-adjusted, 30-day readmissions following a planned and unplanned index admission, in financial year 2011/12 (Department of Health, 2011). Additionally, I calculated dose-response curves for readmissions following admissions for acute myocardial infarction, heart failure and pneumonia, given the policy focus of HRRP on readmissions for those initial admissions (CMS, 2016).

I used SAS Enterprise Miner for the initial data manipulation and performed the analyses using STATA version 13.

5.5 Results

5.5.1 Study sample and patient characteristics

I identified 41,084,426 admissions within 99 PCTs between 1st April 2006 and 28th February 2013. The average number of admission per PCT was 47,494 in 2012/13

and increased by an average of 7,128 from 40,092 in 2006/07. I removed approximately 26.2% of indexed admissions due to the study exclusion criteria, leaving 32,555,013 admissions in our study sample.

I observed an increase in the average age on admission and average number of comorbidities at admission between 2006/07 and 2012/13. The average age recorded for patients admitted to hospitals within PCTs was 57.9 years (range 53.2 years to 63.4 years) in 2012/13, an increase by 1.2 years from 56.7 years (range 52.1 years to 61.5 years) in 2006/07. Similarly, the average number of comorbidities recorded at admission increased by 0.15 from 0.26 (range 0.14 to 0.47) in 2006/07 to 0.41 (range 0.31 to 0.51) in 2012/13. The mean length of admission decreased by 1.3 days from 3.9 days (range 3.0 days to 6.2 days) in 2006/07 to 2.6 days (range 1.9 days to 3.4 days) in 2012/13. I observed small variations in the average proportion of female patients across time and constant average proportions of patients from ethnic groups (White, Black, Asian) across years (see Table 14).

Table 14.

Summary statistics of the study sample and for seven financial years

Variables	2006/07	2007/08	2008/09	2009/10	2010/11	2012/13	2012/13
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
No. admissions	40092 (20799)	42593 (22349)	46046 (24179)	50802 (27251)	50802 (27251)	51577 (28118)	47494 (25855)
Avg. patient age (y)	56.7 (1.9)	56.7 (1.9)	57.1 (1.9)	57.2 (2.0)	57.4 (2.0)	57.8 (2.0)	57.9 (1.9)
Female (%)	54.8 (1.3)	54.7 (1.3)	54.9 (1.1)	54.9 (1.2)	54.8 (1.1)	54.6 (1.1)	54.5 (1.0)
White (%)	89.0 (10.2)	89.1 (10.5)	90.3 (10.1)	90.2 (10.3)	90.0 (10.4)	90.0 (10.6)	89.7 (10.9)
Black (%)	1.7 (3.3)	1.8 (3.4)	1.8 (3.4)	1.8 (3.4)	1.8 (3.4)	1.8 (3.4)	1.8 (3.4)
Asian (%)	3.5 (4.6)	3.7 (4.8)	3.8 (4.9)	3.9 (5.1)	4.0 (5.10)	4.1 (5.2)	4.1 (5.3)
Charlson index	0.2 (0.0)	0.2 (0.0)	0.2 (0.0)	0.3 (0.0)	0.3 (0.0)	0.3 (0.0)	0.4 (0.0)
Disc. to usual place resid.	98.4 (0.6)	98.5 (0.6)	98.5 (0.6)	98.6 (0.6)	98.6 (0.5)	98.7 (0.5)	98.6 (0.5)
Length of stay (days)	3.9 (0.5)	3.3 (0.4)	3.2 (0.4)	3.0 (0.3)	2.8 (0.3)	2.7 (0.3)	2.6 (0.3)
Mortality (risk-adj.)	2.7 (0.4)	2.3 (0.4)	2.1 (0.3)	1.7 (0.2)	1.5 (0.2)	1.3 (0.3)	1.2 (0.2)
30-day readm.rate-all (%)	7.0 (0.7)	6.7 (0.7)	6.9 (0.7)	7.0 (0.7)	7.0 (0.6)	6.9 (0.6)	6.2 (0.6)
30-day readm.rate – emergency (%)	11.8 (1.0)	11.8 (1.0)	12.4 (1.0)	13.1 (1.0)	13.2 (1.0)	13.2 (1.0)	12.0 (1.0)
30-day readm.rate – elective (%)	3.2 (0.3)	3.1 (0.4)	3.1 (0.3)	3.1 (0.3)	3.0 (0.3)	2.9 (0.2)	2.6 (0.2)
Prev. / CHD (%)	3.8 (0.9)	3.8 (0.9)	3.7 (0.9)	3.7 (0.8)	3.7 (0.8)	-	-
Prev. / heart failure (%)	0.8 (0.2)	0.8 (0.2)	0.8 (0.2)	0.8 (0.2)	0.8 (0.2)	-	-
Prev. / stroke (%)	1.7 (0.4)	1.7 (0.4)	1.7 (0.4)	1.8 (0.4)	1.8 (0.4)	-	-
Prev. /hypertension (%)	12.7 (1.7)	13.1 (1.8)	13.4 (1.9)	13.9 (1.9)	13.9 (2.0)	-	-
Prev. / COPD (%)	1.6 (0.5)	1.7 (0.5)	1.7 (0.5)	1.8 (0.5)	1.8 (0.5)	-	-
Prev. / asthma (%)	5.8 (0.6)	5.8 (0.6)	6.0 (0.6)	6.0 (0.6)	6.0 (0.6)	-	-
Prev. / dementia (%)	0.4 (0.1)	0.4 (0.1)	0.4 (0.1)	0.5 (0.1)	0.5 (0.1)	-	-
Financial penalty	-	-	-	-	-	-	-
No. of PCTs	99	99	99	99	99	99	99

Note. ¹Summary statistics calculated across PCTs and financial years; SD: Standard deviation; Disc: Discharge; Resid: Residence; Readm.: Readmission; CHD: Coronary Heart disease; COPD: Chronic Obstructive Pulmonary Disease; PCT: Primary Care Trust

5.5.2 Outcome measures and study covariates

In 2012/13, the average risk-adjusted, 30-day readmission rate across all PCTs was 6.2%; a 0.8% decrease compared with the level seen in 2006/07 (7.0%), and a decrease by 0.9% from the level seen in 2010/11 (7.1%). In total, 85% of PCTs showed a reduction in risk-adjusted readmission rates following policy introduction compared with rates in 2011/12. There was, however, substantial variation in risk-adjusted readmission rates in 2012/13, with a range 4.8% to 7.3% across PCTs.

Table 13 provides summary statistics of PCT characteristics. I observed a decrease in the average number of GPs per PCT across the five-year pre-policy period, from 57.1 (range 11 to 148) in 2006/07 to 56.4 (range 12 to 146) in 2010/11. Moreover, a large proportion of the population had at least one chronic health condition. For example, in 2010/11 the disease prevalence for chronic heart disease was 7.1% (range 4.2% to 10.0%), prevalence for heart failure was 5.1% (range 3.9% to 6.0%), prevalence for chronic obstructive pulmonary disease was 6.1% (range 5.2% to 6.9%), prevalence for asthma was 2.3% (range 1.9% to 3.0%), and prevalence for dementia was 1.8% (range 1.5% to 2.2%).

5.5.3 Generalised Propensity Score and diagnostic testing

I estimated the GPS by first predicting the observed treatment level based on covariates as described in equation (1) and present OLS output in Table 15. Based on these predictions I then estimated the formula described in equation (2), including the final list of covariates after all iterations to achieve best possible balance.

Table 15.

Ordinary Least Squares regression output of the observed treatment level (financial penalties)

Covariate	Coefficient	Std. Error
Intercept	-584.84	598.22
Number of admissions – stroke (06/07)	.00	.00
Number of admissions – stroke (07/08)	.00	.00
Number of admissions – stroke (08/09)	-.00**	.00
Number of admissions – stroke (09/10)	.00	.00
Number of admissions – stroke (10/11)	.00	.00
Number of admissions – pneumonia (06/07)	.00	.00
Number of admissions – pneumonia (07/08)	.00	.00
Number of admissions – pneumonia (08/09)	.00	.00
Number of admissions – pneumonia (09/10)	.00	.00
Number of admissions – pneumonia (10/11)	.00	.00
Discharge to usual place of residence (06/07)	1.39	8.99
Discharge to usual place of residence (07/08)	-19.30	12.22
Discharge to usual place of residence (09/10)	40.66	21.44
Discharge to usual place of residence (10/11)	-16.54	17.69
Discharge to care home (06/07)	1.63	11.53
Discharge to care home (07/08)	-10.08	14.94
Discharge to care home (08/09)	8.46	14.90
Discharge to care home (09/10)	16.89*	25.84
Discharge to care home (10/11)	-10.97	19.48
Length of stay (06/07)	-4.50	4.62
Length of stay (07/08)	-6.17	7.12
Length of stay (08/09)	-9.15	8.51
Length of stay (09/10)	44.56**	18.55
Length of stay (10/11)	-17.04	13.62
Risk-adjusted mortality (06/07)	-6.28	6.63
Risk-adjusted mortality (07/08)	8.13	6.19
Risk-adjusted mortality (08/09)	-9.31	12.69
Risk-adjusted mortality (10/11)	-2.60	16.99
Number of practice (06/07)	-1.22	2.50
Number of practice (07/08)	.02	.03
Number of practice (08/09)	-.02	.02
Number of practice (09/10)	-.03**	.02
Number of practice (10/11)	.03**	.01
Prevalence – HF (06/07)	2.04	9.58
Prevalence – Stroke (06/07)	46.64	65.46
Prevalence – Stroke (07/08)	-37.48	127.69
Prevalence – Stroke (08/09)	-30.20	133.67
Prevalence – Stroke (09/10)	-115.73	117.90
Prevalence – Stroke (10/11)	141.24	87.01
Prevalence – Hypertension (08/09)	-2.28	14.81
Prevalence – Hypertension (09/10)	9.34	23.22
Prevalence – Hypertension (10/11)	-6.10	13.46
Prevalence – COPD (06/07)	-9.84	62.95
Prevalence – COPD (07/08)	-22.76	98.74

Covariate	Coefficient	Std. Error
Prevalence – COPD (08/09)	71.58	99.48
Prevalence – COPD (09/10)	-21.27	81.84
Prevalence – COPD (10/11)	-23/45	39.87
Prevalence – Asthma (10/11)	-7.01*	4.04
Prevalence – Dementia (08/09)	-73.47	118.30
Prevalence – Dementia (09/10)	125.96	188.47
Prevalence – Dementia (10/11)	-58.34	118.17
Admissions (06/07)	.00	.00
Admissions (07/08)	.00	.00
Admissions (08/09)	.00	.00
Admissions (09/10)	.00	.00
Admissions (10/11)	.00	.00
Risk-adjusted readmission rate (06/07)	-.47	4.14
Risk-adjusted readmission rate (06/07)	-4.68	4.69
Risk-adjusted readmission rate (06/07)	4.51	5.26
Risk-adjusted readmission rate (06/07)	3.74	5.68
Observations	99	
R-squared	.72	

Note. *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%.

Table 16 provides balance statistics based on differences in means and t-statistics before and after GPS adjustment. Before adjustment, balance across all three groups and 61 covariates (adding to a total number of 183 differences in means and t-statistics) was good, with 181 of 183 covariate mean differences having a t-statistic below 1.96. Before adjustment, t-statistics was above 1.96 for the number of admission for pneumonia in 2007/08 (group 3; t-statistics = 1.98) and discharge rate to care homes in 2006/07 (group 1; t-statistics = -2.25). After adjustment, t-statistics improved for all 61 variables and across all groups. In case of admission numbers for pneumonia in 2007/08 (group 3), t-statistics reduced by 1.08 to 0.90, and for discharge rate to care homes in 2006/07 (group 1), t-statistics reduced by 1.52 to -0.73 (see Figure 9). The figure shows that following adjustment, t-statistics are constrained within a tighter range (0.90 to -0.73). Importantly, t-statistics of pre-policy risk-adjusted, readmission rate 2010/11 decreased across all groups, with the greatest decrease observed for group 1, from 0.22 to 0.00.

Table 16.

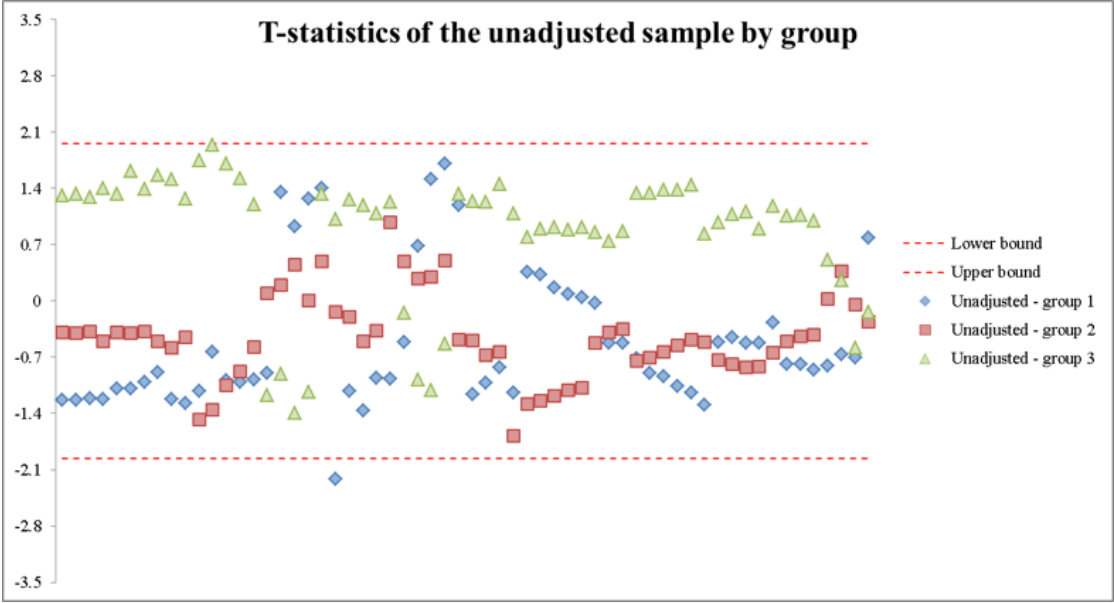
Balancing statistics showing differences in means and t-statistics across three groups based on distribution of the financial penalty variable

Covariate	Unadjusted: Mean differences (t-statistics)			Adjusted: Mean differences (t-statistics)		
	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
Number of admissions - stroke (06/07)	-3671.25 (-1.13)	-3183.75 (-0.98)	4570.00 (1.74)	-2299.61 (-0.25)	-3965.77 (-0.39)	4876.49 (0.74)
Number of admissions - stroke (07/08)	-3393.75 (-1.04)	-2450.00 (-0.75)	3895.83 (1.47)	-1129.62 (-0.12)	-2890.69 (-0.29)	4063.20 (0.58)
Number of admissions - stroke (08/09)	-4820.00 (-1.34)	-2370.00 (-0.65)	4793.33 (1.64)	-1452.40 (-0.13)	-2345.25 (-0.23)	5023.12 (0.68)
Number of admissions - stroke (09/10)	-5606.25 (-1.41)	-2081.25 (-0.52)	5125.00 (1.58)	-1591.07 (-0.13)	-2186.32 (-0.19)	5353.35 (0.65)
Number of admissions - stroke (10/11)	-5443.75 (-1.29)	-1512.50 (-0.35)	4637.50 (1.35)	-2018.91 (-0.17)	-1667.52 (-0.14)	4795.35 (0.55)
Number of admissions - pneumonia (06/07)	-3606.25 (-0.73)	-7518.75 (-1.54)	7416.66 (1.87)	-131.85 (-0.00)	-9299.78 (-0.56)	8164.50 (0.85)
Number of admissions - pneumonia (07/08)	-5056.25 (-0.98)	-7212.50 (-1.41)	8179.16 (1.98)	573.56 (0.03)	-8455.92 (-0.54)	9332.28 (0.90)
Number of admissions - pneumonia (08/09)	-6253.75 (-1.00)	-7210.00 (-1.15)	8975.83 (1.78)	902.01 (0.04)	-7204.26 (-0.38)	9666.31 (0.81)
Number of admissions - pneumonia (09/10)	-5932.50 (-0.90)	-6632.50 (-1.01)	8376.66 (1.57)	629.38 (0.03)	-6542.33 (-0.32)	9228.26 (0.75)
Number of admissions - pneumonia (10/11)	-7166.25 (-0.88)	-5491.25 (-0.67)	8438.33 (1.27)	204.23 (0.00)	-5141.98 (-0.20)	9639.24 (0.63)
Discharge usual place of residence (06/07)	-0.97 (-0.39)	-1.24 (-0.50)	1.47 (0.73)	-1.78 (-0.18)	-1.39 (-0.21)	1.64 (0.32)
Discharge usual place of residence (07/08)	0.16 (1.06)	0.01 (0.09)	-0.12 (-0.94)	0.04 (0.11)	0.00 (0.01)	0.12 (-0.27)
Discharge usual place of residence (09/10)	0.20 (1.36)	0.05 (0.37)	-0.17 (-1.42)	0.07 (0.20)	0.00 (0.01)	0.18 (-0.42)
Discharge usual place of residence (10/11)	0.20 (1.46)	-0.01 (-0.16)	-0.12 (-1.09)	0.05 (0.12)	-0.06 (-0.11)	0.14 (-0.32)
Discharge to care home (06/07)	-0.34 (-2.25)	0.06 (0.42)	0.18 (1.47)	-0.30 (-0.73)	0.07 (0.17)	0.19 (0.51)
Discharge to care home (07/08)	-0.15 (-1.11)	-0.01 (-0.12)	0.11 (1.01)	-0.11 (-0.30)	0.02 (0.04)	0.09 (0.30)
Discharge to care home (08/09)	-0.20 (-1.44)	-0.02 (-0.15)	0.14 (1.30)	-0.18 (-0.53)	0.01 (0.04)	0.13 (0.45)
Discharge to care home (09/10)	-0.12 (-0.97)	-0.06 (-0.47)	0.12 (1.18)	-0.10 (-0.34)	-0.00 (-0.01)	0.10 (0.40)
Discharge to care home (10/11)	-0.11 (-0.95)	-0.03 (-0.29)	0.10 (1.02)	-0.05 (-0.16)	0.03 (0.09)	0.08 (0.36)
Length of stay (06/07)	-0.11 (-0.70)	-0.18 (-1.09)	0.19 (1.48)	-0.25 (-0.47)	-0.10 (-0.18)	0.18 (0.56)
Length of stay (07/08)	0.08 (0.76)	-0.06 (-0.54)	-0.01 (-0.17)	0.02 (-0.07)	0.01 (0.05)	0.08 (-0.35)
Length of stay (08/09)	0.15 (1.50)	-0.02 (-0.28)	-0.08 (-0.98)	0.03 (0.10)	0.02 (0.09)	0.12 (-0.38)

