Understanding the potential (and limitations) for avoiding secondary care through management of ambulatory care sensitive conditions

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Stephen John Beales

Department of Surgery & Cancer

Imperial College London

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Declaration of Originality

I, Stephen Beales, declare that the work presented in this thesis is my own, completed under the supervision of Professor Ara Darzi and Professor Pete Smith. Where information has been derived from other sources this has been indicated and appropriately referenced.

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Abstract

Background and Aim: There is a subset of conditions – Ambulatory Care Sensitive Conditions (ACSCs) – for which emergency admission into secondary care is thought to be avoidable through better primary care. This research aims to: develop a model to predict ACSC-admission rates by GP practice; determine whether ACSC-admission rates are a viable performance metric; identify how much inefficiency exists among practices; and identify interventions that reduce ACSC admissions.

Methods: The work uses routine administrative datasets (e.g. HES and Attribution Dataset), linked at the level of the general practice, for all practices in England providing NHS care. It uses techniques including multiple linear regression, corrected ordinary least squares, stochastic frontier analysis and propensity score matching to test its hypotheses.

Results: Adjusting for population characteristics (e.g. deprivation and disease prevalence), some QOF indicators and GP patient survey results were associated with lower admissions rates.

Aggregating admission rates across more practices improved the accuracy of predicted rates; at average CCG size (33 practices), the 95% confidence interval is ±8.6%.

If all GP practices in England became as efficient as those that were top performing, allowing for practices' population characteristics, there would be a 20.4% reduction in the number of ACSC admissions, based on 2010/11 data.

Two interventions were found to lower admission rates. Patient advice and liaison service led to 5.9% fewer admissions for diabetes and 6.5% fewer admissions for hypertension. Information and support for diabetes led to 4.1% fewer admissions for diabetes.

Conclusions:

Improving the efficiency of practices to best-practice levels would mean 242,143 fewer admissions per year – a £411m annual saving – however a metric for judging practices' quality based on ACSC-admission rates would need a degree of leniency.

Interventions can be found that reduce ACSC admissions and commissioners should consider expanding them. ACSC-impact assessments should be carried out before commissioning such interventions.

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List of Abbreviations

2SLS Two-Stage Least Squares

A&E Accident and Emergency

ACSC Ambulatory Care Sensitive Condition

ANOVA Analysis Of Variance

ATT Average Treatment effect on the Treated

ATU Average Treatment effect on the Untreated

CCG Clinical Commissioning Group

CCM Chronic Care Model

CHF Chronic Heart Failure

COLS Corrected Ordinary Least Squares

COPD Chronic Obstructive Pulmonary Disease

CQC Care Quality Commission

DEA Data Envelopment Analysis

eGFR estimated Glomerular Filtration Rate

ENT Ear, Nose and Throat

EPP Expert Patients Programme

FCE Finished Consultant Episode

FHSA Family Health Services Authority

FTE Full Time Equivalent

GMS General Medical Services

GP General Practitioner

HES Hospital Episode Statistics

HMO Health Maintenance Organisation

HRG Healthcare Resource Group

ICD International Classification of Diseases

IDACI Income Deprivation Affecting Children Index

IDAOPI Income Deprivation Affecting Older People Index

IHA Integrated Healthcare Association

IMD Index of Multiple Deprivation

LOS Length of Stay

LSOA Lower Layer Super Output Area

LVD Left Ventricular Dysfunction

MSOA Middle Layer Super Output Area

NHAIS National Health Applications and Infrastructure Services

NHS National Health Service

NICE National Institute for Health and Care Excellence

OLS Ordinary Least Squares

ONS Office for National Statistics

P4P Pay for Performance

PALS Patient Advice and Liaison Service

PCT Primary Care Trust

PSM Propensity Score Matching

QIP Quality Incentive Programme

QOF Quality Outcomes Framework

SFA Stochastic Frontier Analysis

SHA Strategic Health Authority

SUR Seemingly Unrelated Regression

YHPHO Yorkshire and Humber Public Health Observatory

1 Introduction

Health services around the world are facing the daunting task of containing increasing costs whilst improving the quality of care provided to their patients. In the UK an ageing population with more long-term conditions, combined with higher expectations about the quality of care the National Health Service (NHS) should deliver, are increasing overall demand for services. Unit costs are also increasing as new technologies and drugs are developed and introduced.

In England the coalition government has restructured the way services are commissioned. Groups of general practices – Clinical Commissioning Groups (CCGs) – have been given approximately £63 billion a year (money which was previously controlled by Primary Care Trusts (PCTs)) to commission secondary care services for patients that are on their lists or in their catchment area (Wood and Heath, 2014). Meanwhile primary care and some specialist (low volume and/or high cost) services are commissioned at the national level by NHS England.

Given the economic climate, commissioners are accountable for significant financial restraint. Going forward CCGs will therefore need to focus on costs that they can control. In particular, through the general practitioners (GPs) that are members of their consortium, they should be able to control the costs of primary care and impact on the quantity of secondary care required. At the same time, CCGs are equally accountable for associated patient outcomes and health inequalities in their area.