Covariate	Unadjusted: Mean differences (t-statistics)			Adjusted: Mean differences (t-statistics)		
	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
Length of stay (09/10)	0.16 (1.74)	-0.03 (-0.35)	-0.08 (-1.12)	0.07 (0.29)	0.045 (0.16)	0.13 (-0.47)
Length of stay (10/11)	0.10 (1.17)	-0.03 (0.45)	-0.04 (-0.58)	0.04 (0.17)	0.02 (0.11)	0.08 (-0.34)
Risk-adjusted mortality (06/07)	-0.19 (-1.40)	-0.07 (-0.51)	0.17 (1.57)	-0.26 (-0.76)	-0.00 (-0.02)	0.16 (0.46)
Risk-adjusted mortality (07/08)	-0.08 (-0.84)	-0.06 (-0.61)	0.10 (1.19)	-0.10 (-0.36)	-0.03 (-0.13)	0.08 (0.26)
Risk-adjusted mortality (08/09)	-0.09 (-1.11)	-0.02 (-0.28)	0.08 (1.14)	-0.09 (-0.40)	0.00 (0.03)	0.05 (0.20)
Risk-adjusted mortality (10/11)	-0.08 (-1.47)	-0.01 (-0.25)	0.06 (1.41)	-0.09 (-0.60)	-0.00 (-0.03)	0.05 (0.33)
Number of practices (06/07)	-836.96 (-1.22)	-260.50 (-0.37)	734.74 (1.31)	-65.65 (-0.03)	-584.26 (-0.32)	445.68 (0.23)
Number of practices (07/08)	-871.25 (-1.28)	-290.00 (-0.42)	774.16 (1.39)	-154.47 (-0.07)	-582.58 (-0.32)	482.29 (0.25)
Number of practices (08/09)	-853.75 (-1.26)	-272.50 (-0.40)	750.83 (1.36)	-157.09 (-0.07)	-560.14 (-0.32)	468.99 (0.24)
Number of practices (09/10)	-843.75 (-1.25)	-362.50 (-0.53)	804.16 (1.47)	-122.38 (-0.05)	-648.70 (-0.36)	532.75 (0.28)
Number of practices (10/11)	-771.25 (-1.14)	-383.75 (-0.56)	770.00 (1.40)	-105.81 (-0.05)	-672.00 (-0.37)	507.37 (0.27)
Prevalence – Heart Failure (06/07)	0.03 (0.51)	-0.11 (-1.87)	0.05 (1.09)	0.02 (0.15)	-0.09 (-0.51)	0.05 (0.36)
Prevalence – Stroke (06/07)	0.04 (0.47)	-0.13 (-1.46)	0.05 (0.80)	0.07 (0.30)	-0.14 (-0.60)	0.06 (0.25)
Prevalence - Stroke (07/08)	0.03 (0.34)	-0.12 (-1.36)	0.06 (0.82)	0.05 (0.22)	-0.13 (-0.55)	0.06 (0.26)
Prevalence - Stroke (08/09)	0.02 (0.27)	-0.11 (-1.29)	0.06 (0.83)	0.04 (0.20)	-0.12 (-0.52)	0.06 (0.26)
Prevalence - Stroke (09/10)	0.02 (0.23)	-0.11 (-1.24)	0.06 (0.81)	0.04 (0.19)	-0.12 (-0.50)	0.07 (0.26)
Prevalence - Stroke (10/11)	0.01 (0.18)	-0.11 (-1.21)	0.06 (0.84)	0.04 (0.18)	-0.12 (-0.49)	0.07 (0.26)
Prevalence - Hypertension (08/09)	-0.14 (-0.31)	-0.29 (-0.63)	0.29 (0.77)	-0.04 (-0.04)	-0.40 (-0.31)	0.32 (0.25)
Prevalence - Hypertension (09/10)	-0.15 (-0.31)	-0.23 (-0.49)	0.26 (0.66)	-0.04 (-0.03)	-0.32 (-0.24)	0.29 (0.22)
Prevalence - Hypertension (10/11)	-0.24 (-0.50)	-0.21 (-0.43)	0.31 (0.76)	-0.10 (-0.09)	-0.27 (-0.20)	0.35 (0.25)
Prevalence - COPD (06/07)	-0.06 (-0.54)	-0.13 (-1.08)	0.13 (1.34)	-0.05 (-0.16)	-0.11 (-0.32)	0.14 (0.49)
Prevalence - COPD (07/08)	-0.07 (-0.56)	-0.12 (-1.01)	0.13 (1.29)	-0.05 (-0.17)	-0.10 (-0.28)	0.14 (0.48)
Prevalence - COPD (08/09)	-0.08 (-0.67)	-0.12 (-0.95)	0.14 (1.33)	-0.06 (-0.19)	-0.09 (-0.25)	0.16 (0.51)
Prevalence - COPD (09/10)	-0.10 (-0.76)	-0.11 (-0.87)	0.14 (1.34)	-0.08 (-0.22)	-0.07 (-0.20)	0.16 (0.52)

Covariate	Unadjusted: Mean differences (t-statistics)			Adjusted: Mean differences (t-statistics)		
	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
Prevalence - COPD (10/11)	-0.12 (-0.92)	-0.10 (-0.78)	0.15 (1.40)	-0.10 (-0.29)	-0.06 (-0.16)	0.17 (0.52)
Prevalence - Asthma (10/11)	-0.08 (-0.52)	-0.07 (-0.49)	0.10 (0.83)	-0.14 (-0.29)	-0.15 (-0.29)	0.11 (0.16)
Prevalence - Dementia (08/09)	-0.00 (-0.25)	-0.02 (-0.98)	0.01 (1.01)	0.00 (0.10)	-0.02 (-0.37)	0.01 (0.29)
Prevalence - Dementia (09/10)	-0.00 (-0.31)	-0.02 (-1.00)	0.02 (1.08)	0.00 (0.08)	-0.02 (-0.40)	0.02 (0.31)
Prevalence - Dementia (10/11)	-0.00 (-0.31)	-0.02 (-0.99)	0.02 (1.06)	0.00 (0.07)	-0.02 (-0.40)	0.02 (0.29)
Admissions (06/07)	-1869.53 (-0.35)	-4828.85 (-0.91)	4465.59 (1.03)	699.61 (0.04)	-5670.28 (-0.34)	5364.65 (0.51)
Admissions (07/08)	-4565.85 (-0.81)	-4021.16 (-0.71)	5724.67 (1.25)	-573.78 (-0.03)	-4529.52 (-0.27)	6944.95 (0.60)
Admissions (08/09)	-4966.80 (-0.81)	-3474.05 (-0.57)	5627.23 (1.14)	-604.24 (-0.03)	-3520.29 (-0.19)	6783.84 (0.55)
Admissions (09/10)	-5695.06 (-0.88)	-3306.18 (-0.51)	6000.83 (1.14)	-765.02 (-0.04)	-3448.21 (-0.18)	7184.38 (0.56)
Admissions (10/11)	-5621.06 (-0.82)	-3442.62 (-0.50)	6042.45 (1.08)	-140.45 (-0.00)	-3827.33 (-0.19)	7177.85 (0.52)
Risk-adjusted readmission rate (06/07)	-0.21 (-0.84)	-0.07 (-0.29)	0.19 (0.92)	-0.29 (-0.37)	-0.07 (-0.10)	0.21 (0.37)
Risk-adjusted readmission rate (07/08)	-0.19 (-1.05)	0.09 (0.50)	0.06 (0.44)	-0.11 (-0.24)	0.10 (0.20)	0.05 (0.12)
Risk-adjusted readmission rate (09/10)	0.04 (0.25)	0.02 (0.13)	-0.04 (-0.32)	0.11 (0.22)	-0.04 (-0.08)	-0.05 (-0.13)
Risk-adjusted readmission rate (10/11)	0.03 (0.22)	-0.05 (-0.34)	0.01 (0.09)	0.00 (0.00)	-0.09 (- 0.20)	0.01 (0.03)

(i)



(ii)

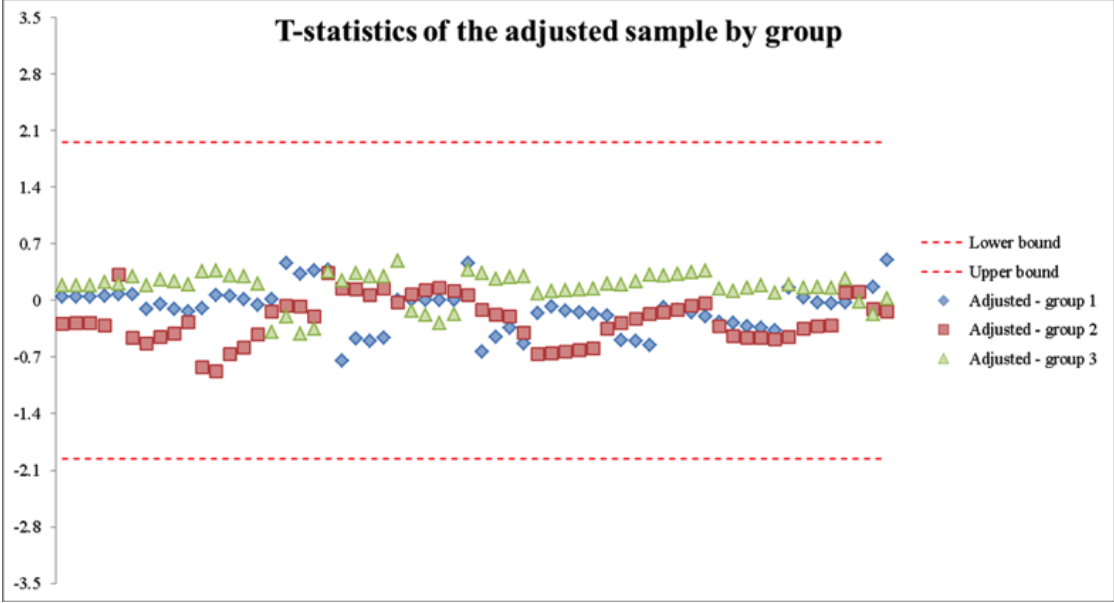
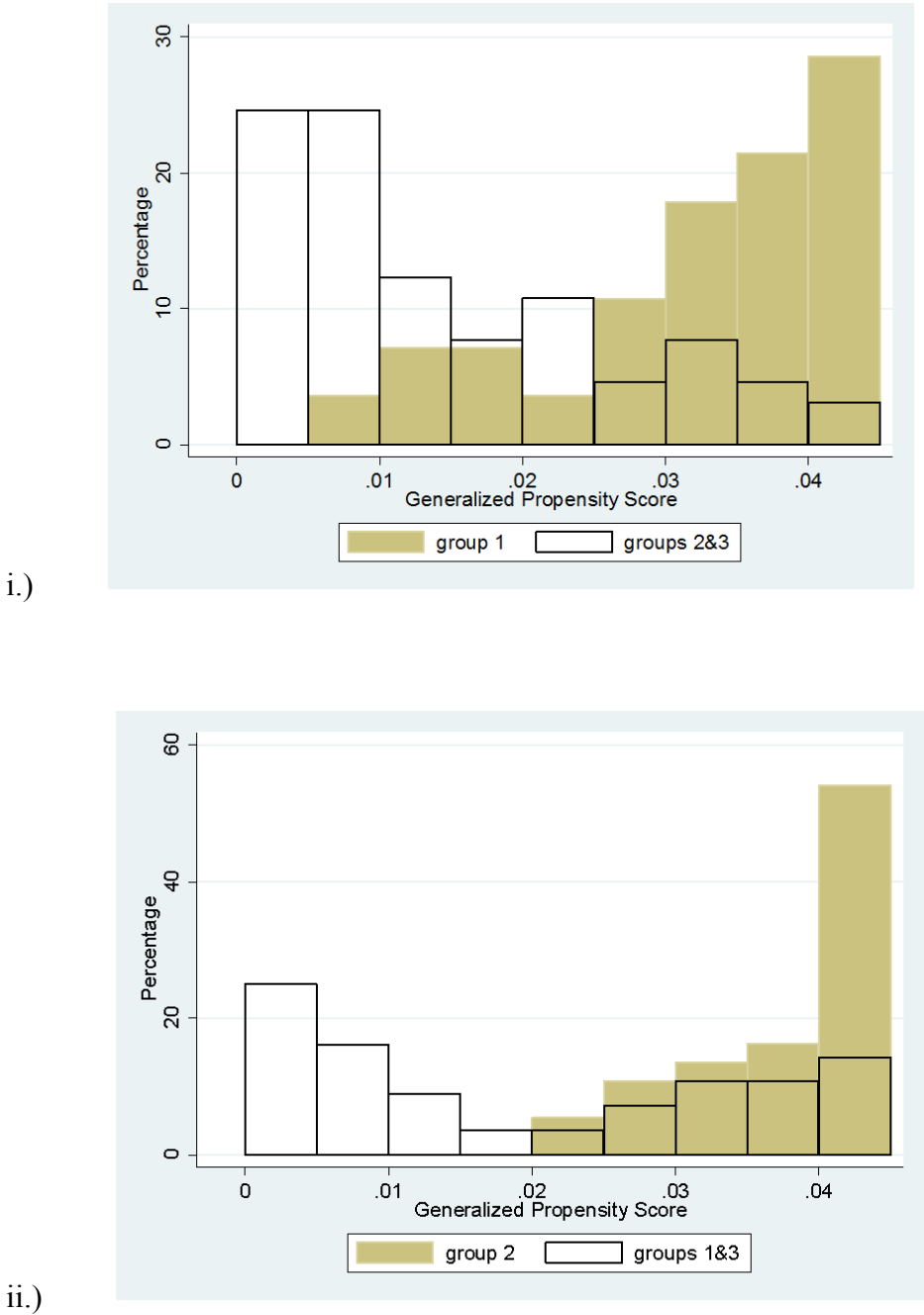


Figure 9. Balancing statistics – plots of t-statistics across groups before (i) and after (ii) GPS adjustment

Figure 10 depicts the overlap of GPS distributions for a visual assessment of common support. Overall, I found a good overlap of distributions between groups, but a poor overlap on the lower tail of the first and second group.



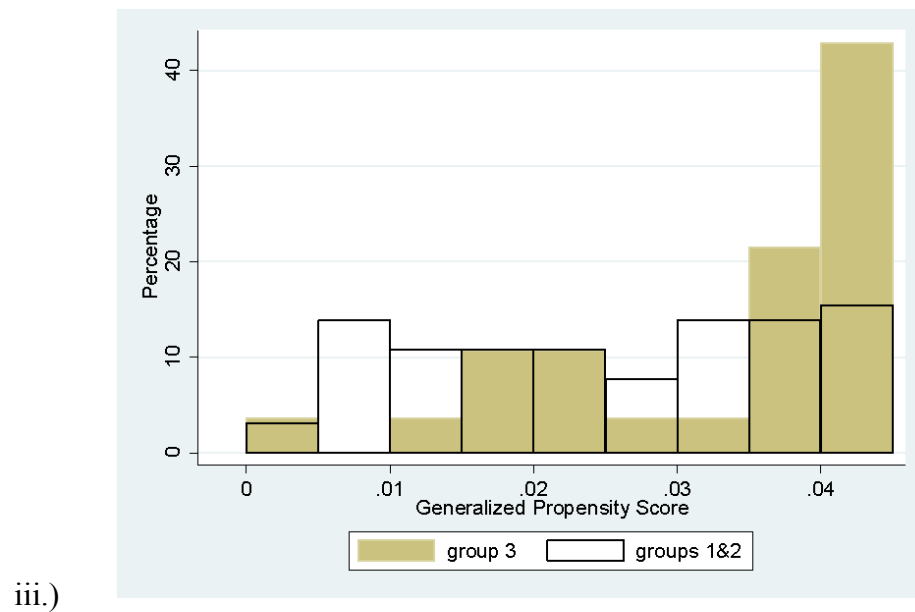


Figure 10. Overlap of GPS distributions by tertiles of the treatment level (i) level 1; (ii) level 2; and (iii) level 3

*Figure Note.*¹ Tertile 1: 11.0% (median), 2.7% to 14.3% (range); Tertile 2: 22.9% (median), 14.5% to 28.4% (range); Tertile 3: 33.7% (median), 29.1% to 52.6% (range).

5.5.4 Estimation of the relationship between treatment levels and financial penalties

Following the satisfaction of adequate balancing statistics and good overlap, I modelled the conditional expectation of the outcome Y_i , given the level of financial penalty T_i , and the estimated Generalised Propensity Score $\widehat{GPS}_i$, described in equation (3) (see Table 17), and calculated the average dose-response curve according to equation (4).

Table 17.

Model output of the conditional expectation of the risk-adjusted, 30-day readmission rates in 2012/13, given the level of financial penalty and the estimated Generalised Propensity Score.

Covariate	Coefficient	Std. Error
GPS	-127.27	428.13
GPS ²	1155.67	13796.48
GPS ³	9693.35	246770.10
Financial Penalty	-.21	.15
Financial Penalty ²	.00	.00
Financial Penalty ³	.00	.00
GPS*Financial Penalty	8.82	7.11
GPS ² *Financial Penalty	-119.64	108.89
GPS*Financial Penalty ²	-.03	.05
Intercept	8.83**	4.32
Observations	99	
R-Squared	.07	

Note. *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%.

Figure 11 shows the main dose-response curve, *i.e.* the interaction between financial penalties and risk-adjusted readmission rates in 2012/13. The mean risk-adjusted readmission rate across all PCTs in 2012/13 was at 6.1% and is indicated by the dotted horizontal line. I found a u-shaped dose-response curve with a diminishing marginal rate of impact at low (<6.0 %) and high (>25.0 %) financial penalty rates. The lowest point of the dose-response curve, *i.e.* vertex, was at 13.0%, and therefore below the national mean financial penalty of 22.5%. The corresponding readmission rate at the vertex was 6.0% (95% CI, 5.9% to 6.0%). CIs also dipped below the mean risk-adjusted readmission rate and narrowed around the average observed financial penalty rate, widening below 17.0% and above 31.0% of the financial penalty rate.

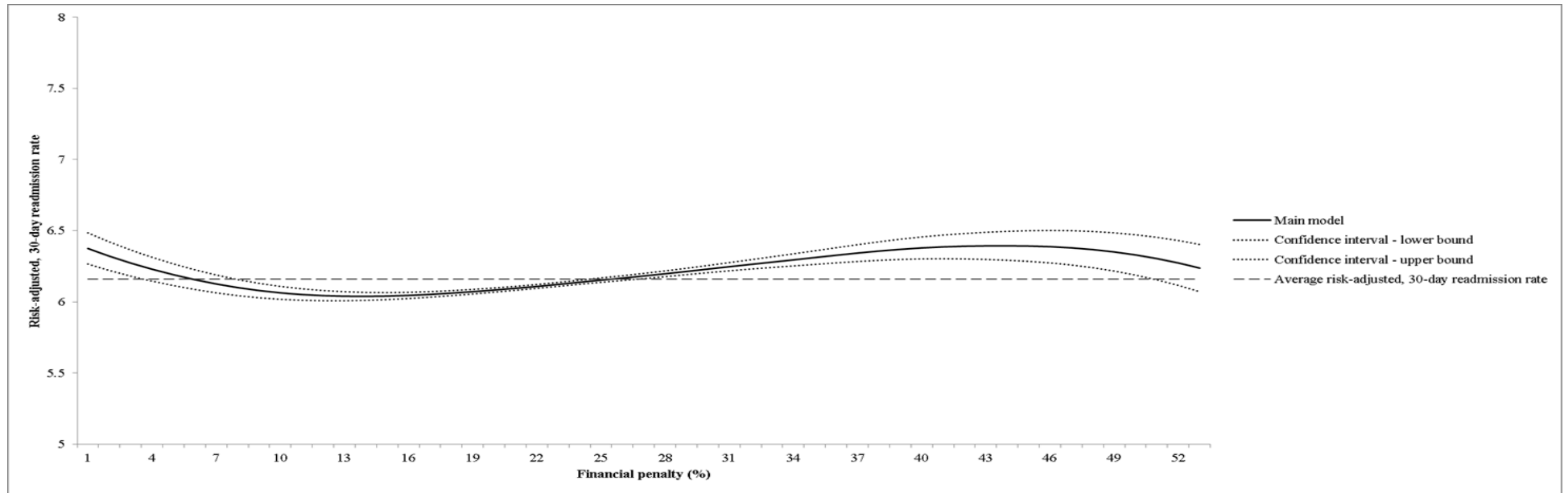


Figure 11. Main dose-response model relating different levels of financial penalties to risk-adjusted, 30-day readmission rates

Figure Note: ¹Treatment effects were calculated using bootstrapped standard errors (2000 replications); ²Horizontal line represents the mean observed risk-adjusted 30-day readmission rate across all PCTs from 01 April 2012 to 28 February 2013.

5.5.5 Subgroups and sensitivity analyses

To test the robustness of the estimated dose-response curve with cubic specification in the main model, I estimated equation (3) with quadratic, cubic and quartic estimators. The dose-response curve for all specifications was u-shaped, with the vertex of the quadratic dose-response curve at approximately 9%, and quartic polynomial dose-response curve at approximately 11% (see Figure 12). While our results tended to be sensitive to model specification, importantly, all dose-response curves followed a u-shape, indicating higher readmission rates at lower and higher levels of financial penalties.

I estimated equation (3) for risk-adjusted, 30-day readmission rates separately for indexed emergency admissions and indexed non-emergency admissions (see Figure 13). The mean risk-adjusted readmission rate following any indexed emergency admissions was 11.8%, with the dose-response curve dipping below this rate between 1% and 22% of financial penalty rate. Similar to the main model, the dose-response curve was u-shaped with the vertex at 9.0%. In comparison, the shape of the dose-response curve for readmissions following any indexed elective admissions is s-shaped, with financial penalties above 40%, leading to a reduction in readmission rates below the 22.5% mean readmission rate 2012/13. Small penalties below 19% were found to increase readmission rates.

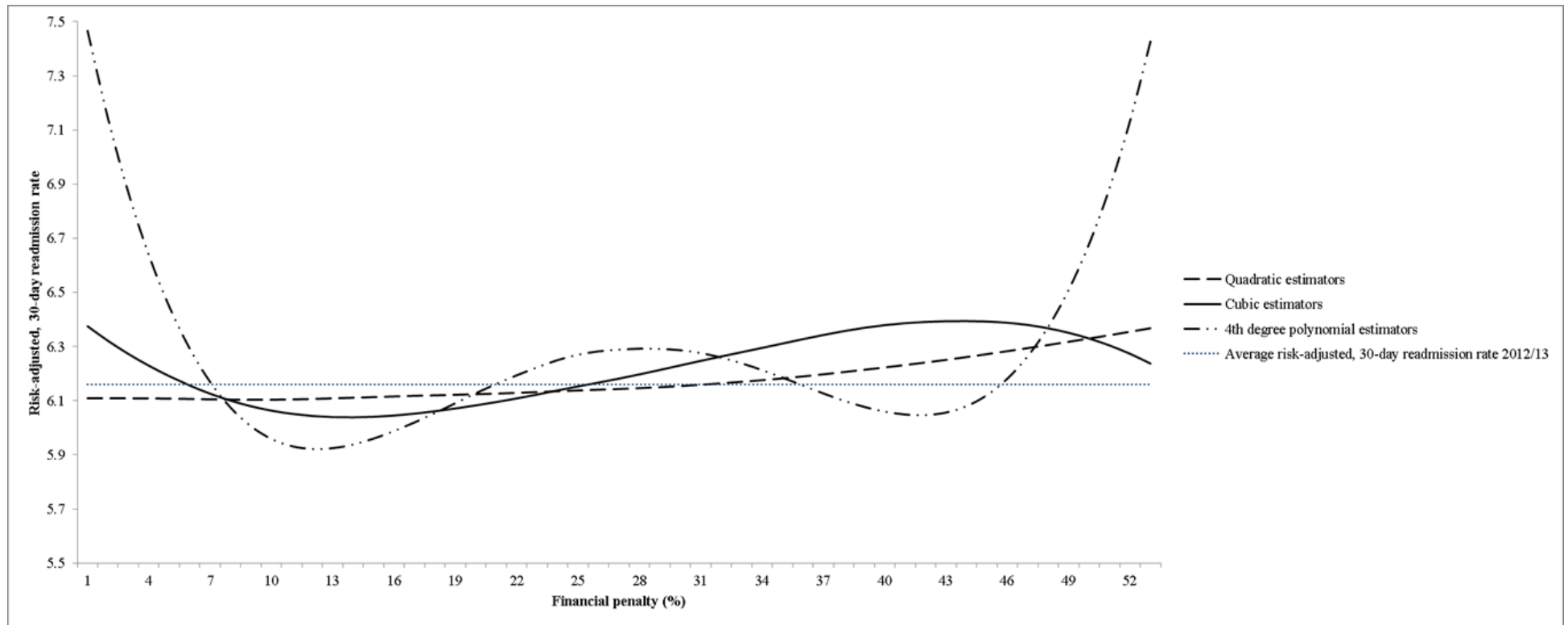
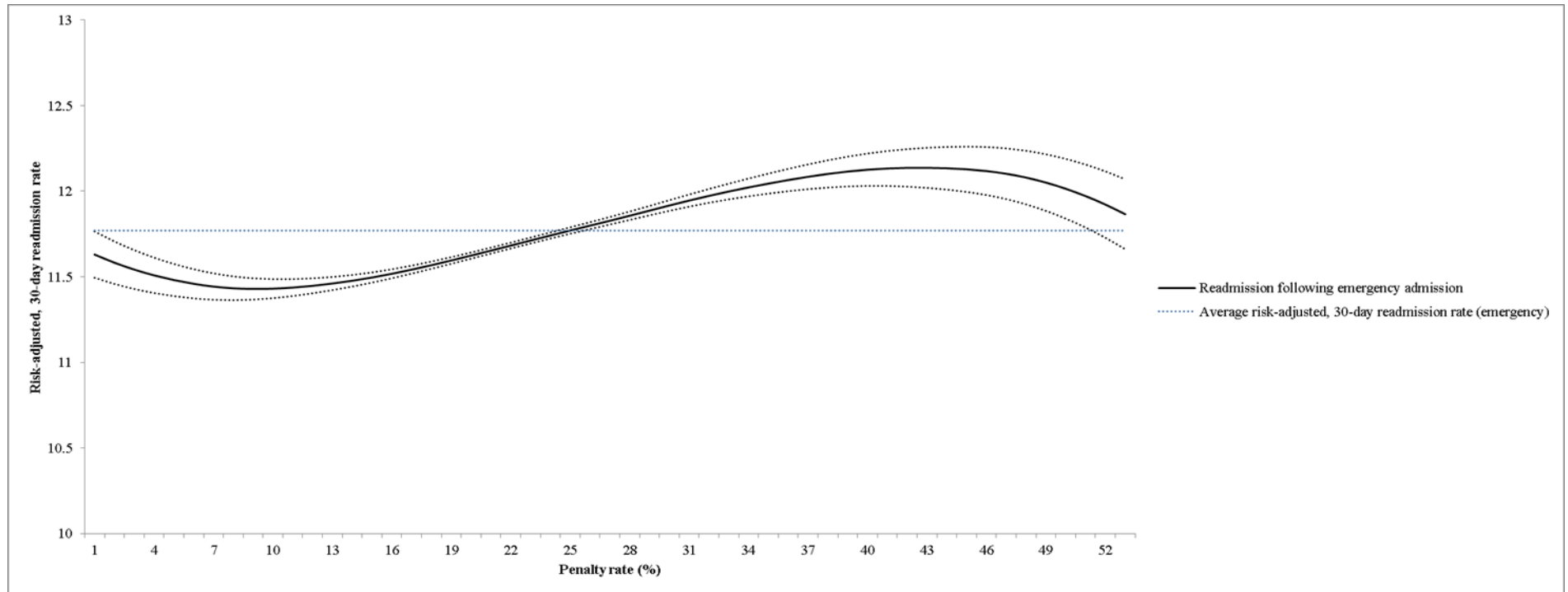


Figure 12. Sensitivity analysis, comparing quadratic, cubic and quartic estimator

Figure Note: ¹Treatment effects were calculated using bootstrapped standard errors (2000 replications); ²Horizontal line represents the mean observed risk-adjusted 30-day readmission rate across all PCTs from 01 April 2012 to 28 February 2013.

(i)



(ii)

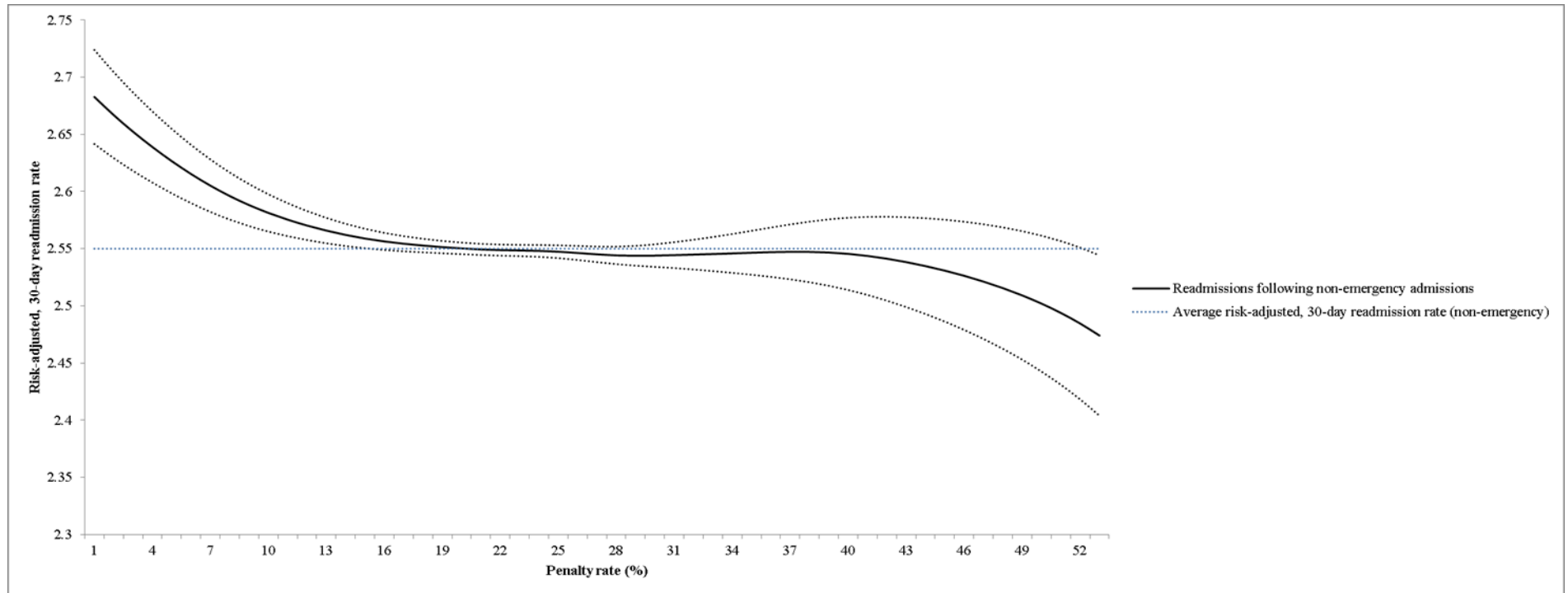


Figure 13. Subgroup analysis for risk-adjusted, 30-day readmission rates following (i) indexed emergency admissions and (ii) indexed elective admissions

Figure Note. ¹Treatment effects were calculated using bootstrapped standard errors (2000 replications); ²Horizontal line represents the mean observed risk-adjusted 30-day readmission rate across all PCTs from 01 April 2012 to 28 February 2013.

Figure 14 shows the dose-response curve for risk-adjusted, 30-day readmission rate in 2011/12 and 2012/13 combined, and follows a similar trend compared with the main model. However, the vertex at 16.0% is found to be closer to the mean financial penalty 2012/13.

Figure 15 shows the dose response curves for risk-adjusted, 30-day readmission rates following indexed admissions for acute myocardial infarction, heart failure and pneumonia. I found variation in the vertex across subgroups, with generally smaller financial penalties causing lower readmissions. For example, the vertex of the dose-response curve for pneumonia was 10.5% lower than the average employed financial penalty at 12%. Financial penalties below 4% and above 25% were found to increase readmission rates.

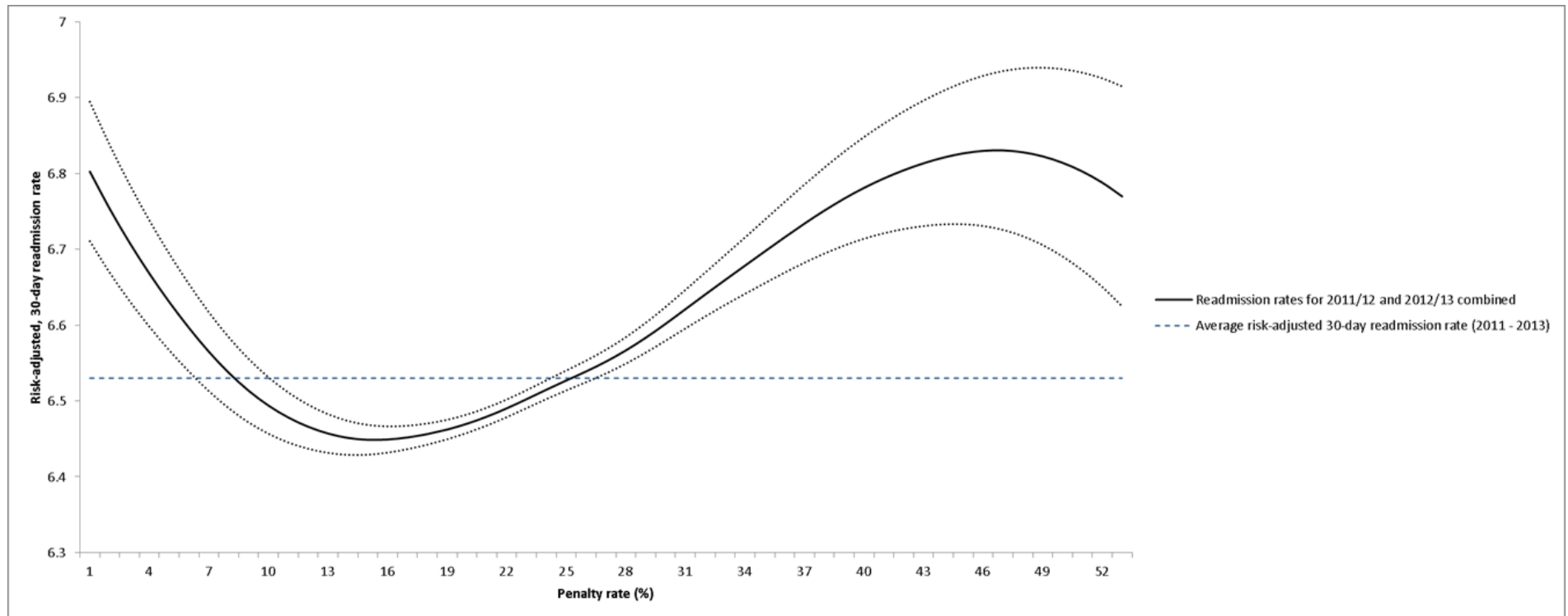
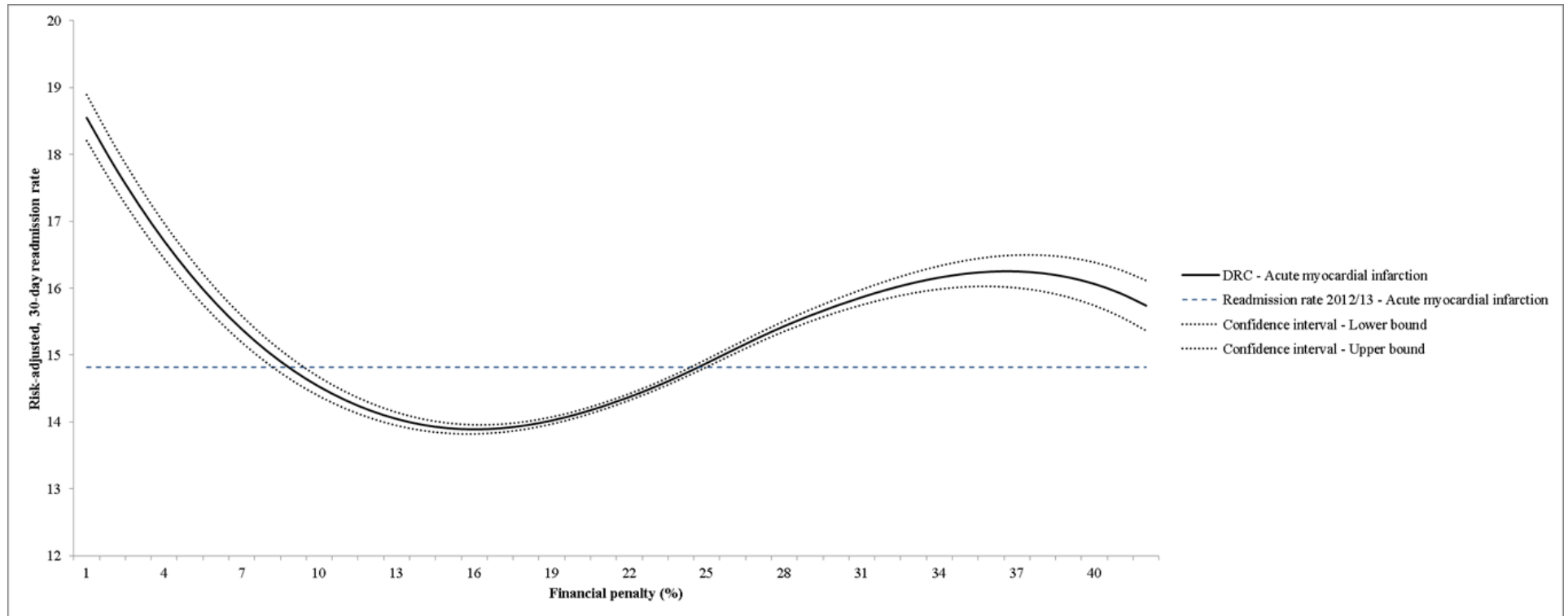


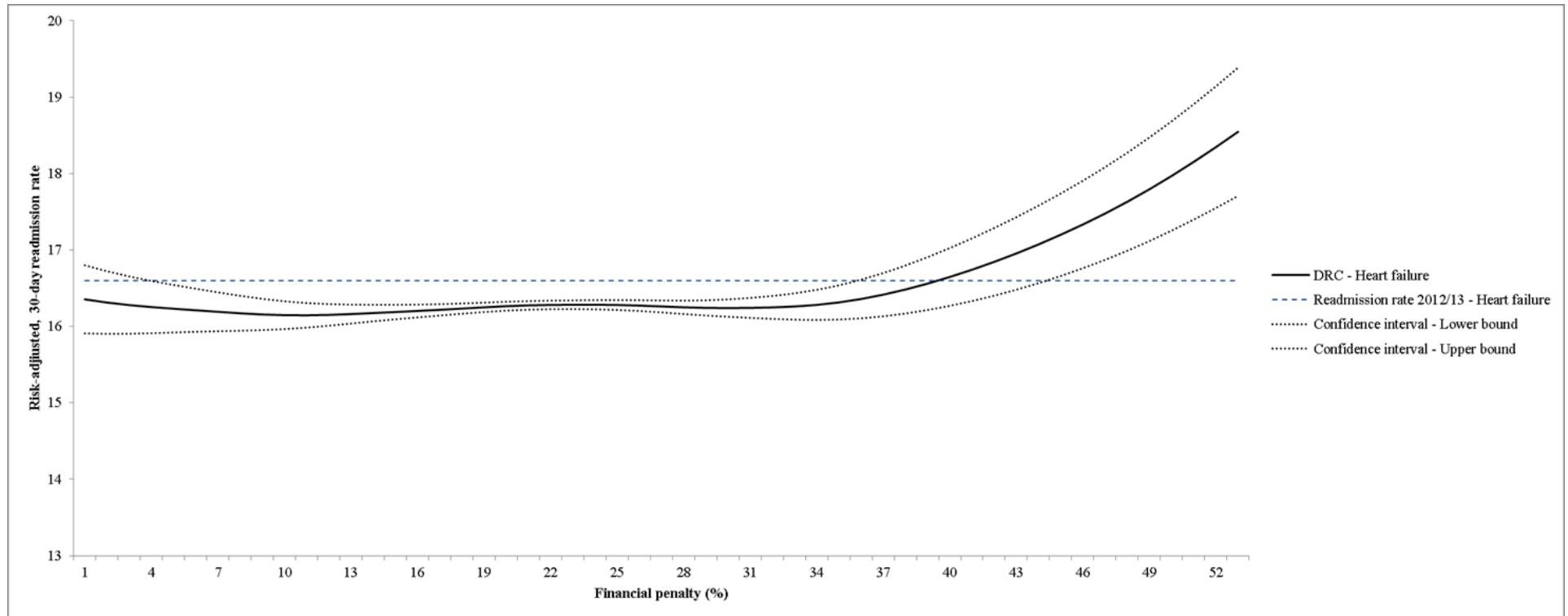
Figure 14. Sensitivity analysis using risk-adjusted, 30-day readmission rates for the period of 1st April 2011 to 28th February 2013

Figure Note: ¹Treatment effects were calculated using bootstrapped standard errors (2000 replications); ²Horizontal line represents the mean observed risk-adjusted 30-day readmission rate across all PCTs from 01 April 2012 to 28 February 2013.

(1)



(11)



(iii)

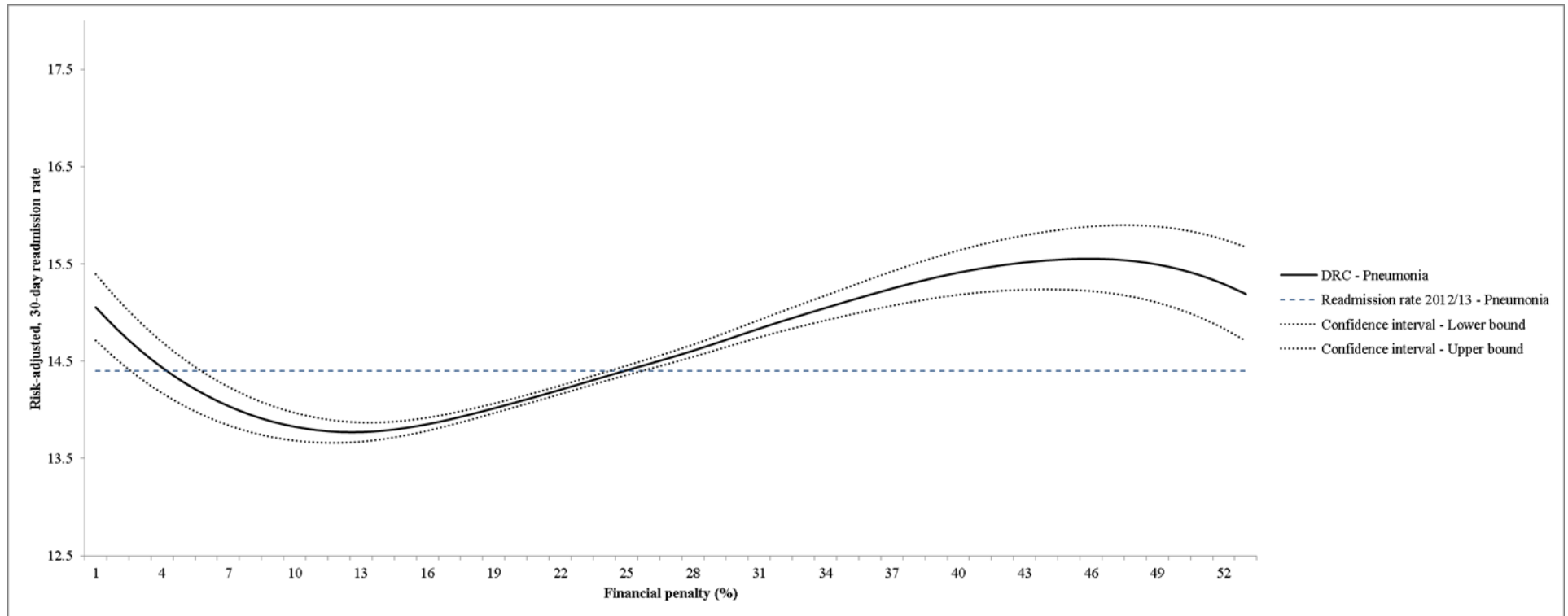


Figure 15. Subgroup analyses for the risk-adjusted, 30-day readmission rate following indexed admissions for (i) acute myocardial infarction, (ii) heart failure, and (iii) pneumonia.