Primary care is well placed to take on this task. The provision of primary health care is widely acknowledged to improve population health and reduce the costs of care (Starfield et al., 2005b).

Emergency admissions into secondary care are expensive. They create difficulties for those responsible for planning and delivering services and are distressing for patients and their families. Emergency admissions are therefore likely to be an important area where commissioners focus in order to reduce demand for secondary care.

Even before CCGs took over responsibility for commissioning services, the reduction of emergency admissions was important to GPs as the General Medical Services (GMS) contract for 2011/12 included payments for reducing emergency admissions, as part of the productivity indicators.

Admissions to hospital are an increasing source of financial pressure on health systems internationally (Squires, 2011). In England there was a 37% increase in the number of emergency admissions between 2000 and 2009 (IC, 2010). Emergency admissions made up 32% of total admissions in 2012/13 (Morse, 2013).

Deciding which conditions or patient types to focus on and what interventions are most effective at reducing secondary care use is vital for commissioners who want to improve their financial position whilst improving the quality of care provided to their patients.

1.1 Key concepts and definitions

1.1.1 Primary care and general practice

Definitions of what constitutes primary care differ depending the perspective taken, be it clinical, organisational, functional, professional or academic. From a clinical perspective, Goroll and Mulley (2009) define primary care by its several tasks: medical diagnosis and treatment; psychological diagnosis and treatment; personal support of patients of all backgrounds in all stages of illness; communication of information about prevention, diagnosis, treatment and prognosis; and prevention and care of chronic disease and disability through risk assessment, health education, early disease detection, preventive treatment and behavioural change. It is this clinical or operational definition that is used throughout this thesis.

Primary health care provides the first point of contact in the health care system. The aim is to provide an easily accessible route to care, whatever the patient's problem. Primary health care is based on caring for people rather than specific diseases. This means that professionals working in primary care are generalists, dealing with a broad range of physical, psychological and social problems, rather than specialists in any particular disease area.

An important role is acting as the patient's advocate and co-ordinating the care of the many people who have multiple health problems. Since primary care practitioners often care for people over extended periods of time, the relationship between patient and doctor is particularly important. Primary health care involves providing treatment for common illnesses, the management of long term illnesses such as diabetes and heart disease and the prevention of future ill-health through advice, immunisation and screening programmes.

In the NHS, the main source of primary health care is general practice. Since 2004, patients have been registered with a practice, rather than with an individual. So the patient of today increasingly has a relationship with a general practice team rather than with 'their own' GP. First contact with a care professional may be provided in a range of ways, including (Jones et al., 2010): GP consultations; nurse practitioner triage; practice nurse and health visitor consultations; telephone consultations with the 'duty' doctor; and deputising services that provide out-of-hours care. The consultation with a GP remains at the core of general practice. The purpose of the consultation may

be to manage a pre-existing condition or to make an effective diagnosis of a presenting problem. The consultation may involve the practitioner giving advice and information, prescribing medication, treating the patient, or referring them to a specialist or other service. Over the years, practice activities have expanded and today services include: screening and immunisation; health promotion; active disease management programmes; and responsibility for a number of services previously provided in hospital and community settings.

1.1.2 Case management

Case management is a generic term with no single definition. However the premise of the Case Management model is that targeted, proactive, community-based care is typically more cost-effective than downstream acute care. Time-limited case management is the level of care targeted at those with the greatest risk of emergency admission. People at lower risk of admission can be targeted with disease management programmes or support to self-manage, although both these elements may also form part of a case management programme. Programmes can focus on a specific condition or group of conditions, but most often they are generic and aimed at individuals with complex needs (Ross et al., 2011).

There are typically four key steps involved in case management. First is case finding, where the patients are identified as being in need of more intensive care (such as those with multiple long term conditions, or those at high risk of hospital admission). It is a systematic method typically used to identify individuals who are at high risk of hospital admission, though it may also be used to predict other events. Research has shown that the distribution of health care utilisation across a population tends to be very uneven, with a small proportion of people accounting for a large share of total resources (Cummings et al., 1997). Therefore, in order to ensure that an intervention is cost-effective, it is crucial that resources target the individuals at highest risk.

Second is assessment. Once an individual has been identified through case-finding, it is important that they are assessed in terms of both their current level of ability and their physical and social care needs. Most people requiring an intervention such as case management have complex health and social care needs, so it is important that the assessment is not restricted to health needs only. Social care services use various assessment tools that could be incorporated within a clinical and wider well-being assessment. The package of care offered in a case management programme will depend on the results of the individual's assessment process. While most case-finding techniques offer an indication of the individual's level of risk, the assessment stage seeks to identify all of the individual's needs, and how they can best be met.

Third is the care plan. The personal care plan is at the heart of any case management programme. The care planning process brings together an individual's personal circumstances (including housing situation, welfare benefits status and access to informal care) with their health and social care needs to create a plan that aims to match needs with service provision. It is important that the case manager co-produces the care plan with the individual to facilitate shared decision-making and give them a choice about possible care options. Where possible and appropriate, the process can involve other care professionals, such as a patient's GP, and informal carers (Schraeder et al., 2008). The main purpose of the care plan is to support the case manager in providing a structure to the individual's care and to ensure that the goals of all the different services are aligned with each other. It is used as a reference tool to map the different types of service or input required, and their frequency.