Figure Note. ¹Treatment effects were calculated using bootstrapped standard errors (2000 replications); ²Horizontal line represents the mean observed risk-adjusted 30-day readmission rate across all PCTs from 01 April 2012 to 28 February 2013.

5.6 Discussion

Policies employing financial penalties as a catalyst for triggering comprehensive whole-system changes were introduced across a number of healthcare systems (Kristensen, Bech and Quentin, 2015). To assess the effectiveness of such policies at reducing readmission rates, policy-makers had to previously rely on before-and-after studies, which cannot fully account for the impact of secular trends through other changes to the healthcare system (Zuckerman *et al.*, 2016), or expert opinion (Joynt *et al.*, 2016). In this study I applied a method based on the GPS (Hirano and Imbens, 2004) to estimate a dose-response curve for the relationship between the financial penalty rates and risk-adjusted, 30-day readmission rates in the English NHS. Such an approach relied on endogenous variation in the level of the financial penalty rates between PCT areas, which arose through local threshold agreements between PCTs and healthcare providers. In our study, I risk-adjusted readmission rates for the characteristics of patients, and also adjusted for 61 covariates using the GPS. I found improved balance in covariates between treatment groups after adjustment for the GPS, with all of the covariates meeting our pre-specified threshold for adequate balance after adjustment.

The contribution of this study lies in the comparison between treatment levels based on the condition of policy introduction, with an estimated dose-response curve that followed a u-shape, and a vertex (*i.e.* lowest point) corresponding to a financial penalty equal to 13.0%. This was 9.5% below the average employed financial penalty of 22.5%, in 2012/13. I estimated that, at the lowest point of the dose-response curve, risk-adjusted readmission rates were at 6.0% (95% CI, 5.9% to 6.0%), slightly below the observed mean risk-adjusted readmission rate across all PCTs at 6.2% in 2012/3. The observed readmission rate in 2012/13 is significantly below the readmission rate observed in the pre-policy period, which could indicate an overall policy impact on reducing readmissions. However, such before-and-after comparisons offer no robust evidence on the impact of policies.

Studies from the US have highlighted potential concerns about unintended consequences of financial penalties introduced under HRRP, including the potential adverse effect of large penalties for safety-net hospitals. Safety-net hospitals were found to receive larger financial penalties compared with non-safety-net hospitals, and raised concerns related to potential funding shortages, which could adversely affect quality improvement efforts. Our findings support such concerns, with a u-shaped dose-response curve highlighting that penalties above 13.0% of monetary value lead to an increase in readmission rates. This effect was supported by evidence on dose-response curves for patient subgroups, which are also covered by HRRP.

This study was the first attempt globally to conduct a controlled estimation of the causal impact of varying levels of financial penalties on risk-adjusted, 30-day readmission rates, but it is important to consider the limitations of this study. I relied on data from multiple sources, and subsequently was affected by variation in coding practice. Firstly, I included patients with complete information on key variables required for risk-adjustment, and as a result lost about 3.0% of admissions due to incomplete health records. However, this is a concern consistent across all health policy evaluations that are based on administrative data, as is the lack of additional information that would be desirable for risk-adjustment of readmission rates. For example, this includes information on disease severity on admission, or physical and cognitive abilities at discharge. Secondly, I observed a lack of consistency in the reporting of financial penalties, resulting in the loss of 36 PCTs out of a total of 151 PCTs, despite mandatory requirements to record penalties and their subsequent reinvestment for transparency purposes. I concluded that readmission rates above 60.0% could be the result of poor coding practice and had to remove 16 PCTs. No universal system was in place for the recording of financial penalties employed in 2011/12, thus limiting our evaluation to 2012/13. However, I used sensitivity analysis to investigate the relationship between financial penalties in 2012/13 and readmission

rates for 2011/12 and 2012/13 combined, and found no significant difference regarding the shape of the curve and only a slight upward shift of the vertex to 16.0%.

I acknowledge that this study was conducted retrospectively and thus, I was not able to examine the processes involved in setting the thresholds, and instead had to rely on documentation that describe the process, as well as existing data to adjust for confounders. This could be of a particular concern, should unobservable factors such as clinical experience of the review team or certain managerial factors have influenced how local thresholds were set. Furthermore, a key challenge of our method is the potential misspecification of the model and outcome (Kreif *et al.*, 2015). However, the covariate inclusion was guided by published literature on the predictors of readmission rates, and also closely linked to the protocol used in the clinical review to set thresholds. Further, I performed balancing tests (Hirano and Imbens, 2004) and performed a visual assessment of overlap (Kluve *et al.*, 2007) to test the unconfoundedness assumption and only proceeded once best possible balance was reached. Moreover, I performed sensitivity analysis around model specification and estimated dose-response curves with different quadratic and quartic estimators. I found that all models followed a similar trend compared with our main cubic model specification. Additional research could adopt the Super-Learner approach, which could help to overcome issues of misspecification by improving estimators through selection of optimal weights across a range of algorithms (van der Laan and Dudoit, 2003). However, previous work by Kreif *et al.* (2015) showed little difference between the GPS approach and the Super-Learner.

The effect of any payment or service delivery change will depend on the context in which it is introduced. The English NHS is publicly funded with a fixed and central budget, and historically there have been strong barriers to exit, with closures of services being met with strong social and political resistance. In 2012/13, majority of Trusts reported a surplus, with the number of Trusts reporting a deficit decreasing from 31 Trusts in 2011/12 to 25 in 2012/13

(National Audit Office, 2013). Within this context, I estimated an 'optimal' point of financial penalty at 13.0%, which is below the average employed financial penalty in 2012/13. In contrast, readmission penalties in other healthcare systems have been much lower and in the US, they are only up to 3.0% of base operating payment. This raises the possibility that healthcare delivery is more sensitive to financial penalties in market-based systems such as the US than in England. However, the salient point from our analysis is that the dose-response curve followed a u-shape, with deteriorations in outcomes at high or low level of penalties. Therefore, penalisation levels must be carefully set and impacts closely monitored to avoid unintended consequences.

Chapter 6 The impact of centralisation of stroke services in London on quality of care: Impact evaluation using two treatment groups

6.1 Preamble to chapter 6

The centralisation of healthcare services has been reported to be an effective tool in improving quality of care, for example through the bundling of clinical expertise. Research has shown measureable quality improvements for non-acute health care services, such as in the treatment of cancer patients in specialist treatment centres. However, the impact they have on the quality of care for acute services is less clear. From 2010, stroke patients in the London catchment area are expected to receive acute stroke care services within one of eight Hyper Acute Stroke Units (HASUs), with the centralisation of stroke care ensuring that patients receive best possible access to stroke processes within the first 72 hours after stroke onset, including Computed Tomography (CT) scans and thrombolysis treatment. While several studies have already evaluated the impact of centralised stroke care for London as a whole, previous work has overlooked the heterogeneous policy-impact for stroke patients who are still admitted to a non-HASU. This goes against the overall objective of the centralisation policy, and evaluating the differential policy impact might help uncover quality of care concerns regarding the provision of stroke care services in London.

In this chapter, I employed a panel data analysis with difference-in-difference (DiD) estimators for two treatment groups, London HASUs and London non-HASUs to investigate the impact of the centralisation policy. Compared to all preceding chapters, the focus of chapter 6 was not restricted to changes in readmission rates. Moreover, I

expanded the scope of the evaluation to capture other indicators that were found to correlate with health care quality, thereby addressing some of the criticism and limitations of readmission rates that were discussed in previous sections of this thesis.

A research paper derived from this chapter has been published in *Health Economics* (Friebel, Hauck and Aylin, 2017). Dr Katharina Hauck and Prof Paul Aylin had the idea to evaluate the centralisation of stroke care in London in June 2014. Prof Paul Aylin provided the data and also offered insightful advice during the data analysis and write up stage of this chapter. Dr Katharina Hauck provided very useful technical insights to the development of the panel data model and offered supportive comments throughout the write-up of this chapter. Rocco Friebel expanded the existing policy evaluation to include two-treatment groups, performed the analyses and derived interpretations, and wrote-up the manuscript for this chapter.

I would like to particularly thank my two co-authors, Dr Alex Bottle, Anna Starling, Prof Lalit Kalra and two unnamed peer-reviewers for their invaluable contributions, discussions and feedback on the published research article.

6.2 Introduction

Improving the quality and efficiency of care provided in hospitals is undoubtedly becoming one of the top priorities of healthcare officials and systems around the world (Scott, 2009). To this end, one of the more popular steps taken is that of bundling together clinical expertise into centralised treatment centres; the expectation being that these centres would be able to provide specialised care, which is delivered efficiently, and

which would eventually ensure better clinical outcomes for relevant patient groups. Such expectations are evidenced as being realised, for instance, through centralised units set up for cancer care (Gooiker *et al.*, 2011; Lemmens *et al.*, 2011), where reductions in 30-day mortality rates and overall costs were observed, the latter primarily due to decreases in the length that patients stay within the hospital. The central premise guiding the set-up and implementation of such specialised units is that through constant repetition of tasks, clinical staff are able to improve their clinical skills and ability at performing those key tasks and procedures, and thereby improve outcomes for the patient.; a concept known as the physician/unit-volume effect (Schmidt *et al.*, 2010; Freeman *et al.*, 2012; Svendsen *et al.*, 2012; Halm *et al.*, 2000). However, while there is a sound evidence base documenting the success of centralisation of services for surgical interventions such as in orthopaedic care (Briggs, 2015), the effectiveness of this strategy for acute conditions, such as stroke, remains relatively unexplored (Kanhare *et al.*, 2012).

In developed countries, stroke has been found to be one of the leading causes of disability and death (Mathers, Boerma and Ma Fat, 2009), making stroke care an important area of investigation. Specifically, stroke levies a substantial burden on society and healthcare providers, not only due to its high incidence, but more importantly, due to the devastating, potentially life-changing clinical effects it leaves on its victims (Di Carlo, 2009; Fattore *et al.*, 2012; Persson, Ferraz-Nunes and Karlberg, 2012; Smith *et al.*, 2012). Moreover, the costs related to stroke are enormous; for instance, in England, the direct treatment costs were estimated to be approximately £3 to 4.4 billion (Houses of Parliament, 2014), with additional costs associated to treatment outcomes and recovery time, both of which are found to be highly variable (Reistetter *et al.*, 2014). Stroke outcomes are not only affected by the severity of the stroke episode, but equally by the efficiency and quality of treatment provided to the patient after stroke onset (Clarke and

Forster, 2015). A key quality of care indicator is the quick diagnosis of a stroke episode based on the early symptoms, as well as responding to those symptoms with relevant treatment, such as having access to and providing specialist thrombolytic drugs (Lecouturier *et al.*, 2010).

In a bid to improve stroke care quality, such as the quick treatment of stroke, as well as reduce costs in the long-run (Healthcare for London, 2008), English policy makers introduced the centralisation of stroke care services in Greater Manchester and London in 2010. Specifically, the policy dictated that, post 2010, patients suffering from an acute stroke episode are to be treated in HASUs. In London, eight out of the 30 Trusts that were providing stroke care at the time were converted to HASUs. The idea behind selecting Trusts that should be converted to HASUs was based on a modelling exercise (Fulop *et al.*, 2013). This exercise accounted for several factors such as population need, configuration requirement, and most importantly, a maximum of 30 minutes for any patient in the entire London catchment area to be brought to the closest facility by an ambulance. Each HASU is set up with specialist staff, where patients suffering from an acute stroke episode are expected to receive 24/7 high quality care for the initial 72 hours following the stroke episode (Healthcare for London, 2008). After 72 hours, patients are to be redirected to one of twenty-four stroke units based on the proximity of the unit to their place of residence (which is also most often a non-HASU Trust), or, after a thorough assessment of their medical needs, they are discharged.

Previous studies have attempted to investigate the impact of this centralisation policy (Liu, Rudd and Davie, 2011; Fulop *et al.*, 2013; Hunter *et al.*, 2013; Morris *et al.*, 2014; Ramsay *et al.*, 2015), with early research indicating its success. For instance, Liu *et al.* (2011) found evidence suggesting that centralisation of stroke services had directly led to an increase in rates of thrombolysis (up 12.0% pre and post policy), discharge to home

rates (up 35.0%), and reductions in 30-day mortality rates (down 6.0%). However, certain methodological limitations might dilute such findings. For instance, the study conducted a comparative analysis of before and after impacts of centralisation by examining data from a single HASU, and relied on crude rates that were unadjusted for patient case-mix. While the analysis did not account for secular trends, it also did not take into account the heterogeneity of performance between Trusts before the policy was implemented, and results could therefore have been influenced by general improvements in stroke care within the NHS, and not necessarily due to the policy itself. For instance, some Trusts that were converted to HASUs were documented as already providing leading, high quality stroke care (*e.g.* thrombolysis treatments in the King's College London Trust), whereas other HASUs had to be newly built, and had shown low levels of pre-policy engagement in similar processes. By not adjusting for such differences, the results of improved thrombolysis and decreased mortality rates might have been biased by and perhaps reflective of Trusts that were performing better at baseline.

Another study investigated the cost-effectiveness of the centralisation policy, with a focus on the trends in mortality rates and length of hospital stay over time, and used Cox Proportional hazards and Weibull survival analysis to evaluate changes in outcome and cost (Hunter *et al.*, 2013). Results indicated a positive impact of the reorganisation efforts on survival rates, as highlighted by Kaplan-Meier survival curves, fewer overall mortality, and importantly, a cost reduction of £811 per patient. While these findings are promising, it must be noted the study used data from various datasets, which included the South London Stroke Register as well as two North London hospitals. The data, and by extension, the findings therefore remain unrepresentative of the policy's impact on whole London stroke patient population.

A third study conducted by Morris *et al.* (2014) was the first to assess the impact of the stroke care reorganisation in both London and Greater Manchester. The study conducted a comparative analysis of stroke care outcomes and area-wide changes occurring in London, Manchester and the rest of England by using DiD regression methods. Patient-level information from the HES database was used, which included data on all urban-living patients who had been admitted to an English hospital within the study period; the analysis was conducted at the institutional-level and the DiD methodology allowed authors to control for time trends. Like previous studies, results reflected improvements in outcomes, with significant decreases in 30-day mortality rates (-1.3%) and length of stay (-1.4 days) for London HASUs. However, certain limitations must be highlighted. First, the authors tackled only two outcome indicators, minimising a more comprehensive picture of the impact of stroke care reorganisation. Second, by using the classical DiD analysis, Morris *et al.* (2014) averaged the London provider performance and compared it to changes in average provider performance in the rest of England (*i.e.* they used a single population group). However, working under the assumption that post-policy, a small percentage of patients in London continued to be treated in non-HASUs, Morris *et al.* (2010) may have overlooked the differential impact on stroke patients in London. Specifically, while the DiD analysis allowed for an assessment of the area-wide impact of the policy, it did not account for the heterogeneity in implementation uptake between Trusts. This is particularly important since any kind of deviation from policy guidelines could impact the efforts to improve care quality and consequently dilute previously reported area-level treatment effects.

Past research therefore fails to answer a critical question – was the centralisation policy implemented, as it was intended, uniformly across London? Specifically, post 2010, there should be no evidence suggesting that the 22 hospitals that were meant to

discontinue acute stroke services, in fact continued to provide such care. In order to answer this question and allow for an insight into performance variation, in this chapter, I will build on Morris *et al.*'s (2014) work and employ a DiD analysis with an important adaptation of using of two treatment groups instead of one (HASUs and non-HASUs).

A second innovative contribution of this chapter is to assess the impact of stroke care centralisation on seven outcome and process indicators, separated for patients admitted to HASUs and non-HASUs. The period of investigation is April 2006 till April 2014, allowing for a comparison of four years before and after policy implementation, and data will include all English stroke patients recorded in HES. This comprehensive approach should afford policy makers and researchers with a more substantive picture of the stroke care centralisation, from its uptake by providers, as well as its impact on quality of stroke care.

6.4 Data

The HES data for this analysis contained panel information on 16 quarters pre-policy intervention and 16 quarters post-policy intervention, with the observation period ranging from April 2006 to April 2014. The dataset contained information on stroke patients receiving care in a total of 186 English NHS Trusts, which included Trusts that merged or dissolved during the study period. I followed the assumption that after Trust mergers, the stroke patient was recorded under the provider code of the new Trust. Consequently, the original Trust disappeared from the analysis dataset, which was recorded as a missing value and dealt with estimating an unbalanced panel data model. As a way to address the potential impact on Trust status change, I added specific dummy

variables for Trusts that merged during the observation period, and also for those that were integrated into an existing Trust, or had been dissolved.

As inclusion criteria, I selected all Trusts with at least one recorded stroke patient per quarter. Some Trusts presented with a recorded missing value in the dataset, *i.e.* zero patients or missing values for some variables. It is possible that these Trusts received no stroke patient in that quarter, but it might also indicate poor coding practice, which may impact on the results of this chapter. As mentioned in the background section, Greater Manchester also performed a re-organisation of their existing stroke services in 2010, and to avoid that the control group, *i.e.* Trusts situated in the rest of England, are driven by any changes occurred in this area, I removed eight Trusts from the Greater Manchester catchment area from this analysis. In addition, I also removed the Epsom and St. Helier University Hospital NHS Trust, as it was not possible to determine whether it should be treated as control or treatment group due to its location on the periphery of Greater London.

I made use of Trust-level data that was aggregated from the patient-level and included all patients with a primary diagnosis recorded as stroke. Similar to analyses performed in chapter 3 to 5, patients were identified from their records in the HES database. The data was manipulated in a way that the final dataset was based on ‘super-spells’, which captured a patient’s hospital treatment, from admission to discharge, even if the patient had to change hospital as part of their stay. By definition, ‘super-spells’ are constructed from ‘spells’, which are separated by less than two days. Combining spells into ‘super-spells’ was particularly important for this chapter, as it avoided double counting of patients if they were repatriated to a regular stroke unit, which might have been situated in a non-HASU Trust, following an acute episode in a HASU Trust.

I used the following ICD-10 codes to identify stroke patients from the HES data: I61 (intracerebral haemorrhage); I62 (other non-traumatic intracranial haemorrhage); I63 (cerebral infarction); and I64 (stroke, not specified as haemorrhage or infarction). I only included patients whose diagnosis was considered to be part of the implemented hyper acute stroke care pathway in London, and thus, I excluded those with a primary diagnosis of subarachnoid haemorrhage.

As measures to examine changes in the quality of care provided to stroke patients, I focussed on seven stroke specific processes and outcome measures. This is an expansion of focus on readmission rates in previous parts of this thesis, but the metrics in this analysis were chosen to cover different critical points in the quality of stroke care along the medical pathway. A focus on only readmission rates would have not been able to capture the complexities involved in this stroke service reorganisation and their impacts on patients. The selection of measures was based on a study by Palmer *et al.*, (2013), who assessed the feasibility of using HES to derive metrics for an evaluation of quality of stroke care at the Trust-level. The following list of process and outcome measures was used in this analysis: 24-hour brain scan rate, thrombolysis treatment rate, rate of patients suffering from hospital acquired aspiration pneumonia, 7-day and 30-day in-hospital mortality rate, rate of patients discharged to their usual place of residence within 56 days of admission, and 30-day emergency readmission rates. A definition of all measures is depicted in Table 18, whereas Table 19 provides summary statistics of the study sample.

I entered the following average Trust-specific covariates into the regression models: patient age, Charlson Index, gender ratio and hospital transfers rate. The transfer rate captured the percentage of patients coming from another A&E department prior to obtaining acute stroke care. I addressed time invariant regional variation of outcomes by

entering dummy variables for each of seven English regions. This included the North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, South East Central, South Central, and South West.

Table 18.

Definitions of selected stroke processes and outcome measures

Stroke Measures	Definition	Inclusion/Exclusion Criteria
24-hour brain scan rate	Patients (%) receiving a CT or MRI brain scan within 24 hours of admission	OPCS codes = U05.1, U05.2, U21.1 or U05.2 with Z01.9/ Death on day of admission
Thrombolysis rate	Patients (%) receiving clot-bursting drug treatment	OPCS codes = X83.3/ Patients excluded from license agreement (<18 and >80 years)
Aspiration pneumonia rate	Patients (%) contracting aspiration pneumonia	ICD-10 codes = J69.0, J69.8 recorded as primary or secondary diagnosis/ Exclusion if episode is prior to stroke
7-day in-hospital mortality rate	Patients (%) dying within 7-days of admission	HES discharge method = 4 if length of stay ≤ 7 days/ None
30-day in-hospital mortality rate	Patients (%) dying within 30-days of admission	HES discharge method = 4 if length of stay ≤ 30 days/ None
Discharge rate to the usual place of residence within 56 days	Patients (%) discharged to their usual place of residence within 56 days of readmission	HES discharge destination = 19 if length of stay ≤ 56 days / Spell ending in death
30-day emergency readmission rate	Patients (%) readmitted within 30-days following discharge	HES admission method = 21, 22, 23, 24, 25, or 28 and admission < disdate (index) + 30 days/None

Note. ¹Definitions, inclusion/exclusion criteria are adopted from Palmer *et al.* (2013); OPCS indicates Classification of Interventions and Procedures; ICD-10 indicates International Classification of Diseases, version 10; HES indicates Hospital Episode Statistics

Table 19.