Care co-ordination is the essence of case management. It involves continual communication with patients, their carers, and the various professionals and services they come into contact with. Fundamental to care co-ordination is the presence of an individual (a case manager) who often works with a team of professionals to organise and deliver a person's care. So, while the individual or team does not necessarily provide all aspects of the person's care, they take responsibility for overseeing and co-ordinating that care and helping them to navigate the system. This navigational role is important because most individuals selected for case management need services or input from one or more providers. Case managers help patients and carers navigate the different services and processes that might otherwise prove too complicated. Case managers can also provide patients with information about the services they are being referred to, and/or discuss choices about their care options (Hudson and Moore, 2006).

1.1.3 ACSC admissions

It is clear that not all emergency admissions are preventable. Previous work has looked at identifying which admissions are most likely to be preventable. An ambulatory or primary care sensitive condition (ACSC) is one for which admission is potentially avoidable through good quality primary and preventative care (Bindman et al., 1995). As well as treatment, ambulatory care also includes preventive measures such as screening and the management of risk factors such as cholesterol and blood pressure. When patients are admitted to hospital for the treatment of an ACSC this can be thought of as an avoidable hospital admission. Different sets of ACSCs are used for research and policy analysis (Purdy et al., 2009) and indeed researchers, policy makers and commissioners of care may view the concept of ACSC admissions in different ways depending on the

purpose for which they are going to be used. The concept of ACSC will also vary in different healthcare systems. In the USA, for example, where the concept was first developed, ACSC admissions were originally used as a measure of health system performance, reflecting ease of access to primary care. In the UK, where access to primary care is universal and free at the point of delivery, ACSC admissions are seen as a performance measure of the quality of care delivered. The most common ACSC definition used in England is based on a set of conditions initially derived to measure access to primary care in the United States, which were then refined for use in Australia (Purdy, 2010). Nedel et al. (2011) propose a conceptual framework for developing a list of ACSCs in countries where they do not already exist. They suggest that factors, such as the role of the state in prevention activities, should be considered when developing new lists to ensure that they are comparable between countries.

The analysis in this paper aims to be as relevant to different groups as possible and will therefore use the set of ACSCs most commonly used in England, defined by Purdy et al. (2009). Purdy et al. (2009) identified 1,900,409 admissions during 2005/6 for ACSCs in England, or just less than 41% of all emergency admissions that year. Ham et al. (2010) noted that ACSCs fall into three subsets: chronic conditions, where effective care can prevent flare-ups; acute conditions, where early intervention can prevent more serious progression; and preventable conditions, where immunisation and other interventions can prevent illness. Table 1.1 lists the ACSCs along with the International Classification of Diseases (ICD) 10 codes of the diagnoses that were considered to constitute that particular condition.

Table 1.1 – Ambulatory care sensitive conditions and their ICD-10 codes

Condition Classification	Ambulatory Care Sensitive Condition	ICD-10 Code(s)
Chronic	Angina	I20 I240 I248 I249 I25 R072 R073 R074 Z034 Z035
	Asthma	J45 J46
	Congestive heart failure (CHF)	I110 I50 J81 I130 I255
	Chronic obstructive pulmonary disease (COPD)	J20 J41 J42 J43 J47 J44 J40
	Diabetes complications	E100 E101 E102 E103 E104 E105 E106 E107 E108 E110 E111 E112 E113 E114 E115 E116 E117 E118 E120 E121 E122 E123 E124 E125 E126 E127 E128 E13 E14
	Hypertension	I10 I119
	Iron-deficiency anaemia	D501 D508 D509 D460 D461 D463 D464 D510 D511 D512 D513 D518 D520 D521 D528 D529 D531 D571 D580 D581 D590 D591 D592 D599 D601 D608 D609 D610 D611 D640 D641 D642 D643 D644 D648
	Nutritional deficiency	E40 E41 E42 E43 E550 E643
Acute	Cellulitis	L03 L04 L080 L088 L089 L88 L980 I891 L010 L011 L020 L021 L022 L023 L024 L028 L029
	Convulsions and epilepsy	G40 G41 R56 O15 G253 R568
	Dehydration and gastroenteritis	E86 K522 K528 K529 A020 A04 A059 A072 A080 A081 A083 A084 A085 A09 K520 K521
	Dental conditions	A690 K02 K03 K04 K05 K06 K08 K098 K099 K12 K13
	Ear nose and throat (ENT) infections	H66 H67 J02 J03 J06 J312 J040
	Gangrene	R02
	Pelvic inflammatory disease	N70 N73 N74
	Perforated/ bleeding ulcer	K250 K251 K252 K254 K255 K256 K260 K261 K262 K264 K265 K266 K270 K271 K272 K274 K275 K276 K280 K281 K282 K284 K285 K286 K290 K291 K292 K20 K210 K219 K221 K226
	Pyelonephritis	N10 N11 N12 N136 N300 N390 N159 N308 N309
Vaccine-preventable	Influenza and pneumonia	J10 J11 J13 J14 J153 J154 J157 J159 J168 J181 J18 J120 J121 J122 J128 J129 J160 A481 A70
	Other vaccine-preventable diseases	A35 A36 A37 A80 B05 B06 B161 B169 B180 B181 B26 G000 M014

A general practice's ACSC admissions rate is one way to judge how well the practice is doing at providing good quality primary care and preventing costs further downstream in secondary/specialist care. A criticism of many pay-for-performance programs that focus on improving quality indicators (such as the Quality and Outcomes Framework (QOF) in England, for instance) is that they encourage better recording of care, rather than better care. One advantage of looking at the number (or rate) of ACSC admissions as an indicator should be that it avoids this issue by looking at the outcome of care.

1.2 Policy context

1.2.1 Why are we trying to avoid unplanned hospital admissions?

Policy makers and clinicians want to reduce the number of unplanned admissions into an inpatient setting. There are three key reasons why we would want to reduce the number of unplanned admissions.

First is cost. If equally good care can be given in another, cheaper setting then this increases the value for money of the healthcare provided as it allows the resource freed up to be redistributed on additional care.

Second, admission into an acute setting has associated risks. Brennan et al. (2004) showed that, in hospitals in New York State, 3.7% of hospitalisations resulted in an adverse event (defined as an injury that resulted from medical management). Of these 2.6% caused permanently disabling injuries and 13.6% led to death. In Australia, Hauck and Zhao (2011) showed that a hospital stay carried a 5.5% risk of an adverse drug reaction, 17.6% risk of infection and a 3.1% risk of ulcer. Furthermore, the risk of suffering an adverse event increased with the duration of the hospital stay. There is, therefore, clearly an imperative to keep patients out of hospital unless absolutely necessary.

Third, if we are able to prevent patients from becoming ill (or the illness from becoming so severe the patient requires acute care) then, as well as the associated cost saving, this is a better outcome from the patient's perspective.

This introduction will look at what is being done internationally to reduce admissions into secondary care. It will focus on the actions of primary care and the role they play in reducing admissions. It will, therefore, exclude public health programmes except where they can be 'actioned' by primary care. For instance, requiring people to wear seat-belts while in a car is likely to reduce admissions for trauma. This however would not be considered as it is not within the scope of primary care. A stop smoking campaign is an example of a public health programme which would be relevant.

Although this review focuses on high-income countries, it is worth noting that primary care also has a significant impact in low- and middle-income countries. However, since their health systems are still developing, improvements in primary care in these countries are likely to focus on reducing child mortality, improved access among the poor and addressing wealth-based disparities in mortality (Kruk et al., 2010) rather than reducing the number of patients being admitted into secondary care. In fact, initiatives encouraged by governments in low- and middle-income countries are likely to increase admission rates.

1.2.2 The GP contract and QOF

Before 2004, most GPs in England were employed under a nationally negotiated General Medical Services (GMS) contract, through which GPs were contracted as individuals and received payment for each piece of work according to their number of registered patients. In April 2004, a new GMS contract was introduced that was held by the practice rather than the GP. The contract provides a 'global sum' based on a needs-adjusted capitation. Additional funding is available for the provision of 'enhanced services' – for example, extended opening hours, minor injuries services and other services designed in negotiation with the PCT. The Quality Outcomes Framework, or QOF**,** is a voluntary process for all surgeries in England and was introduced to support the new GP contract in 2004.

The other main contract is the Personal Medical Services (PMS) contract, which since 1998 has allowed GPs and other NHS staff to enter into locally negotiated contracts with PCTs. These contracts enable providers to develop services outside the scope of GMS to meet the specific needs of the local population. The provider need not be a traditional GP partner-led practice; NHS trusts, PCTs and other health care professionals, including nurses and dentists, can also be contracted. PMS providers are paid a fixed annual rate to provide services negotiated with their PCT. The differences between PMS and GMS contractual arrangements have decreased since 2004. For example, the arrangements for out-of-hours contracting are the same, and most PMS providers take part in QOF (see below) and provide enhanced services.

Another contract – the Alternative Provider Medical Services (APMS) contract – enables PCTs to commission primary care from commercial or voluntary providers, or from foundation trusts. The opening of the market to alternative providers was intended to plug gaps in provision in under-doctored areas and to provide a greater choice of primary care provider to patients. However, use of APMS remains limited, and very few APMS contracts have been awarded to providers that are not already part of the NHS (Ellins et al., 2009).