Summary statistics for (i) all London Trusts and Trusts in the rest of England, and (ii) London HASU Trusts and London non-HASU Trusts

(i)

	All Trusts in London				All Trusts in rest of England			
	Before (N=404)		After (N=388)		Before (N=2125)		After (N=2230)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of admissions	95.49	59.88	111.70	120.17	129.54	73.11	133.85	85.46
Female patients (%)	47.91	14.30	47.95	14.89	51.78	15.94	51.62	15.08
Age (average)	71.01	6.41	71.81	6.03	75.03	4.88	75.49	5.02
Charlson Index (average)	5.90	2.37	7.97	2.41	5.32	2.35	7.14	2.72
Length of stay (average)	14.11	11.82	9.37	8.62	14.49	17.49	12.59	16.32
Admission from home (%)	84.38	28.07	80.85	28.31	91.31	21.18	87.38	25.94
Admission from hospital (%)	14.75	27.54	18.34	27.46	7.62	19.73	11.90	25.40
Scan rate (%)	37.47	22.69	51.56	22.95	30.16	20.48	51.89	25.08
Thrombolysis treatment rate (%)	0.91	2.62	4.23	6.44	0.64	1.72	4.72	6.11
7-day death rate (%)	7.81	4.93	7.17	10.19	10.44	10.35	8.20	9.09
30-day death rate (%)	15.97	10.54	13.64	12.01	20.49	14.91	15.77	12.54
Discharge to usual place of residence rate (%)	55.79	14.95	57.76	16.97	50.76	16.79	57.43	18.12
30-day readmission rate (%)	9.59	9.51	12.74	9.53	7.31	7.06	9.57	8.91
Aspiration pneumonia rate (%)	6.66	8.11	5.75	5.94	5.14	7.23	5.84	8.07

Note. ¹ Before = quarters 1 to 16; ² After = quarter 17 to 32.

(ii)

	All London HASU Trusts				All London non-HASU Trusts			
	Before (N=128)		After (N=114)		Before (N=276)		After (N=259)	
	<u>Mean</u>	<u>Std. Dev.</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Mean</u>	<u>Std. Dev.</u>
Number of admissions	150.65	58.89	271.75	63.80	69.91	39.74	33.57	26.13
Female patients (%)	47.09	6.03	48.35	3.82	48.29	16.80	47.96	17.79
Age (average)	70.00	4.36	72.49	2.14	71.47	7.12	71.58	7.15
Charlson Index (average)	5.58	1.45	7.68	1.18	6.05	2.68	8.04	2.79
Length of stay (average)	11.50	3.62	5.63	2.61	15.32	13.93	11.09	9.58
Admission from home (%)	88.03	18.63	92.19	15.15	82.69	31.39	78.94	29.52
Admission from hospital (%)	10.44	17.77	7.47	14.53	16.75	30.87	20.25	28.88
Scan rate (%)	44.34	15.23	72.03	10.28	34.29	24.80	41.98	21.10
Thrombolysis treatment rate (%)	1.86	3.95	10.80	6.94	0.47	1.50	1.07	3.08
7-day death rate (%)	8.06	2.69	6.00	1.75	7.69	5.68	7.77	12.37
30-day death rate (%)	14.94	4.52	11.99	2.96	16.45	12.35	14.56	14.45
Discharge to usual place of residence rate (%)	55.70	7.04	62.39	5.87	55.83	17.46	56.03	19.42
30-day readmission rate (%)	8.54	2.95	11.29	2.38	10.08	11.30	13.42	11.47
Aspiration pneumonia rate (%)	5.22	2.93	5.85	2.21	7.33	9.55	5.70	6.97

Note. ¹ Before = quarters 1 to 16; ² After = quarter 17 to 32.

6.5 Econometric framework

To evaluate the stroke service centralisation policy, I employed a DiD analysis (Ashenfelter and Card, 1985). This econometric technic has been widely used for causal inference in health care policies before (Wooldridge, 2002; Propper *et al.*, 2008), and adapted to include two treatment groups (Marini *et al.*, 2008), London HASUs and London non-HASUs. I assumed parallel trends in the dependent variables prior to the policy implementation, as well as constant differences between the two treatment groups and Trusts in the rest of England given the absence of an intervention.

The main model specification of this DiD analysis can be specified in the following equation:

$$(1) Y_{jt} = \beta_0 + \beta_1 * N_j + \beta_2 * H_j + \beta_3 * T_t + \beta_4 * N_j T_t + \beta_5 * H_j T_t + \beta_6 * W_{jt} + \beta_7 * M_j + \beta_8 * R_j + \varepsilon_{jt} + \mu_j$$

Here, Y_{jt} is the dependent variable, which presents one of the seven selected process or outcome indicators, in quarter t and Trust j . For the first treatment group, N_j takes the value of 1 if the Trust is a non-HASU in London, and 0 otherwise. For the second treatment group, H_j takes the value of 1 if the Trust is a HASU, and 0 otherwise. Both variables are time invariant and capture systematic permanent differences between either the first or second treatment group and the control group, and the other treatment group. The coefficient estimate of β_1 presents the differences in outcomes of non-HASU Trusts in London compared to the rest of England and HASU Trusts, whereas β_2 indicates the differences in outcome of HASUs compared to the rest of England and non-HASU Trusts, for reasons unrelated to the reorganisation. Time dummy T_t captures the time varying impacts on the dependent variable that affects both treatment and control groups, and takes the value of 1 for quarters after the reorganisation (17 to 32),

and 0 before (1 to 16). From quarter 17, the interaction term N_jT_t and H_jT_t is 1 for non-HASUs and HASUs, respectively. The coefficient estimates for β_4 and β_5 capture the impact of the reorganisation purged from the effects of other time varying and time invariant observed and unobserved impacts on the dependent variable. Time varying covariates, such as average age and gender rate, are represented in vector W_{jt} . I further include a time invariant merger dummy M_j , and regional dummies R_j . The time invariant error μ_j captures unobserved random variations in processes and outcome across Trusts that are stable over time; and the normally distributed error ε_{jt} captures unobserved random shocks.

I estimated several alternative model specifications. First, I replicated previous analyses conducted by Morris *et al.* (2014), which compared changes in 30-day mortality rates and length of stay for all London Trusts (HASUs and non-HASUs combined) to a control group consisting of Trusts in the rest of England. This model used DiD estimators with random effects. I recognise that due to several factors, previous findings reported by Morris *et al.* (2014) may not be fully replicable in this analysis. First, Morris *et al.* (2014) performed analysis at the hospital-level using patient-level data, whereas the current analysis is restricted to aggregate data at the Trust-level. Second, in my estimation I calculated the treatment effect of stroke care centralisation in London by comparing the treatment group London to a control group that comprised of all stroke patients admitted to Trusts in the rest of England, but exclusive of Trusts in the Greater Manchester area. In contrast, Morris *et al.*'s (2014) evaluation was confined to patients living in urban areas only. Last, my analysis measured in-hospital mortality that was derived from in-patient HES records, whereas Morris *et al.* (2014) was able to access mortality data on all deaths, which also included those occurred after discharge from

hospital. Taking all these differences together, this might have led to significant variations in replicating previous results.

The replication study of Morris *et al.* (2014) can be expressed in the following equation:

$$(2) Y_{jt} = \beta_0 + \beta_1 * L_j + \beta_2 * T_t + \beta_3 * L_j T_t + \beta_4 * W_{jt} + \varepsilon_{jt} + \mu_j$$

Here, the dummy variable L_j takes the value of 1 if the Trust is located in London, and 0 otherwise. The time dummy T_t is 1 after the reorganisation (April 2010 to March 2012), and 0 before (January 2008 to March 2010). The coefficient estimates of $L_j T_t$ showed the policy effect on the dependent variable Y_{jt} , namely 30-day mortality and length of stay. Time varying covariates are represented in vector W_{jt} .

Furthermore, I assessed the validity of the control group chosen in my main model to a specification that compared HASUs and non-HASUs in London to a control group that encompassed Trusts located in seven English metropolitan areas. Specifically, Trusts in Birmingham, Bristol, Leeds, Liverpool, Newcastle, Sheffield, and Southampton. To assess whether random or fixed effects should be entered into the model, I performed Hausman model specification tests. Moreover, I conducted a lead analysis to test the validity of the parallel trends assumption, which as previously described was a prerequisite of the employed DiD methodology. I have not used sampling weights in the main model specification, despite variation in the number of admissions per Trust and quarter. To investigate the sensitivity of my initial findings to sampling weights, I re-estimated my models using sampling weights based on the average number of admissions observed in quarter 1 to quarter 16 within my analysis.

6.6 Results

I identified 678,968 patients with a primary diagnosis of stroke in England, from April 2006 to April 2014. There was a general increase in the number of quarterly recorded strokes, with the number of strokes in quarter 32 being 12.4% higher than at the beginning of this observation period. Longitudinal trends in stroke admissions per quarter are depicted in Figure 16. It is visible that the proportion of London stroke patients admitted to HASU Trusts after the reorganisation, and those admitted to non-HASU Trusts after the reorganisation, was evenly split at approximately 50.0% before service reorganisation in 2010. However, immediately after the policy introduction, admission rates started to diverge, aligning with the policy objective, and I observed a gradual increase in the percentage of patients being admitted to HASU Trusts. At the same time, I observed a substantial decrease in the number of patients admitted to a non-HASU Trust in London. However, the data also showed a levelling effect in quarter 23, beyond which stroke admissions to London HASU Trusts remained at approximately 85%.

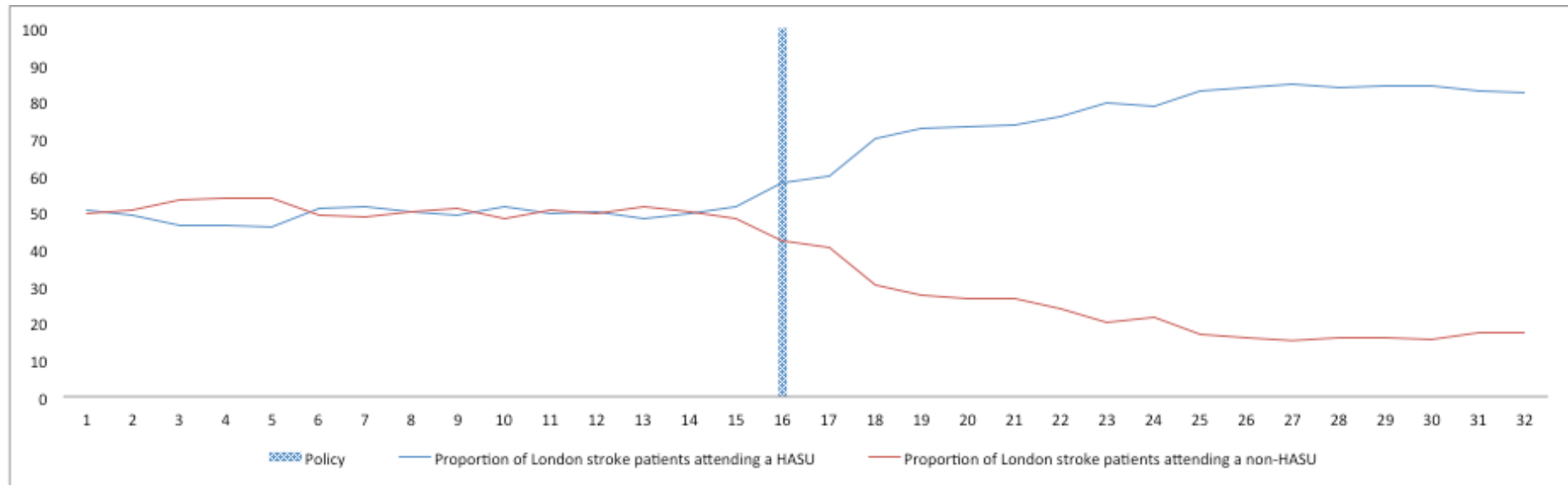
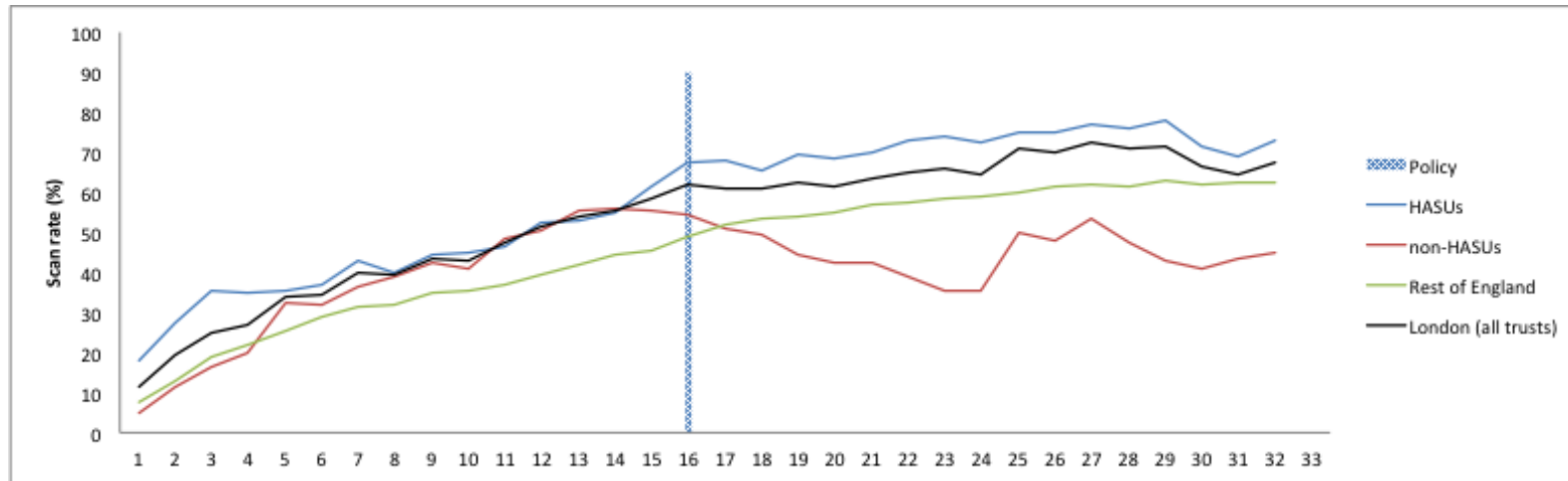


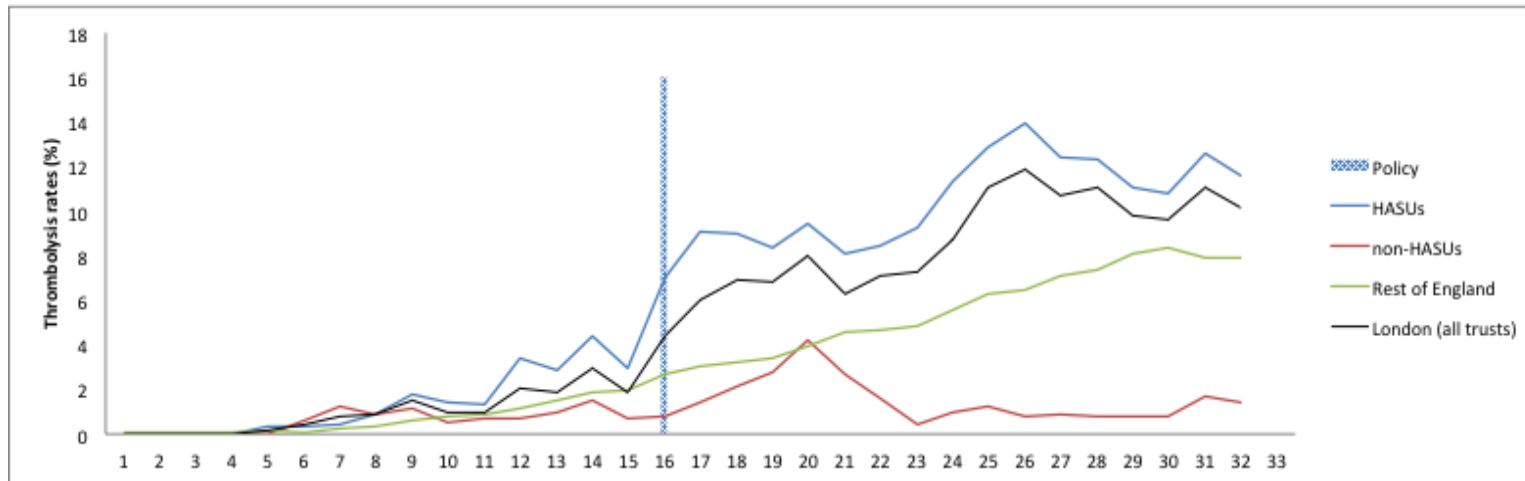
Figure 16. Proportion of stroke admissions divided by London HASU Trusts and London non-HASU Trusts.

Figure 17 depicts weighted trends of the selected seven process and outcome indicators across the observation period. I found a general improvement for all metrics in England. In the post-policy period, weighted rates were found to follow the time trend of HASUs closely, suggesting that the quality of care provided in HASUs was the key driver for stroke care performance observed in the whole of London. The visual inspection of time trends in outcomes for different groups also supported the parallel trends assumption.

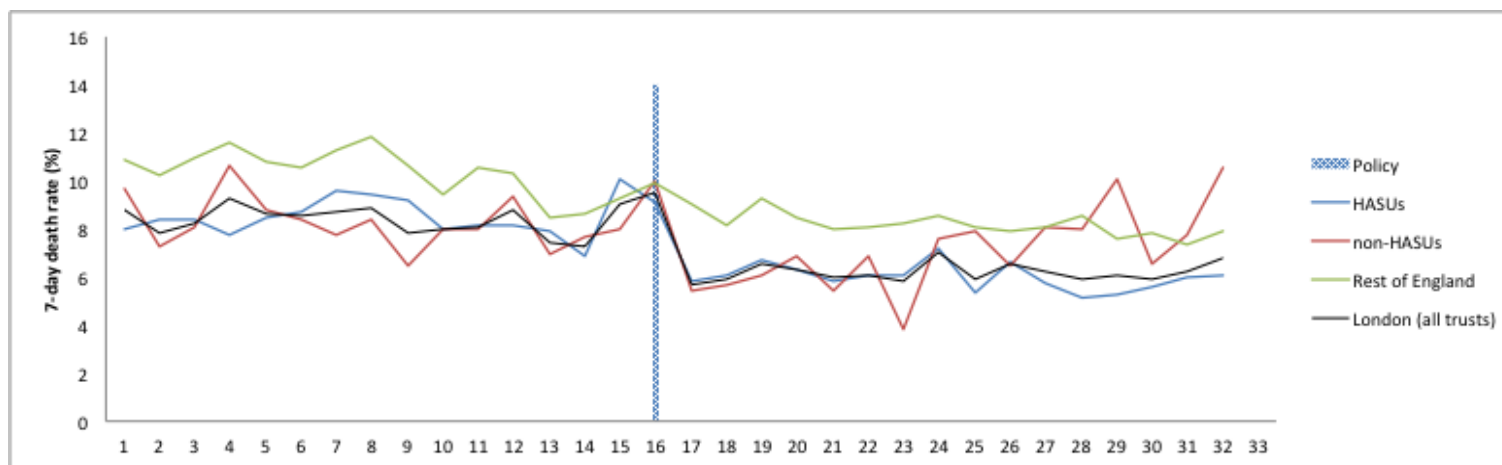
i)