In 2004, the UK committed £1.8 billion to a pay-for-performance contract for GPs. During the first year, the levels of achievement exceeded those anticipated by the government, with an average of 83.4% of the available incentive payments claimed (Doran et al., 2006). However, the quality of care in GP practices had already begun to improve in response to a wide range of initiatives including: national standards for the treatment of major chronic diseases; and a national system of inspection. Family practitioners already had some experience with financial incentives from the limited use of incentive programs that were initiated in 1990. It was, therefore, unclear whether the high levels of

quality attained after the pay-for-performance contract was introduced in 2004 reflected improvements that were already under way or whether existing trends toward improvement were accelerated. However, Campbell et al. (2007) examined three of the conditions covered by QOF (CHD, diabetes and asthma) using a longitudinal analysis over the period that QOF was introduced and found a statistically significant increase in the rate of improvement in clinical quality for diabetes and asthma, but not for CHD.

Ashworth et al. (2011) studied practices in England over the four year period from 2005 to 2008. They identified a cohort of 212 (2.7%) practices which remained in the lowest decile for total QOF scores in the four years following the introduction of the QOF. This small minority of practices remained poor performers in terms of measurable performance indicators over the four-year period. The strongest predictors of poor QOF performance were found to be singlehanded and small practices, and practices staffed by elderly GPs. Further work is required to determine if poor QOF performance truly reflects poor performance, or whether, because these practices were small and staffed by older GPs, they were less able to comply with the necessary processes and returns required to get a good QOF score.

1.3 The role of primary care in reducing admissions for ACSCs

1.3.1 Characteristics that impact on ACSC admission rates

Kringos et al. (2010) found that the primary care process is determined by four dimensions: access; continuity of care; coordination of care; and comprehensiveness of care. Through these four dimensions, they found there to be considerable evidence that primary care contributes to overall health system performance.

Access with regard to primary care services consists of seven core components: the availability of primary care services (i.e. the volume and type of primary care services relative to population needs); the geographic accessibility of primary care services (i.e. the remoteness of services in terms of travel distance for patients); the manner in which resources are organized to accommodate access (e.g. appointment system, after-hours care arrangements, home visits); affordability of primary care services (e.g. the financial barriers patients experience such as co-payments and cost-sharing arrangements); patient satisfaction with the organisation of primary care; utilisation of primary care services (i.e. actual consumption of primary care services); and equality in access (i.e. the extent to which access to primary care services is provided on the basis of health needs, without systematic differences on the basis of individual or social characteristics).

The influence of access on the provided quality of care (lower hospitalisation rates for ambulatory care sensitive conditions (ACSCs) and prescribing quality) was confirmed by a number of studies (Starfield et al., 2005b) (Ansari, 2007) (Leibowitz et al., 2003) (Wilson and Childs, 2006). Further, greater supply of family physicians was associated with lower total costs of health services, and Starfield et al. (2005b) concluded that access was a core dimension of a strong primary care system. Patient reported access to consultations within two days was associated with lower levels of admissions for COPD (Calderon-Larranaga et al., 2011). Zhan et al. (2004) found in the US that a 10% increase in health maintenance organisation (HMO) penetration was associated with a 3.8% decrease in preventable hospitalisations. Roberts and Mays (1998a) also showed large reductions in demand for A&E care following an expansion in the provision of local primary care services. Although, interestingly, Weinberger (1996) studied the effect of increased primary care on re-admission rates and found that greater primary care use was actually associated with greater admission levels (although patients were more satisfied with their care).

The continuity of care dimension can be summarised as a hierarchy of three features: longitudinal continuity of care (i.e. having a long-term relationship between primary care providers and the patients in their practice, beyond specific episodes of illness or disease); informational continuity of care (e.g. an organized collection of each patient's medical information readily available to any health care provider caring for the patient); and relational continuity of care (i.e. the quality of the longitudinal relationship between primary care providers and patients, in terms of accommodation of patients' needs and preferences, such as communication and respect for patients).

Continuity of care was related to improved receipt of preventive services (Starfield et al., 2005b). Continuity of care was also associated with decreased hospitalisations, improved early diagnoses and greater efficiency of services (Starfield et al., 2005b) (Sans-Corrales et al., 2006) (Worrall and Knight, 2006). Starfield et al. (2005b) found that continuity of care is a core dimension of a strong primary care system. High continuity of care with a primary care physician was associated with reduced odds of ACSC hospitalisations among adults aged over 67, controlling for demographic and self-reported health-related measures (Menec et al., 2006), although it was not found to be related to hospitalisations for conditions more widely.

The coordination of care dimension reflects the ability of primary care providers to coordinate use of other levels of health care (Macinko et al., 2003). The following features were identified from coordination of care studies: gatekeeping system (i.e. the level of direct access for patients to health care providers without a referral from a primary care provider); primary care practice and team

structure (such as shared practices, team premises and team size and tenure); skill-mix of primary care providers; integration of primary care and secondary care; and integration of primary care and public health (i.e. the extent to which primary care providers collaborate with practitioners from the public health sector to provide services that influence health).

Studies consistently found a relation between coordination of care and higher quality of care and increased efficiency of care (Stille et al., 2005) (Xyrichis and Lowton, 2008). Coordination of care was also associated with reduced patient costs (Smith et al., 2007). Starfield et al. (2005b) found that coordination of care is positively associated with primary care strength.