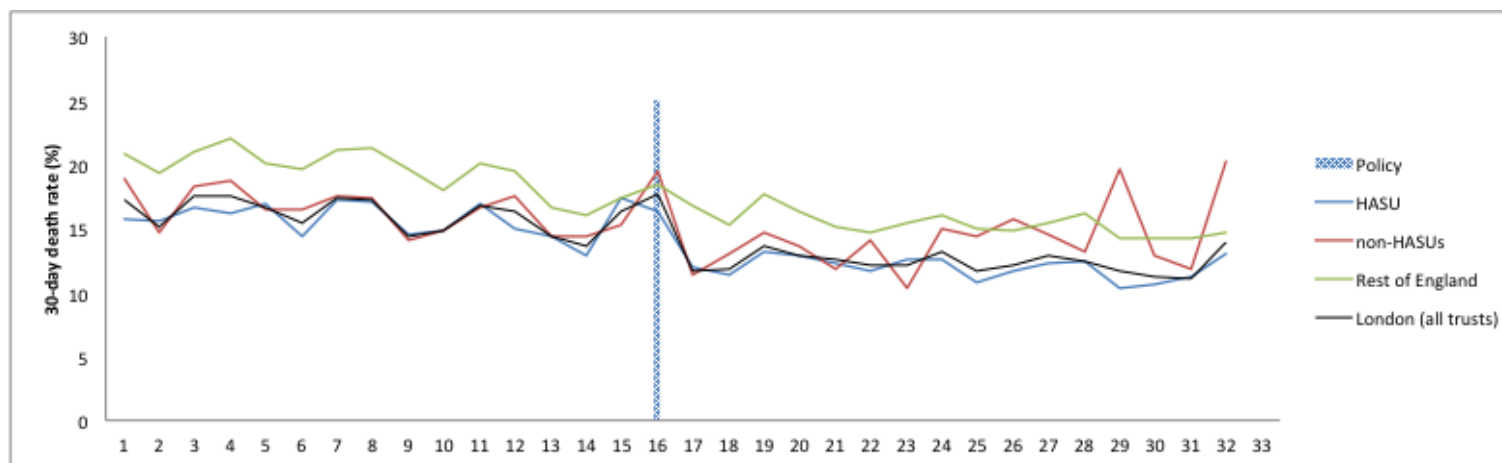
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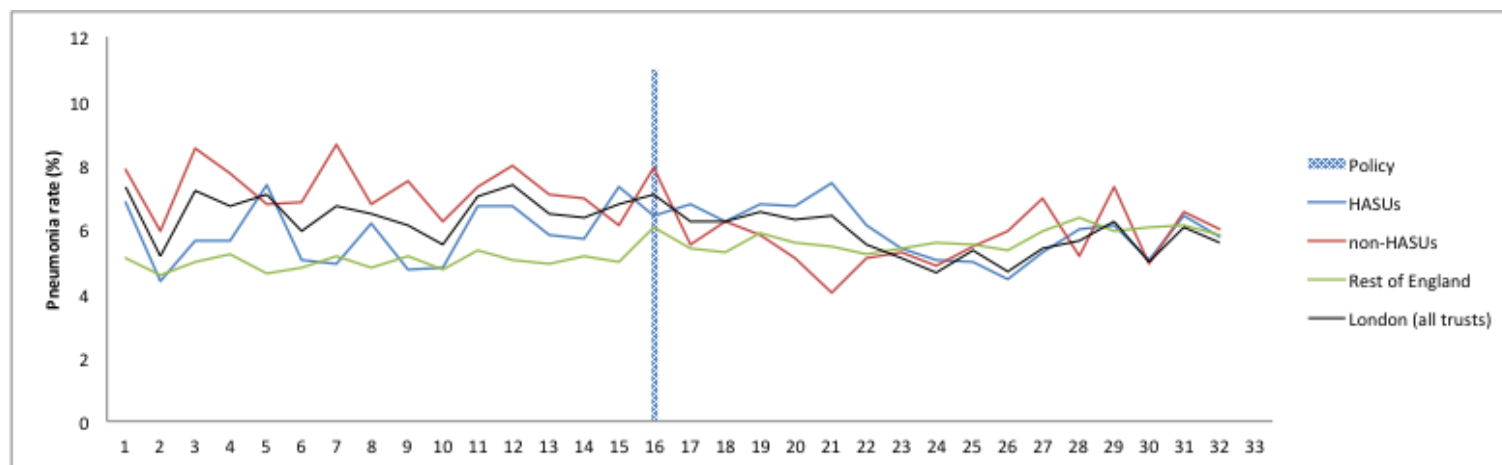
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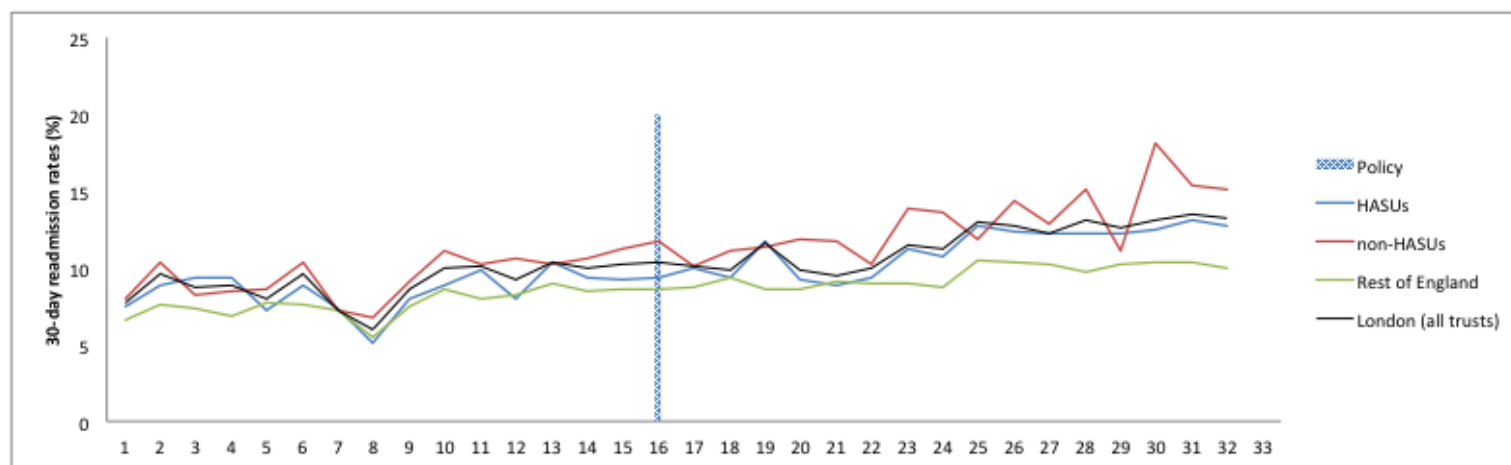
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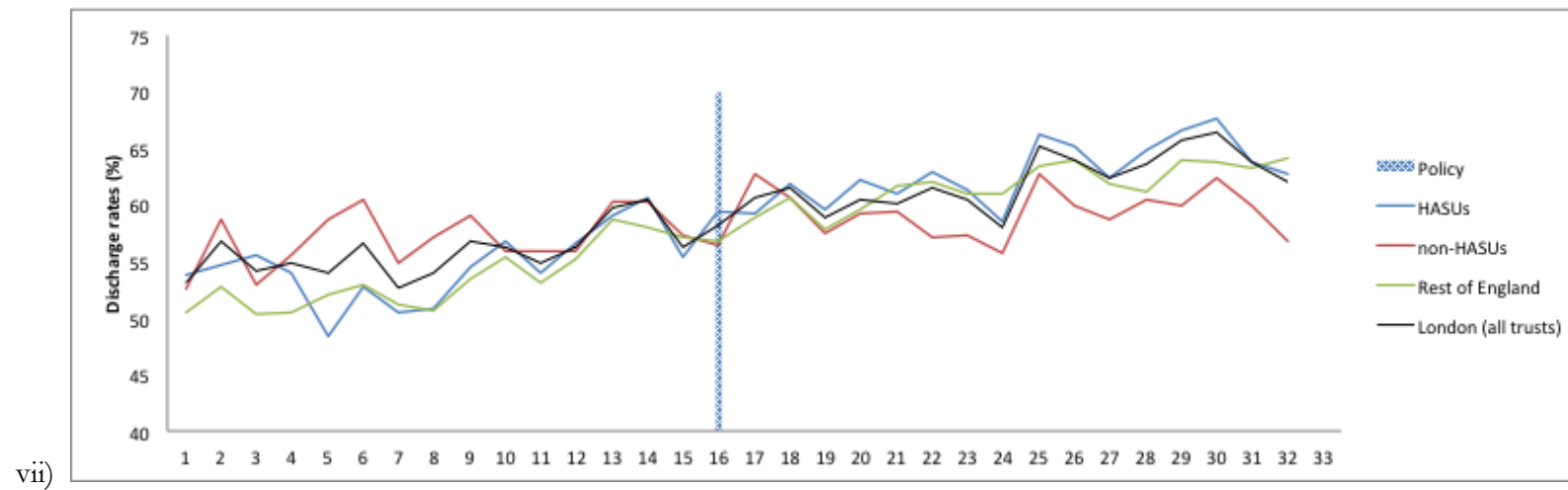


Figure 17. Trends in stroke specific process and outcome measures weighted by the number of admission

6.6.1 Results from main model specification

Estimates of the DiD analysis with two treatment groups that were compared to the performance recorded in Trusts located in the rest of England and the other treatment group, respectively, are presented in Table 20. The total number of observations used per analysis was 4665. Based on the outcome of the Hausman model specification test, for some dependent variables, I rejected the random effect specification. In case of panel data models with fixed effect specification, I omitted all time invariant variables and results of the fixed effect specification for the models that failed the Hausman test are presented in Table 21.

Table 20.

Panel data model using two treatment groups for London HASUs and London non-HASUs

	24 hour brain scan (FE)	Thrombolysis treatment (FE)	Death within 7- days (RE)	Death within 30-days (RE)	Aspiration pneumonia (RE)	Discharge to usual place of residence (FE)	30-day emer. readmission (FE)
IVs							
London non-HASUs	-	-	2.70**	3.88*	5.23***	-	-
London HASUs	-	-	3.77***	5.02**	2.90	-	-
T	21.16***	3.92***	-1.91***	-3.70***	.41***	6.96***	1.39***
DiD (non-HASUs)	-15.07***	-4.06***	1.92***	2.56***	-1.79***	-7.03***	1.37***
DiD (HASUs)	-.23	1.97***	-.20	.53	-1.52***	-.48	1.18**
Merger dummy	-	-	.11	1.52	.45	-	-
Average age	-.06	.00	.14***	.33***	.16***	-.87***	-.06**
Avg. Charlson Index	1.95***	.25***	-.08**	-.08*	.16***	.41***	.32***
Gender	-.07*	.00	.00	.02**	.00	-.07***	-.00
Hospital transfers	.06***	-.00	-.02***	-.02***	-.01**	-.03***	-.01**
North East	-	-	4.85***	7.44***	2.09	-	-
North West	-	-	3.86***	5.67**	1.41	-	-
Yorkshire & Humber	-	-	4.61***	7.53***	.60	-	-
East Midlands	-	-	4.26***	5.04**	.08	-	-
West Midlands	-	-	4.47***	5.93***	.90	-	-
East England	-	-	4.57***	6.37***	2.07	-	-
South East Central	-	-	4.05***	6.53***	1.20	-	-
South Central	-	-	3.80***	4.18***	1.65	-	-
South West	-	-	4.96***	7.58***	.50	-	-
Constant	29.07***	-.15	-4.66**	-13.30***	-9.93***	120.23***	11.51***
R-Squared	.24	.31	.15	.21	.05	.02	.09
Hausman test (prob>chi ²)	.00	.00	.20	.51	.52	.00	.00

Note. N=4665; *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%; The Hausman test was used to determine the preferred model effect; Fixed effect models omit time invariant variables. FE: Fixed effects; RE: Random effects; IV: Independent Variable

Table 21

Fixed effect models versus random effect models (two treatment groups) for London HASUs and London non-HASUs

IVs	24 hour brain scan		Thrombolysis treatment		Death within 7-days		Death within 30-days		Aspiration pneumonia		Discharge to usual place of residence		30-day emer. readmission	
	FE	RE	FE	RE	FE	RE	FE	RE	FE	RE	FE	RE	FE	RE
London non-HASUs	-	27.04***	-	2.18**	-	2.70**	-	3.88*	-	5.23***	-	10.73***	-	-.91
London HASUs	-	44.64***	-	4.91***	-	3.77***	-	5.02**	-	2.90	-	6.02	-	-.30
T	21.16***	20.93***	3.92***	3.88***	-1.83***	-1.91***	-3.61***	-3.70***	.42***	.41***	6.96***	6.96***	1.39***	1.44***
DiD (non-HASUs)	-15.07***	-15***	-4.06***	-4.02***	1.93***	1.92***	2.59***	2.56***	-1.84***	-1.79***	-7.03***	-6.86***	1.37***	1.27***
DiD (HASUs)	-.23	.14	1.97***	2.08***	-.27	-.20	.45	.53	-1.56***	-1.52***	-.48	-.53	1.18**	1.09**
Merger dum.	-	-8.85	-	-3.67***	-	.11	-	1.52	-	.45	-	2.34	-	1.94
Average age	-.06	-.18*	.00	-.03*	.16***	.14***	.35***	.33***	.18***	.16***	-.87***	-.82***	-.06**	-.02
Avg. C.Ind.	1.95***	1.98***	.25***	.25***	-.11***	-.08**	-.12**	-.08*	.15***	.16***	.41***	.41***	.32***	.30***
Gender	-.07*	-.06*	.00	-.00	.00	.00	.02**	.02**	.00	.00	-.07***	-.07***	-.00	-.00
Hospital transfers	.06***	-.02	-.00	-.01***	-.01***	-.02***	-.01*	-.02***	-.00	-.01**	-.03***	-.04***	-.01**	-.01**
North East	-	27.31***	-	1.83**	-	4.85***	-	7.44***	-	2.09	-	6.93**	-	-1.74
North West	-	36.22***	-	3.41***	-	3.86***	-	5.67**	-	1.41	-	10.71***	-	-2.46
Yorkshire & Humber	-	25.60***	-	1.85**	-	4.61***	-	7.53***	-	.60	-	8.07**	-	-2.39
E. Midlands	-	23.93***	-	1.55*	-	4.26***	-	5.04**	-	.08	-	11.50***	-	-1.87
W. Midlands	-	23.50***	-	2.80***	-	4.47***	-	5.93***	-	.90	-	5.05	-	-3.29**
East England	-	26.76***	-	3.25***	-	4.57***	-	6.37***	-	2.07	-	8.73***	-	-2.79*
S.E. Central	-	34.88***	-	3.21***	-	4.05***	-	6.53***	-	1.20	-	6.47*	-	-3.44*
South Central	-	30.29***	-	2.10**	-	3.80***	-	4.18***	-	1.65	-	6.88*	-	-2.07
South West	-	25.46***	-	2.69***	-	4.96***	-	7.58***	-	.50	-	7.46**	-	-3.45**
Constant	29.07***	6.10***	-.15	-.59	-1.79	-4.66**	-8.09***	-13.30***	-9.81***	-9.93***	120.23***	108.91***	11.51***	10.95***
R-Squared	.24	.30	.31	.36	.08	.15	.19	.21	.01	.05	.02	.23	.09	.11

Note. N = 4665; ***indicates that the variable has robust impact on dependent variable at 1% significance level, **5%, and *10%; emer.: emergency; FE: Fixed Effects; RE: Random effects; dum: dummy; C.Ind.: Charlson Index; E.Midlands: East Midlands; W.Midlands: West Midlands; S.E. Central: South East Central

Based on the coefficient estimate of T_t , I found an improvement in process and outcomes for stroke care over time; specifically this improvement was unrelated to the reorganisation. For all English Trusts included in this analysis, stroke specific processes were higher in the quarter after the reorganisation, for example 21.1% more patients received a CT scan of their brain within the first 24-hours of being admitted to the hospital. Furthermore, 3.9% more patients received thrombolytic drug treatment. Similar improvements were also observed for outcome metrics, for instance 7-day mortality and 30-day mortality decreased by 1.9% and 3.7%, respectively. The data also showed increases in aspiration pneumonia rates (+0.4%), discharge to usual place of residence rates (+6.9%) and 30-day readmission rates (+1.3%).

The coefficient estimates of N_j (HASU) and H_j (non-HASU) represented the underlying time invariant differences in process and outcome measures between the two treatment groups and the control group. I found that there were generally no underlying differences, except that London non-HASUs had a 2.7% higher 7-day mortality rate across all quarters, and also a 5.2% higher rate of aspiration pneumonia. On the other hand, London HASUs showed higher 7-day mortality rates and 30-day mortality rates, 3.7% and 5.0%, respectively. I reported no additional underlying differences between HASUs, non-HASUs and Trusts located in the rest of England.

The underlying assumption of this chapter was to investigate the impact of the heterogeneous policy effect. This research question arose from the observation that London non-HASUs continued the provision of stroke care services for a small proportion of the overall stroke population in London. The panel data analysis with two treatment groups showed that the DiD coefficient of interest, DiD (non-HASUs), was significantly smaller for both processes, in addition to aspiration pneumonia rates, and

discharge to usual place of residence rates. Furthermore, in the post-policy period the DiD (non-HASUs) coefficient was significantly larger for 7-day mortality rates and 30-day mortality rates, but also 30-day readmission rates. In particular, the rate of 24-hour brain scans decreased by 15.0% in non-HASUs compared to HASUs and Trusts in the rest of England. In comparison, I found no policy effect on 24-hour brain scan rates for HASUs when compared to non-HASUs and Trusts in the rest of England. Interestingly, I found an opposing policy effect for thrombolysis treatment rates, with a significant decrease of 4.0% in patients treated in non-HASUs, but a significant increase of 1.9% for those treated in a HASU. Further policy effects for patients treated in a non-HASU were significant increases in 7-day mortality rates (+1.9%), 30-day mortality rates (2.5%) and 30-day readmission rates (1.3%), but also significant decreases in aspiration pneumonia rates (1.7%) and rates of discharges to usual place of residence (7.0%). Except for thrombolysis treatment, aspiration pneumonia and 30-day readmission rates, I found no policy effect for HASUs. However, importantly there were negative policy effects on processes and outcomes for patients admitted to non-HASUs following the centralisation of stroke care in London. This suggests that the centralisation policy led to varying policy impacts for patients admitted to HASUs and London non-HASUs – an effect, which was disguised in previous analyses. The separate dummies that were entered into the regression model to capture regional variation in the dependent variables showed significant differences for 7-day mortality rates and 30-day mortality rates across England.

6.6.2 Alternate specifications and sensitivity analysis

In the replication analysis of Morris *et al.* (2014), I was able to confirm reductions in length of stay due to the introduction of centralised stroke care services in London. However, I was not able to replicate the suggested decrease in 30-day mortality rates.

Regression output for the replication study is presented in Table 22. As discussed in the methods section of this chapter, this is likely to be caused by the limitations of my dataset. Specifically, the estimation of a policy effect using aggregated patient-level data, the inclusion of all patients regardless of whether they were residing in rural or urban areas, but probably most importantly, the use of 30-day in-hospital mortality rates, rather than mortality cases that occur outside the hospital.

Table 22.

Panel data model using random effects and replicating Morris et al. (2014)

IVs	Death within 7 days	Death within 30 days	Length of hospital stay
X _t	-1.96	-1.09	-5.52
T	-.93***	-2.40***	-1.51***
DiD	-1.05	-.26	-2.54**
Average age	.16***	.43***	-.37***
Avg. Charlson index	-.13	-.33***	-.25*
Gender	-.02**	-.05***	.02
Hospital transfers	-.05***	-.09***	.24***
Constant	.55	-6.24	44.68***
N	2372	2372	2372
R-squared	.05	.10	.16

Note. *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%.

In further sensitivity analyses, I compared changes in London HASU and non-HASU Trusts to a control group, which was restricted to Trusts located in seven English metropolitan areas. Compared with the main model specification, I found no significant policy effect on 7-day mortality rates and 30-day mortality rates for both HASUs and non-HASUs in London. Regression output of the sensitivity analyses is presented in Table 23.

Table 23.

Panel data model comparing London HASUs and London non-HASUs to Trusts in seven English metropolitan areas as control group

IVs	24 hour brain scan (FE)	Thrombolysis treatment (FE)	Death within 7-days (RE)	Death within 30-days (RE)	Aspiration pneumonia (RE)	Discharge to usual place of residence (FE)	30-day emer. readmission (FE)
London non-HASUs	-	-	.14	.83	3.50	-	-
London HASUs	-	-	1.38	1.61	1.41	-	-
T	17.28***	4.13***	-1/04***	-2.43***	.96**	4.89***	1.30**
DiD (non-HASUs)	-10.89***	-4.09***	.67	.72	-2.01***	-4.23***	1.32*
DiD (HASUs)	3.72*	1.74***	-1.43	-1.03	-1.94***	2.02*	1.02
Merger dummy	-	-	.04	1.63	.21	-	-
Average age	-.00	.08**	.13***	.22***	.27***	-.73***	-.01
Avg. Charlson Index	1.88***	.18***	.09	.14	.00	.09	.39***
Gender	-.06	.00	.02	.05**	.07***	-.01	.01
Hospital transfers	.02	-.00	-.02***	-.01	-.01	-.04**	-.00
Constant	27.07**	-6.64**	-3.49	-5.21	-18.20***	109.75***	6.66
N	1148	1148	1148	1148	1148	1148	1148
R-Squared	.15	.33	.08	.11	.10	.11	.10

Note. *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5%, and * for 10%; Controls are Trusts in Birmingham, Bristol, Leeds, Liverpool, Sheffield, Southampton and Newcastle.

While the visual inspection of trends in selected process and outcome measures suggested parallel trends in the pre-policy period, I further performed a regression analysis with ‘leads’, which are widely used to investigate the parallel trends assumption and only focussed on data from the pre-policy period. To conduct this analysis, I included hypothetical DiD interactions (*i.e.* leads) for each quarter included in the pre-policy period, excluding the dummy for the quarter before the policy implementation (quarter 16) as a reference case. Theoretically, one can accept the null hypothesis of parallel trends if the hypothetical estimators are close to 0 and non-significant. Table 24 depicts hypothetical DiD estimators for London HASUs and non-HASUs and the results showed parallel trends for 24-hour brain scans, thrombolysis treatment, 7-day and 30-day mortality rates, aspiration pneumonia and discharge rates. All of these measures contained a few outliers, but in the great majority, estimators are non-significant and close to 0. Based on these findings, I am relatively confident that I can assume that the parallel trends assumption holds for the analysis in this chapter. However, for 30-day readmission rates five out of fifteen hypothetical points are significant, suggesting a potential breach of the parallel trends assumption because of underlying trends. Reassuringly, parallel trends seem to exist across the four time points prior to the policy introduction.

Table 24.

Lead analysis testing for parallel trends in the pre-policy period

IVs	24 hour brain scan (FE)	Thrombolysis treatment (FE)	Death within 7- days (RE)	Death within 30-days (RE)	Aspiration pneumonia (RE)	Discharge usual place resid. (FE)	30-day emer. readm. (FE)
DiD (non_HASU)_q ²	9.14**	.05	-.80	.61	.91	-4.06*	-.94
DiD (HASU)_q ²	12.60***	.04	-.37	.08	-.28	.56	-.22
DiD (non_HASU)_q ³	2.62	-.11	2.03	-1.06	.51	9.99***	3.14***
DiD (HASU)_q ³	-1.5	-.15	-.45	.36	-1.12	-.91	.41
DiD (non_HASU)_q ⁴	7.09	-.14	-.45	.73	-1.27	-3.65	-3.47***
DiD (HASU)_q ⁴	.19	.39	.83	.03	2.13	-2.94	-1.36
DiD (non_HASU)_q ⁵	.78	.29	-.30	1.32	.16	-1.37	1.35
DiD (HASU)_q ⁴	.77	.28	.15	-1.68	-2.27**	5.09**	1.74
DiD (non_HASU)_q ⁶	5.90	.02	-1.73	.14	2.31**	-5.41**	-4.20***
DiD (HASU)_q ⁶	2.84	.54	1.32	2.44	-.23	-5.21**	-1.41
DiD (non_HASU)_q ⁷	.67	.13	1.23	-.85	-3.32***	5.67**	1.05
DiD (HASU)_q ⁷	-1.24	-.02	-1.13	-1.55	1.57	2.48	-2.07*
DiD (non_HASU)_q ⁸	1.23	.14	-2.19	-4.66	1.80	1.60	2.06*
DiD (HASU)_q ⁸	6.06	.24	.62	1.00	-.51	-.46	1.76
DiD (non_HASU)_q ⁹	-3.14	-.59	1.98	2.81	-1.71	-3.39	.34
DiD (HASU)_q ⁹	-.28	-.27	-1.15	-1.47	-.52	3.64	2.31*
DiD (non_HASU)_q ¹⁰	8.22	.31	-.97	1.22	1.80	-1.57	.24
DiD (HASU)_q ¹⁰	3.04	.11	1.07	1.48	.57	-.37	.10
DiD (non_HASU)_q ¹¹	.53	.27	1.56	.80	-.23	-.98	2.34*
DiD (HASU)_q ¹¹	2.85	.90	.51	-.26	1.39	-.44	-2.32*
DiD (non_HASU)_q ¹²	4.75	.09	-1.43	-1.57	.05	3.98	-3.02**
DiD (HASU)_q ¹²	1.20	-.34	-1.10	-.76	-.97	2.47	2.66**
DiD (non_HASU)_q ¹³	-2.00	.13	.26	-.41	-.32	1.86	.84
DiD (HASU)_q ¹³	.17	1.47	-.62	-1.66	-.51	.67	-1.25
DiD (non_HASU)_q ¹⁴	-.14	-.74	-.50	-.44	-.2	-.49	2.02
DiD (HASU)_q ¹⁴	.81	-1.5**	3.38***	4.29**	.24	4.71*	.65
DiD (non_HASU)_q ¹⁵	-2.63	-.06	3.22**	5.47***	1.17	-3.72	-1.38
DiD (HASU)_q ¹⁵	5.66	2.69***	-.82	-.01	-.97	1.14	-.54

Note. *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5% and * for 10%; IV: Independent variable; FE: Fixed effects; RE: Random effects; resid. : residence; emer. readm.: emergency readmission

In the main model specification I made no use of sampling weights, despite variation in the number of admissions per Trust and quarter. To investigate the sensitivity of my findings to sampling weights, I re-estimated the main models using sample weights based on the average number of admissions observed in quarter 1 to quarter 16 within the analysis. Findings comparing the DiD estimators from the original analysis using no weights versus DiD estimators using weights are presented in Table 25. For non-HASUs and the outcome 24-hour brain scans' weighted impact was slightly higher than unweighted impacts, whereas the thrombolysis treatment weighted impact is slightly smaller, but both indicators are still significant at the 1% level. For 7-day and 30-day mortality rates, magnitude of impact decreased slightly by .02% and .01%, respectively and significance remained at the 1% level. For aspiration pneumonia rate results were still significant at the 1% level, but slightly smaller in magnitude, whereas results for discharge to usual place of residence were slightly larger in magnitude. For 30-day readmission rates, results were slightly higher but turned non-significant. For HASUs, the DiD coefficient on thrombolysis treatment increased in magnitude and became significant at the 5% level. For aspiration pneumonia, magnitude decreased slightly and significance turned from the 1% to the 5% level. In summary, unweighted estimates of policy impact were either broadly the same or slightly more conservative than weighted estimates, for most indicators.

The use of sampling weights is seen as preferential when estimating descriptive statistics for a population on the basis of sample data, particularly to make the analysis sample representative of the target population (Solon *et al.*, 2013). In my analysis, graphical representations of trends in process and outcome measures were based on weights for the number of stroke admissions. This was chosen to illustrate that despite patients being treated in London non-HASU Trusts, the general stroke performance

across the whole of London follows closely the processes and outcomes at the London HASU Trusts (where the majority of patients are receiving care).

When estimating causal effects, however, Solon *et al.* (2013) also argued that the use of sampling weights is more “nuanced” and should be handled with care. The study provided several examples of how the use of weights led to wrongful interpretations. One key intention of using population weights, is to improve the precision of the estimation based on the heteroscedasticity argument if the dependent variable is a group average, and the averages for different groups are based on widely varying within-group sample sizes. Many studies have shown that using weights often harms the precision of estimation, because of the wrongful assumption of individual error term independence. A study by Dicken’s (1990) showed that individual error terms within groups are often positively correlated with each other because of common unobservable group-level factors. This could also be the case in my analysis; in particular, it is possible that unobservable factors such as spill-over learning effects, for example in the use of thrombolysis treatment, influenced staff in other Trusts to also uptake new techniques, subsequently leading to an increase of treatment rates or reduced mortality rates. Another example relates to standardisation of procedures across the NHS, such as the standardised guideline of when to provide CT scans or perform other medical tasks, which I would argue also violates the heteroscedasticity argument.

It is also important to stress the advantages of using panel data for evaluating the policy impact of centralised stroke care in London, including high sample variability, controlling for omitted variable bias by measuring Trust performance at several points in time and being able to uncover dynamic relationships (Hsiao, 2007).

Table 25.

Panel data analysis weighted for the average number of quarterly stroke admissions observed in quarter 1 to quarter 16

IVs	24 hour brain scan		Thrombolysis treatment		Death within 7-days		Death within 30-days		Aspiration pneumonia		Discharge to usual place of residence		30-day emer. readmission	
	Non-W.	W.	Non-W.	W.	Non-W.	W.	Non-W.	W.	Non-W.	W.	Non-W.	W.	Non-W.	W.
London non-HASUs	-	-	-	-	-	-	-	-	-	-	-	-	-	-
London HASUs	-	-	-	-	-	-	-	-	-	-	-	-	-	-
T	21.16***	21.35***	3.92***	3.87***	-1.83***	-1.70***	-3.61***	-3.42***	.42***	.41*	6.96***	6.86***	1.39***	1.42***
DiD (non-HASUs)	-	-	-4.06***	-4.12***	1.93***	1.91***	2.59***	2.58***	-1.84***	-1.89***	-7.03***	-7.02***	1.37***	1.38
DiD (HASUs)	-.23	-.20	1.97***	2.07**	-.27	-.23	.45	.41	-1.56***	-1.47**	-.48	-.40	1.18**	1.20
Constant	29.07***	29.31***	-.15	4.25**	-1.79	-.22	-8.09***	-10.08	-9.81***	-6.11	120.23** *	124.29** *	11.51***	12.44***
R-Squared	.24	.24	.31	.31	.08	.12	.19	.18	.01	.01	.20	.20	.09	.09

Note. *** indicates that the variable has robust impact on dependent variable at 1% significance level, ** for 5% and * for 10%.

6.7 Discussion

The centralisation of acute stroke care services in London carried two objectives: first, to increase the provision of stroke specific processes and improve outcomes, and second, to contain costs (Healthcare for London, 2008). The results presented in this chapter showed that this objective was achieved through higher rates of thrombolysis treatment for patients admitted to a London HASU. However, the analysis also revealed that several quarters after the policy implementation, approximately 15% of all London stroke patients still received acute stroke care in London non-HASU Trusts and that these patients are less likely to receive 24-hour brain scans and thrombolysis treatment, but also patients treated in London non-HASU Trusts have worse outcomes, such as a higher risk of mortality. The analysis produced in this chapter is the first of its kind to evaluate the policy effect of stroke centralisation in London, by accounting for heterogeneity in provider performance that was not addressed by so far published evaluation studies.

Following the centralisation of stroke care, it was intended that eight dedicated London HASUs provide acute stroke services for patients within the first 72-hours. As a consequence, acute stroke care services were believed to terminate in the remaining 22 London non-HASU hospitals. The findings presented in this chapter could be due to several reasons. First, some of the trends in policy uptake seen within the data might be related to variation in coding practices. Specifically, it may be that some stroke rehabilitation patients were in fact coded as acute patients within HES. The patients observed in non-HASU Trusts could be there for rehabilitation purposes, who naturally would not receive 24-hour brain scans or thrombolysis treatments because of the clinical stage of their treatment. Furthermore, rehabilitation patients are also more likely to experience adverse health outcomes, as they are considered sicker than stroke patients who are able to leave the hospital after receiving acute stroke services. To address this concern, I

conducted this analysis at the ‘super-spell’ level, which in theory addressed the issue of repatriation, but also the potential for double counting stroke patients.

Second, the results could be related to selection bias at non-HASU Trusts, which could be caused by differences in patient complexity that remain unobservable within the available HES data. This is particularly likely as London non-HASU Trusts had no financial incentive to continue treating stroke patients. For instance, it could be that non-HASUs received patients with more complex presentation of symptoms or more serious health conditions, and transferring such patients to HASUs might be seen as either inviable or worse so, irresponsible. Additionally, there might be potential delays in diagnosing a stroke episode in multi-morbid patients in non-HASU settings, since multi-morbid presentations might mask stroke symptoms. In such circumstances, length of delay in diagnosis may make it unsuitable for a patient to be transferred to a HASU. Though the analysis in this chapter controlled for factors such as comorbidities (via the Charlson Index), age and other variables associated with patient complexity, HES data does not contain any information about the severity of the initial stroke episode. Having access to and including such a stroke-specific measure might have allowed for a more accurate identification of patients who were classified as being unfit for transportation.

Keeping in mind the arguments made above, a last possible explanation for the findings in this chapter could be that there are significant differences in the care quality provided by London HASU and non-HASU Trusts. Specifically, London non-HASUs may be bereft of the specialist stroke staff or equipment for diagnosis and treatment that London HASUs are made to be equipped with, consequently impacting the care quality provided in the former settings. This in turn decreases the odds that patients in non-HASUs received stroke specific services such as 24-hour brain scans and thrombolysis treatment, and on the other hand, increases the odds of consequences such as being more likely to die within 7 days and 30 days. However, it is also

possible that there may be a small population of stroke patients admitted to a HASU that are not receiving appropriate care.

6.7.1 Strengths and Limitations

This chapter has its share of limitations. The first is in relation to the weakness of the HES database itself, which has been discussed extensively in previous chapters (*e.g.* consistency of coding practices). Specific to stroke data, previous reports have flagged up that in comparison to independent hospital stroke registers, HES fails to account for 16% of all stroke patients (Barer and Cassidy, 2014). However, the same study also highlighted that a second dataset used extensively for evaluating stroke policies, namely the Stroke Improvement National Audit Programme, omitted 30% of all stroke patients, making the HES database source with greater coverage of information. Moreover, it has also been found that there are systematic differences between weekday and weekend coding practices for stroke patients (Li and Rothwell, 2016), although this paper used a very broad definition of stroke to include non-stroke and elective admissions. This highlights the threat of potential confounders and biases when relying on administrative datasets. To keep this risk at a minimum, I used a tighter definition of stroke and only included emergency readmissions in the analysis.

A second limitation is related to the use of Trust-level data; specifically, information regarding the type of stroke was not taken into consideration. This could particularly bias results related to thrombolysis treatment rates and be a predictor for stroke outcomes. However, similar to the previous limitation of this chapter, differences and inconsistencies in stroke coding practices across English hospitals (Britton *et al.*, 2012) suggests that accounting for the stroke type in the two treatment and control groups in a non-random way might create additional bias in results.

Finally, the finding that stroke processes have improved in general across HASUs and non-HASUs could be influenced by improved coding practices brought on by the linking of financial reimbursement to achieving certain processes such as receiving 24-hour brain scans. However, this bias would apply to all hospitals in the study sample.

6.8 Policy implications and Conclusions

Previous work that was published on the impact of centralised stroke care in London reported a significant change in quality improvement. All existing studies suggested consistently favourable processes and outcomes in stroke patients treated in London as compared with those receiving care anywhere else in the country. This finding was supported visually by time trends for selected process and outcome measures depicted in Figure 15, which also showed that stroke services in London are one of the best in the country, with changes in London's service provision possibly translating into learning for the organisation of stroke care elsewhere. However, while over 80% of stroke patients in London received care in a dedicated HASU Trust, findings from this chapter showed that policy makers could benefit from further exploration into the causes for why a substantial number of patients still received their acute stroke care in London non-HASU Trusts. For instance, the three London Sustainability and Transformation Plans could seize this opportunity to jointly review the London hub-model's performance, and thereby create strategies that can pave the way to improve care provision in London in the future. The outcomes of a review could also help to derive learning, which could support other areas in their ambition to improve stroke care provision. Moreover, future research could also explore the impact of small-scale initiatives that were introduced at the local-level, for example within a Trust or a commissioning group, and if deemed successful, explore

routes on how these could be introduced more widely to improve stroke care at the national-level.

In this chapter, I found evidence to support underlying differences in stroke-specific processes and outcome measures between patients admitted to London HASUs and non-HASU Trusts, after the stroke care services in London were centralised in 2010. However, due to the limitations of the utilised data, I was not able to fully determine the causes of this underlying variation. Despite these findings, the provision of stroke services in London remained one of the best in the whole of England, but a renewed engagement of policymakers into the implemented hub-model could result in further improvements for stroke patients.

Chapter 7 Conclusion

This thesis examines the dynamics in quality of care provided to patients in the English NHS by exploiting HES, a large administrative database and using primarily hospital emergency readmission rates as a quality metric, but also other measures that reflect on healthcare quality.

Hospital readmission rates are related to the quality and safety of the initial hospital stay (Ashton *et al.*, 1997; Hansen, Williams and Singer, 2011), transitional care services (Feltner *et al.*, 2014; Lee *et al.*, 2015; Rennke and Ranji, 2015) and post-discharge support (Phillips *et al.*, 2004; Harrison *et al.*, 2014). Therefore, advocates claim, readmissions impose a burden on patients and the healthcare system alike, while being to a certain degree amenable to corrections in the delivery of healthcare services (Dharmarajan, 2016). Despite this evidence, and due to a number of confounding factors, the relationship between readmissions and quality of care is not straightforward. For instance, this includes the regional variation in the propensity of hospitals to admit patients (Bhatia *et al.*, 2014).

The multifactorial nature of readmissions becomes obvious when considering the evidence, which shows that only few hospital readmissions map onto the diagnosis recorded at the indexed (*i.e.* initial) admission. A study by Dharmarajan *et al.* (2013) suggested that 64.8% of all readmissions related to heart failure patients are unrelated to the diagnosis of the indexed admission. This difference becomes even more striking in pneumonia patients (78.0%) and for patients with an indexed admission for acute myocardial infarction (64.8%). However, every hospitalisation carries significant levels of allostatic and physiological stress for patients, which may not be captured by a focus on

the cause for the indexed admission alone. Aspects of a hospitalisation that may lead to adverse effects are poor sleep quality, low levels of nutrition, pain and discomfort, side effects caused by medication, which in combination may increase the patient risk of being readmitted following discharge from hospital (Krumholz, 2013).

Moreover, it is often unclear what number of readmissions are amenable to changes in quality of care, and the working of the healthcare system. For instance, a systematic review by Van Walraven *et al.* (2011) found that the preventability of readmission rates lies somewhere between 5% and 79%, exemplifying the lack of understanding regarding the extent to which readmissions vary based on hospital-level factors, but also those lying outside the control of the discharging hospital. Readmissions are related to care processes at multiple parts of the care pathway. The enhanced focus on reducing readmission rates in the NHS following the 2010 government white paper *Equity and Excellence: Liberating the English*, saw the introduction of financial penalties on hospitals aimed to incentivise improvements within the hospital walls and also to spur co-ordination between primary, ambulatory and secondary care (American College of Emergency Physicians, 2015). It is reasonable to ask, where should the line be drawn? Readmissions are affected by preventive primary care, social care and factors outside of the traditional remit of healthcare, such as social support, income and housing (Marmot and Wilkinson, 2005). To what extent is it reasonable and effective to hold hospitals to account for these aspects?

To answer some of these questions, this thesis provides an in-depth overview of (a) the changes in the English healthcare quality landscape measured through readmission rates; (b) a validation of readmission rates with other measures of quality, specifically the quality of life reported by hip and knee replacement patients; and (c) a causal impact evaluation of two healthcare policies. In this section of the thesis, I will

provide a summary of chapters 3 to 6; discuss their strengths and limitations, together with policy implications.

7.1 Summary of findings

7.1.1 Chapter 3

The third chapter in this thesis provides a high-level analysis of trends and variation in English 30-day readmission rates between April 2006 and February 2016. It examines signs of improvements in quality of care, which is assumed to translate into reduced overall risk-adjusted, 30-day emergency readmission rates and less ‘unwarranted’ variation measured by the SCV score. Reducing variation in care and providing best practice to all patients regardless of where in the country they enter the healthcare system was made a key policy objective in the NHS *Five Year Forward View*. While previous evidence on variation was mainly restricted to information of utilisation, such as hospital admission rates for ambulatory care-sensitive conditions (NHS Confederation, 2004; NHS England and Public Health England, 2015), they were not able to capture time-invariant unobserved heterogeneity across providers within one measure. Moreover, to address the fact that patients may interact with the healthcare system differently depending on their clinical needs, I exploited available information on potentially all patients entering the NHS and examined trends in readmission rates and variation for nine separate clinical specialities. Compared with other metrics such as mortality rates (Goodacre, Campbell and Carter, 2015), readmission rates prove beneficial for this analysis as they signal quality provided along the clinical pathway. I find that for all non-specialist NHS Trusts in England, readmission rates following discharge from any indexed admission increased slightly from 6.56% in 2006/07 to 6.76% in 2012/13,

followed by a small decrease to 6.64% in 2015/16. Over the same observation period, I found a small decrease in the degree of variation measured by the SCV, from 15.60 in 2006/07 to 14.54 in 2015/16. Moreover, I found evidence to suggest that readmission rates and their trends over time varied widely across clinical subgroups. For example, while emergency readmissions for patients discharged following an elective indexed admission decreased by 0.13%, those for emergency indexed admissions increased by 1.27%. Further, I found reductions in emergency readmissions for hip and knee replacement patients (-1.29%), stable emergency readmissions from patients with an indexed admission for acute myocardial infarction (-0.04%), stroke (+0.62%), COPD (+0.41%) and heart failure (+0.15%), whereas emergency readmissions increased for patients with an indexed admission for diabetes (+7.09%), cholecystectomy (+1.86%) and hysterectomy (+2.54%). The level of unwarranted variation in quality of care measured through the SCV score decreased across most clinical conditions, except for cholecystectomy and hysterectomy. The findings suggest that the enhanced policy focus on improving quality of care over the last decade has likely led the NHS to being a healthcare system that provides higher quality of care, and for all.