Comprehensiveness of primary care services represents the range of services available in primary care to meet patients' health care needs. A distinction can be made between the range of: medical equipment available in primary care practices; health problems for which first contact care in primary care is provided; diagnoses for which treatment and follow-up care is provided in primary care; medical technical procedures and preventive care provided in primary care; mother and child and reproductive health care services provided in primary care; and health promotion activities provided in primary care

The literature study by Starfield et al. (2005b) consistently found that a comprehensive scope of primary care services is associated with lower hospitalisation rates for ACSCs.

Beyond the four broad dimensions described by Kringos et al. (2010) there are specific primary care characteristics that have been found to be associated with varying levels of ACSC admissions.

Both higher primary care staffing levels was associated with lower levels of admissions for COPD (Calderon-Larranaga et al., 2011) and, conversely, fewer primary care physicians per capita was significantly associated with more preventable hospitalisations (Zhan et al., 2004).

Griffiths et al. (1997) found that higher admission rates for asthma were strongly associated with small size of practice partnership, with admission rates of single-handed and two-partner practices higher than those of practices with three or more principals by 1.7 times and 1.3 times respectively. Practices with higher rates of night visits also had significantly higher admission rates.

Ferguson et al. (2002) showed that a practice being part of the first-wave of fundholding (a form of capitation budgets) in the UK was associated with reduced levels of admissions (for cataracts).

Shorter distance from the primary-care practice to the hospital and smaller list size were both associated with higher admission rates (Bankart et al., 2011b). The study also found that emergency

admission rates decreased as the proportion of patients able to see a particular practitioner increased.

There also appears to be a supply-induced demand with more hospital beds leading to higher rates of admissions (Zhan et al., 2004). Ferguson et al. (2002) showed that a 10% increase in a practice's experienced waiting time (that is the median wait of patients referred from that practice for secondary care) reduced its admission rate (for cataracts) by 2.5%.

Although ACSCs are described as a set of conditions for which admission into secondary care is thought to be avoidable through better primary care, there likely exists some irreducible minimum that cannot be eliminated. Further, primary care will not have control over all of the factors that will affect the number of ACSC admissions: in particular, the characteristics of the local population.

When trying to measure how good or bad the primary care provided is, or what effect a particular characteristic has, a risk adjustment will need to be made to allow for the different types of patients they have. Many studies have looked at what patient characteristics are associated with increased levels of admissions.

Previous studies (Zhan et al., 2004) suggest that socioeconomic characteristics of a population, health status measured by mortality and low birth rate, and local supply of physicians and hospitals affect hospital use in general. More specifically, previous studies such as those by Downing et al. (2007), Calderon-Larranaga et al. (2011) and Bankart et al. (2011b) suggest that hospitalization rates due to ACSCs are higher among persons who are of advanced age, female gender, poor health and white ethnicity. Calderon-Larranaga et al. (2011) found that higher admission rates for chronic obstructive pulmonary disease (COPD) were also strongly associated with smoking prevalence.

In the most comprehensive study of its type, Ansari et al. (2012) examined the patient characteristics associated with admissions for an ACSC in Victoria, Australia. The authors looked at all individuals who had an ACSC and were admitted as inpatients to any hospital (public or private) in the state of Victoria and discharged in the period 1 July 2003 to 30 June 2004. In addition, a contrast group was assembled consisting of a random sample of patients who did not have an ACSC.

The study included a total of 171,782 admissions for ACSCs: 151,114 among the adult population (those 65 years old or over) and 20,668 among the paediatric population (those 18 years old or younger). It found that the crude admission rates for both ACSCs and non-ACSCs increased with age among the adult population, and decreased with age among the paediatric group. The significant predictors of ACSC admissions varied between the adult and paediatric groups. For both the adult

and paediatric groups, rurality and areas of residence of least accessibility were significantly associated with total ACSC admissions. For the adult population, however, significant differences in ACSC admission rates were observed across sex, age, place of residence, degree of remoteness, and socio-economic disadvantage. Specifically, males were six percent more likely to be admitted with an ACSC compared to females; ACSC admission rates increased by 13% per five-year increase in age category; ACSC admissions were 15% more likely among rural residents compared to their metropolitan counterparts; ACSC admission rates increased by 11% for each degree increase in ARIA category (ARIA is an accessibility measure that gives the relative accessibility and remoteness of local areas in Victoria, with three categories: "Highly Accessible", that is relatively unrestricted accessibility to a wide range of goods and services and opportunities for social interaction; "Accessible", that is some restrictions to accessibility of some goods, services and opportunities for social interaction; and "Moderately Accessible", that is significantly restricted accessibility of goods, services and opportunities for social interaction); and increasing socio-economic disadvantage of an area was associated with a 6% increase in ACSC admission rates.

The characteristics also varied by the type of ACSC considered. For instance, being male, in an inaccessible area, from a disadvantaged socio-economic group and being in an older age group were all associated with higher diabetes admissions. Whereas for dehydration and gastroenteritis, being female, in a mid-inaccessible area, from a disadvantaged socio-economic group and being from a younger age group were all associated with higher admission rates.

1.3.2 Interventions aimed at reducing ACSC admission rates

Interventions in primary care might be expected to reduce use of secondary care in three broad ways: by improving the health of the population; by reducing demand for secondary care once a clinical condition has been identified; and by reducing the intensity of specialist care once an acute need has been identified. (These broadly align with the three categories of ACSC, namely: vaccine preventable, chronic and acute.)

> **Improving the health of the population**, thereby reducing the incidence and severity of disease and the associated need for specialist care.
>
> In this domain, the prime role of primary care might take the form of conventional disease prevention activities, such as vaccination programmes, or influencing behavioural change aimed at reducing the risk of future disease. This would likely impact most on the vaccine preventable ACSCs, but would also, over the slightly longer term, impact on the number of people, and severity of, chronic illness and could therefore impact on the chronic ACSCs. For

instance, a risk factor for COPD is smoking and therefore a programme aimed at reducing the number of people smoking ought to lower the incidence of COPD.

Reducing the demand on secondary care once a clinical condition has been identified.

This will usually be in the form of chronic disease management (for instance, reducing emergency admissions for diabetes complications). Many of the activities in this area can be considered under the generic heading of 'disease management' and will impact most on the chronic ACSCs.

Reducing the intensity of any specialist utilisation once a need for specialist care has been identified.

This role can be considered under the general heading of care integration and may take the form of task substitution (performing some specialist tasks in a lower cost primary care setting) or patient monitoring (allowing earlier discharge of a patient from specialist care). Interventions considered under this heading will have most impact upon the acute ACSCs. They will also impact on other ACSCs should they become more serious (perhaps because they have not been managed properly).

Each of these broad areas for interventions aimed at reducing ACSC admission rates is now considered in turn.

1.3.2.1 Improving the health of the population

There is a longstanding belief that, when effectively used, primary care can improve the health of the population and prevent, mitigate or defer the development of health problems that would otherwise give rise to costly use of health services, including specialist care. Relevant actions might take the form of preventative medicine (immunisation, vaccination etc.), behavioural advice (on smoking, alcohol, diet etc.) and timely intervention when there are early indications of disease (from screening or other diagnostic instruments).

The most rudimentary role of primary care in all health systems is to ensure that children and other vulnerable people are properly vaccinated and immunised against infectious disease. Most developed health systems have arrangements in place to ensure high levels of such interventions are secured, particularly amongst children.

There is less uniformity in approaches to interventions aimed at reducing actions that are considered 'risk factors' for future disease such as smoking tobacco and alcohol consumption. These

interventions are well suited to a primary care setting and, if undertaken effectively, are likely to have an impact on the number of admissions into secondary care.

For example, the National Institute for Health and Clinical Excellence (NICE) in England recommends that a brief intervention in the primary care setting is carried out for each patient, referring those that smoke to a smoking cessation program (NICE, 2006). The intervention is deemed to be cost-effective in England. An area with an adult population of 131,000 could expect to incur additional costs of £18,000, with an 11 year saving for acute myocardial infarction and stroke of £210,000. The estimate is based on the work of Naidoo et al. (2000) who modelled the expected impact of the intervention by altering the survival probability of those it would affect over time.

Godtfredsen et al. (2002) looked at the effect of a Danish smoking cessation program on chronic obstructive pulmonary disease (COPD) admissions. They found that quitting smoking was associated with a significant reduction in the risk of hospital admission. They noted that those who reduced smoking did not show a significantly lower risk of hospitalisation than continuing heavy smokers.

Although smoking cessation interventions carried out in a primary care or community setting are known to be cost effective relative to other medical interventions (Fiore et al., 2000), a study in 2001 found that just 21% of patient visits to their primary care physician included a discussion about tobacco use (Ellerbeck et al., 2001). Of those identified as smokers, 38% were provided with smoking cessation assistance.

NICE recommends that to tackle alcohol abuse an opportunistic screening of adults should take place in primary care. Unlike organised screening, in which sections of a population are identified, contacted and offered a screen, opportunistic screening takes place on an ad-hoc basis, in this case whenever someone visits their GP and the GP deems it necessary. Those that are found to be harmful or hazardous drinkers would then be offered a further session of brief advice on how to reduce their alcohol consumption to a safer level. An economic analysis confirmed that several examples of providing screening and brief advice are estimated as providing cost savings (through providing additional healthcare benefits and an overall reduced health service cost) (Purshouse et al., 2009). The analysis indicated that NHS and personal social services savings over £124.3 million may be realisable over a 30-year time horizon.

Interventions aimed at securing behavioural change are in general at an early stage of development. They may become crucial to the future financial sustainability of publicly funded health systems and it is likely that primary care will play a central role in delivering such interventions. However, although successful behavioural interventions will unambiguously deliver improvements in the

length and quality of life, there remains a question over the sign and magnitude of their long term financial impact on the health system. They may lead to a longer lived population that places new demands on the health system in the form, for example, of long term care. There is a clear need for increased use of population microsimulation methods to assess the long term impact of public health interventions on the health system (Zucchelli et al., 2010).