7.1.2 Chapter 4

Chapter 4 examined the validity of readmission rates as a measure for quality of care, as well as assessed whether the enhanced policy focus on reducing readmission rates in the NHS has resulted in potentially unintended consequences for patients (Friebel and Steventon, 2016; Friebel *et al.*, 2017). For example if the penalties disproportionately impact on some hospital groups (Figueroa, Wang and Jha, 2016), displace follow-up activity from inpatient settings to other care settings (such as observational units) that are not included in the readmission metric, but might impact on

patient care (Zuckerman *et al.*, 2016). The chapter was motivated by the lack of evidence on whether readmission rates map onto PROMs. I made use of publicly available information on PROMs (EQ-5D, EQ-VAS, and Oxford Hip and Knee Score) collected for patients undergoing hip and knee replacements in the NHS since 2009, which was linked to readmission rates data from HES. I used panel data models to examine whether Trusts that had largest reductions in readmission rates also reported greatest improvements in PROMs. I find that each percentage point reduction in risk-adjusted readmission rate for hip replacement was associated with an additional health gain of .0004 for EQ-5D, .39 for EQ-VAS, and .32 for Oxford Hip Score. Corresponding figures for knee replacement were .003 for EQ-5D, .21 for EQ-VAS and .14 in the Oxford Knee Score. The findings suggest that first, fears that efforts to reduce readmission rates have had unintended consequences for patients appear to be unfounded and second, that readmission rates and PROMs may relate to different dimensions in quality with gains materialising through different channels.

7.1.3 Chapter 5

The fifth chapter in this thesis covers the impact evaluation of quality improvement policies at the national-level (*i.e.* financial penalties for hospitals with excess readmission rates in England). This chapter addressed a major gap in the literature regarding the potentially causal relationship between financial penalties and readmission rates. Financial penalties for excess readmission rates in the US and England were introduced across all providers and at the same time, leaving no natural control group. Previous research that investigated the impact of the financial penalty policies relied either on before-and-after study designs (Zuckerman *et al.*, 2016), which assume that the gradient change in outcome is caused by the policy, or report expert opinions (Joynt *et*

al., 2016), which is likely to suffer from selection bias. So far, no study was able to report an unbiased estimation of the true relationship between levels of financial penalties and readmission rates, with a better understanding having great value for policy-makers in designing pay-for-performance policies in the future. The study in this chapter focused on the English NHS and exploited the endogeneity that exists regarding the agreement for financial penalty thresholds between providers and payers. Based on this assumption, I applied the GPS methodology to estimate dose-response functions. For this chapter, I used emergency readmission rates from HES, financial penalties provided by the Department of Health following a Freedom of Information request, and publicly available area-level characteristics. Following the adjustment for the GPS, I estimated a u-shaped dose-response curve, with a vertex (*i.e.* the lowest point in readmission rates) at 16%, thus significantly below the currently employed average financial penalty for 2012/13. More importantly, I showed that too large financial penalties can lead to unintended consequences, *i.e.* readmission rates that lie above the average observed for the observation period, but I also showed that too small financial penalties are likely to have no substantial impact on reducing readmission rates. This chapter fills a significant gap in the literature, as it presents the first unbiased estimation of the impact of different levels of financial penalties on changes in readmission rates.

7.1.4 Chapter 6

The final substantive chapter focused on an area-level policy intended to improve quality of care for stroke patients in London (*i.e.* centralisation of acute stroke care services in London). While several studies have previously evaluated the impact of centralisation of stroke services in England, either qualitatively (Fulop *et al.*, 2013) or quantitatively (Liu, Rudd and Davie, 2011; Hunter *et al.*, 2013; Morris *et al.*, 2014; Ramsay

et al., 2015), none of the previous literature considered the differential impact stroke care centralisation has on patients being admitted to HASUs, as compared to the approximately 15% of London stroke patients that still receive care in non-HASUs. The importance for this study becomes apparent when considering that no stroke patient is intended to receive acute stroke care services in a London non-HASU following the implementation of the centralisation policy in 2010 (Healthcare for London, 2008). I used HES data on all stroke patients receiving care in England and constructed panel data models with a DiD estimator containing two treatment groups. While investigating the impact on readmission rates, I also examined the impact on other patient outcomes and process measures, which can be considered an extension to the use of readmission rates as a quality metric in the previous chapters. As discussed extensively throughout the chapters in this thesis, readmission rates carry significant limitations and it is therefore valuable to expand on the use of quality metrics to understand the wider impact on quality of care for patients. The outcomes of this applied econometric analysis showed underlying heterogeneity in processes and outcome measures between providers following the introduction of an area-level centralisation of acute stroke care services in London. Specifically, stroke patients who receive care in London non-HASU Trusts are less likely to receive 24-hour brain scans and thrombolysis treatment, they are more likely to die within 7 and 30 days, and carry a greater risk of being readmitted within 30 days. The impact evaluated in this study was overlooked by previous research, with findings having the potential to inform future developments of stroke care strategies for London, Manchester and other stroke service centralisations proposed under the Acute Care Collaboration programmes.

7.2 Strength and limitations of the thesis

The main strength of the analyses discussed in this thesis lie within the use of administrative health data, which provides detailed information on patient demographics, diagnoses and treatment procedures for all patients, longitudinally and for all NHS hospitals in the country. Yet, using this rich database also attributes to the key limitation of this thesis, namely the reliance on good quality coding practices and the restriction to derivable quality measures. As is described in chapter 3, coding practices are likely to have improved across the observation period (Navid *et al.*, 2015), which may result in changes to the Charlson Index that was calculated from recorded diagnoses codes, and used for the risk-adjustment of readmission rates. On the other hand, financial incentives to improve coding of certain procedures, such as those used in chapter 6 (*i.e.* 24-hour brain scans, thrombolysis treatment), may have introduced an unobservable bias into the analysis. However, these limitations are representative of problems faced by evaluation teams across the NHS, and by focussing on readmission rates I can evaluate changes in quality based on a metric that, at a crude level, is less likely to be affected by coding practices or gaming. An example for gaming might occur in instances where hospital reimbursement is linked to the performance of certain processes within a set time frame, for instance conducting brain scans within 24 hours. However, there is still a small chance that readmission rates may be affected by gaming, specifically in cases where financial penalties are targeting readmissions of specific patient groups, leaving patients such as those with a record for cancer outside the scope of the policy.

Another overarching limitation of the work produced in this thesis relates to the risk-adjustment of readmission rates as a way to control for the Trust-specific patient case-mix that allows for comparing between-Trust performances. While it is recognised that the risk-adjustment can never be perfect (Marang-van de Mheen and Shojania,

2014), it is critical to ensure that hospitals with sicker patients are not unduly penalised for higher readmissions. However, in this thesis, but also in work produced elsewhere, risk-adjustment is restricted to information collected in administrative health data sets, which for example, includes limited information on patient medical needs, or disease severity. Moreover, it is possible that the reliance on available data might have produced contradictory findings on the correlations between risk-adjusted readmission rates and risk-adjusted mortality rates (Krumholz *et al.*, 2013; Laudicella, Li Donni and Smith, 2013).

The significance of risk-adjustment can also be seen in a current debate in the US, where reportedly financial penalties are more than twice as likely to be imposed on safety-net hospitals (*i.e.* those hospitals that provide care for patients from socially deprived areas) than on hospitals treating less socially deprived populations (Figueroa, Wang and Jha, 2016). These patterns were observed for a total of three penalty programmes: the Hospital Readmission Reduction Programme, the Hospital Value-Based-Purchasing (which targets clinical measures and patient experience), and the Hospital-Acquired Condition Reduction Programme (Strokoff and Grossman, 2010). It is believed that the uneven distribution of financial penalties seen in the US is the result of poor risk-adjustment for the patients' socio-economic background (Figueroa, Wang and Jha, 2016).

In the US, patients living in areas characterised by high levels of poverty were found to having a 25% higher likelihood of experiencing a hospital readmission, than their counterparts from more affluent areas (Hu, Gonsahn and Nerenz, 2014). It is possible that this variation in risk is a consequence of poorer quality services provided in neighbourhoods with higher poverty levels. Accounting for the patients' socio-economic background in the risk-adjustment models would thus set the readmission benchmark

less stringently for poorer patients, which could possibly result in embedding health inequalities. In fact, the lack of adjusting for socio-economic status in readmissions rates in the US was based on guidelines issued by the National Quality Forum (NQF) and based on concerns about health inequalities (Fiscella, 2014).

A natural response to these findings would be to revisit the arguments in favour of risk-adjusting readmission rates for the patients' socio-economic background. Of course, should the high number of readmissions for patients from safety-net hospitals be caused by factors outside the control of the discharging hospital, then higher financial penalties might be unfair, and even more so, if the hospital is proactively working towards reducing the readmission rate (Amarasingham *et al.*, 2013). However, the challenge is to disentangle what readmission is the result of poor quality of care, and what readmission is caused by factors that go beyond the direct influence of the discharging hospital. For example, this might include poor access to primary care services. In reality, patients from poorer socioeconomic background tend to face a number of disadvantages, which might include both poorer quality of care received at the initial hospital visit, but also high burden of access to post-discharge services. Given the difficulty of these relationships, there is no straightforward solution to the risk-adjustment of readmission rates.

There are however studies which have suggested that readmission rates are associated with a patients' socioeconomic status (Calvillo–King *et al.*, 2012; Damiani *et al.*, 2015). But due to the employed study designs these findings cannot be taken to imply causality. In fact, disentangling the problems of need and supply of healthcare services was found to be extremely difficult (Wennberg *et al.*, 2013), specifically since the relationship could be confounded by several aspects, including the quality of care, variation in admission thresholds, or simply unmeasured patient level characteristics out

of which one is the patient's socioeconomic status. It is justified to say that currently available data sets, such as the one used in this thesis, provide no room to isolate these factors. Moreover, while technical advancements to risk-adjustment should be pursued, it must be emphasised that, due to limitations of methodology and data, there is no single 'right answer'. The danger is that too narrow a focus places unreasonable expectations on risk adjustment to resolve the underlying issues.

In chapter 3, I used the SCV, a measure of within and between Trust variations in readmission rates. Within-Trust variation is measured through the predicted readmission rate that was calculated based on patient case-mix information included in the logistic regression model. Limited to information available in the HES dataset, it was not possible to adjust for disease severity or functional status after discharge, which is seen as a relevant driver of readmissions and may have introduced bias (Tabak *et al.*, 2017). However, the same patient-level information was entered into prediction models for each financial year, hence holding any potential bias constant across the observation period.

Chapter 4 uses a panel data study design and makes use of linked information on readmission rates from HES and PROMs from publicly available sources. While panel data models are superior to cross-sectional ones due to the ability to control for omitted variables, *i.e.* account for observable or unobservable Trust-level characteristics, provided they remained constant across the observation period (Hsiao, 2007), no causal interpretations from the study results were derived. Moreover, while conducting analysis at the Trust-level allowed for the creation of a panel across providers and over time, it may explain the modest relationship found between changes in readmission rates and PROMs. Future work would benefit from a patient-level analysis that might uncover the

significance of the association based on the incremental health gains across the study population.

The analysis for chapter 5 was conducted at the PCT-level due to limited information on financial penalties. This information was provided by the Department of Health following a Freedom of Information request. At the time of the analysis, HES data was available up to March 2013, which is possibly not a long enough period to capture the full impact of financial penalties on readmission rates. Moreover, due to missing data, a significant number of PCTs had to be dropped, leading to a relatively small sample size. I have now been able to source additional financial penalty information from producers at Channel 4. This will allow for a Trust-level analysis, which will also include more up-to-date readmission rates information that has become available within HES.

Chapter 6 also made use of a panel data study design and utilised the DiD methodology for a causal impact evaluation. In the main model, all Trusts in the rest of England (*i.e.* excluding Trusts located in Manchester) were used as the natural control group, and include London HASUs and London non-HASUs as two separate treatment groups. The parallel trends assumption was tested, which ensures that the DiD estimates are caused by the treatment (*i.e.* policy). Further, sensitivity analyses were performed with a control group that consists of Trusts in six other metropolitan areas in England to account for possible underlying differences in treatment between rural and urban areas. Despite testing for these assumptions and performing sensitivity analyses, it is possible that the DiD is not estimated using the best possible control group. Additional work should therefore focus on the patient-level and implement matching methods, such as propensity score matching, or genetic matching, followed by treatment effect estimations.

Finally, analyses performed in this thesis are of ecological nature, which in turn presents a major limitation.

7.3 Policy implications

Akin to other international healthcare systems, demand for services provided by the English NHS is projected to rise further over the coming decades, with government expenditures not likely to increase at a competing rate. To deal with this anticipated and increasing funding gap, multiple stakeholders, which range from policy-makers, hospital managers, and clinical staff are required to consistently innovate and improve services to sustain the level of care that is currently provided. With its objectives, this thesis provides not only an overview about the dynamics of quality of care over the last decade, it also offers an insight into the usefulness of readmission rates as a measure of healthcare quality and presents robust evidence on the impact of quality improvement efforts at local and national-levels. In combination, evidence from this thesis could help inform the NHS quality improvement agenda in the future.

7.3.1 Chapter 3

Findings from chapter 3 suggest that quality of care in the NHS measured through readmission rates has seen improvements between 2006 and 2016. Particularly, I find a tenuous but significant decrease in readmission trends following the introduction of policies that were outlined in the 2010 government white paper (Department of Health, 2010). While I am not able to determine a cause behind this improvement, the timing of change may suggest a relationship with policies such as financial penalties, or

cash transfers from secondary care to social care services (Department of Health, 2012). Despite decreases in both, readmission rates and the level of variation remains at a level considered to be high or very high. Similarly, I saw improvements across different clinical specialities, however variation between Trusts was found to be at high levels. While it is important to remember that not every readmission can be avoided, and that the proportion of readmissions deemed avoidable is likely to differ by clinical subgroup, the policy implication from this finding is that more needs to be done to understand mechanisms that will reduce avoidable readmissions and to address variation in quality across providers in England. And therefore, I support efforts highlighted in the NHS *Five Year Forward View* to decrease quality variation, which will allow building a sustainable NHS for the future. This includes the new care models programme, which saw the introduction of fifty vanguard sites, falling under five vanguard types (NHS England, 2016); integrated primary and acute care systems to link up care provided by different stakeholders along the pathway; multispecialty community providers to shift care away from the in-hospital setting; enhanced health in care homes to provide better and more tailored care for the need of the elderly; urgent and emergency care to test approaches that will reduce the demand burden for A&E departments; and lastly, acute care collaborations that aim at linking expertise across Trusts. While each of the vanguard sites present a unique opportunity to improve the care of patients in the NHS, in turn they all require robust evaluations to inform local teams commissioned with the implementation, but also for policy-makers to feedback and to consider either a role out of successful initiatives to other parts of the country, or to inform future policy-making.

7.3.2 Chapter 4

Findings from chapter 4 have key implications for policy-making. While the findings show that an enhanced focus on reducing readmission rates to improve quality

of care had no unintended consequences for PROMs in hip and knee replacement patients, the weak association between both employed metrics suggests that policy-makers cannot rely upon improving readmission rates as a way to improve the patients self-perceived quality of life. It may be that even though a hospital readmission is considered to be undesirable for the affected, the perceived quality may ultimately be more important for the majority of patients. In fact, readmissions only impact a small proportion of patients (*i.e.* less than 7% on average, but varying by clinical condition), and perhaps, this metric might therefore not be able to capture what the majority of patients (*i.e.* those not readmitted, dying or experiencing a safety event) are experiencing in terms of healthcare quality. Based on the findings of this chapter, I propose that policy-makers may want to tap into the wide range of information that is available within audit data, which will allow for quality assessments and benchmarking at a more granular level and for specific clinical specialities (*e.g.* stroke audit), rather than relying on indicators that can be derived from large administrative databases alone.

7.3.3 Chapter 5

Findings from chapter 5 provide policy-makers with the first unbiased estimation about the impact of different levels of financial penalties on readmission rates. This study fills the lack of pre-existing evidence on the impact of such penalisation policies, both here in England, but also in the US. Based on the outcomes of this chapter, policy-makers need to be careful in setting levels of financial penalties and are required to monitor their impact more closely to avoid any unintended consequences caused by too large financial penalties. Moreover, too small financial penalties were found to be having no impact on changes in readmission rates, questioning the cost-effectiveness of such schemes given costs associated with maintaining a monitoring system and overseeing

payments. But despite these potential pitfalls, the policy was a catalyst for improving communication between health service providers along the patient pathway, which in itself may have resulted in efficiency gains, and perhaps were not picked up by the readmission rate metric. Furthermore, the econometric method used in this chapter may also be a useful tool that can be applied by NHS England for evaluating national-level policies that do not present with a natural control group.

7.3.4 Chapter 6

The final chapter conveys a clear message to policy-makers in England, and to centralisation advocates across the country. Service centralisation can lead to a significant step change in quality of care. However, policy-makers should revisit the London stroke model to understand why 15% of stroke patients still receive acute stroke care services in London non-HASU Trusts. Moreover, more needs to be done to incorporate measures of severity within the administrative health data, as it could help to better understand the results found in this study, particularly if patients treated in London non-HASU Trusts were too sick to be transported to a HASU Trust for specialist treatment. However, severity measures may also be useful for other research, such as current debates about the existence of the hospital weekend effect (McKee, 2016). If the trend of using quality measures that can be derived from administrative sources persists, benefits from collecting additional information may outweigh the costs associated with collecting them.

7.4 Future research

Findings from Chapter 3 imply that readmission rates and variation have been reducing over the past decade, yet variation in readmission rates remains high across Trusts in England. This is an interesting angle for future research, since more needs to be done to understand the causes of such high variation, which will help ensure policy-makers focus on the right areas for the improvement of healthcare quality in the future. Moreover, while readmission rates are associated with quality along the patient pathway, this thesis only uses data on secondary care, and thus, I was not able to develop an understanding about the causal relationships between quality in primary care settings, or social care on readmission rates across the observation period. In fact, it might be that the high variation observed across Trusts is in fact due to care provided outside the hospital, for example linked to unobservable differences in the continuity of care provided to patients (Barker, Steventon and Deeny, 2017). Restricting any analysis to information available from inpatient care alone may therefore provide only one element of the real dynamics in quality of care, and future quality assessments could consider using patient-level data that includes information on social care provision, the quality of community care, primary care, or pharmaceutical prescriptions etc.

Chapter 5, which addressed the impact evaluation of a national-level quality improvement policy, is based at the PCT-level and on a short-term analysis. In England, financial penalties have been employed each financial year since their introduction in 2011, and policy-makers could benefit from analysing the impact of each wave of financial penalties in each financial year, individually. Moreover, hospital behaviour could be studied, particularly behaviour changes in agreeing to financial penalty thresholds between providers and payers based on the size of financial penalties employed in the previous year. Unlike in the US, financial penalties in England must be re-invested into

services considered to reduce readmissions in the future, and additional research could examine the impact of investments into specific areas, such as transitional care services.

While chapter 6 adds important aspects on healthcare quality provision to the literature, studying the field of stroke service centralisation also reveals additional research questions. For example, from discussions with clinicians and stroke experts it became apparent that a large proportion of stroke mimics imposes significant strain on resources. These are patients with a suspicion of stroke but where the diagnosis is not confirmed following later assessment, who are initially being transported to a London HASU and then repatriated to another Trust for further treatment. Similarly, following the initial acute episode (72-hours), stroke patients are transferred to a Trust that is located near their registered place of residence via ambulance. Future research should investigate the impact of transferring patients between HASUs and non-HASUs following the 72 hour acute care episode on the availability of London Ambulance Services, and future research could also examine the potential spill-over effects this might have for the provision of ambulance services to other patient groups in London. Findings could be particularly important, since London cardiovascular services follow a similar framework as stroke care, adding to the large frequency of patient transportation between Trusts. Moreover, further research needs to be conducted to understand whether centralisation of services might be an appropriate option for improving quality of care within rural areas, since service consolidation is part of new care models, namely the Working Together Partnership in South Yorkshire, Mid Yorkshire and North Derbyshire.

This thesis tries to make use of the opportunity created by the enhanced policy focus on reducing readmission rates in the English NHS to contribute to the health policy and health economics literature, focussing on quality of care. However, since the

2010 government white paper, quality improvement has developed further in the NHS, with an increasing focus on the new care models and particularly, the efforts to reduce clinical variation through acute care collaborations. While most of the acute care collaboration have been introduced only recently, they also present areas for future evaluations, which will be key in helping policy-makers to identify strategies that could be rolled out to providers in other parts of the country.

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To: "ngurneyrandall@bmj.com" <ngurneyrandall@bmj.com>

Dear Nadia Gurney-Randall,

I am completing my PhD thesis at Imperial College London, and am writing to seek your permission to reprint in my thesis, the published version of my paper published in:

The multiple aims of pay-for-performance and the risk of unintended consequences
Rocco Friebel; Adam Steventon
BMJ Quality & Safety. 25(11):827–831, NOV 2016

I would like to include the paper in my thesis, which will be added to Spiral, Imperial's institutional repository <http://spiral.imperial.ac.uk/> and made available to the public under a Creative Commons Attribution Non Commercial No Derives license.

Many thanks in advance, and I am looking forward to hearing from you,

Best wishes,

Rocco Friebe