1.3.2.2 Reducing the use made of secondary care

Once a health need has arisen, there might be an important role for primary care in its treatment and management, thereby affecting costs. Examples might include treatment by primary care of minor trauma or other interventions that would otherwise require more costly secondary treatment, or the effective management by primary care of established chronic disease (such as diabetes or hypertension), thereby reducing emergency use of specialist care.

A lack of primary care provision might be one cause of increased secondary care usage. Parchman and Culler (1999) found in a US Medicare study, that beneficiaries in fair and poor health, were 1.7 times more likely to experience a preventable hospitalisation if they resided in a primary care health professional shortage area, after controlling for educational level, income and supplemental insurance. Similarly, Macinko et al (2010) showed that, in Brazil, hospitalisation rates for ambulatory care-sensitive chronic diseases were 13% lower in municipalities with high enrolment in their Family Health Program compared to municipalities with low enrolment, when other factors were held constant.

Many acute, minor problems in clinical practice are dealt with in hospital accident and emergency (A&E) departments without referral from general practice, even though they might readily be adequately managed by the primary health care team. Problems brought by patients to A&E which are thought to be more suitable for assessment and management by a GP include minor injuries and lacerations, acute infections, most eye problems and bites (Myers, 1982).

In the UK, for example, as many as a quarter of those attending A&E departments present with minor injuries or illnesses not requiring specialist attention (Lowy et al., 1994). There is therefore large scope for potential savings from providing care for these patients. From a cost-effectiveness perspective, the key question is what, if any, sacrifice in clinical quality arises.

Roberts and Mays (1998b) looked at three controlled trials where GPs were based within A&E departments in inner city locations (King's College Hospital and St Mary's Hospital in London and St James' Hospital in Dublin). They found lower general use of diagnostic investigations by the GPs and fewer referrals to secondary services. The King's College study found a more marked difference in

usage of X-rays and, unlike the Dublin study, also found that hospital doctors were more likely to prescribe than GPs. There was no evidence of any significant difference in patient satisfaction or health outcomes between GP and hospital doctor management. Both the King's College hospital study and the Dublin study found that employing general practitioners resulted in cost savings.

The role of primary care is likely to be most important in the area of chronic disease. One of the key challenges for health systems in the developed world (and many in the developing world) is the rising prevalence of non-communicable diseases associated with an ageing population and increases in risk factors such as obesity. Disease management programs are increasingly being implemented in healthcare systems worldwide in order to enhance the quality and reduce the cost of caring for those with chronic illnesses. Mattke et al. (2007) define disease management as a patient centred approach of coordinated multiple healthcare interventions that structure chronic care to a specific patient group. One influential model of disease management is the Chronic Care Model (CCM) developed in the US by Wagner et al. (2001a) (see Table 1.2 for a breakdown of its components).

Table 1.2 – The Chronic Care Model

The Chronic Care Model

In an effort to create a framework that primary care could use to improve the delivery of interventions that would improve the care of those with chronic conditions in America, the Chronic Care Model (CCM) was developed by Wagner et al. (2001a).

According to Bodenheimer et al. (2002a) there are six key components to the CCM framework:

1. *Health care organisation*

The reimbursement environment of a provider organisation has a major impact on chronic care improvements, which are more likely to survive throughout the long term if they increase revenues or reduce expenses. If purchasers and insurers fail to reward chronic care quality, improvements are difficult to sustain.

2. *Community resources and policies*

The longer time horizon and fluctuating course of many chronic illnesses requires regular interaction between caregivers and patients. To improve chronic care, provider organisations need linkages with community-based resources, e.g. exercise programs, senior centers, and self-help groups, as they are able to provide more frequent support.

3. *Self-management support*

For chronic conditions, patients themselves become the principal caregivers. People live with chronic illness for many years. Management of these illnesses can be taught to most patients and substantial segments of that management — diet, exercise, self-measurement (e.g. using glucometers or bathroom scales), medication use — are under the direct control of the patient.

4. *Delivery system design*

The structure of medical practice must be altered, creating practice teams with a clear division of labour, separating acute care from the planned management of chronic conditions. Physicians treat patients with acute problems, intervene in stubbornly difficult chronic cases and train team members. Non-physician personnel are trained to support patient self-management, arrange for routine periodic tasks (e.g. laboratory tests for diabetic patients, eye examinations and foot examinations) and ensure appropriate follow-up. Planned visits are an important feature of practice redesign.

5. *Decision support*

Evidence-based clinical practice guidelines provide standards for optimal chronic care and should be integrated into daily practice through reminders. Ideally, specialist expertise is a telephone call away and does not always require full specialty referral. Guidelines are reinforced by physician “champions” leading educational sessions for practice teams.

6. *Clinical information systems*

Computerised information has 3 important roles: First as reminder systems that help primary care teams comply with practice guidelines; second as feedback to physicians, showing how each is performing on chronic illness measures such as HbA1c and lipid levels; and third as registries for planning individual patient care and conducting population-based care.

The components of the CCM model listed in Table 1.2 are intended to help with the re-design of primary care to improve care for patients with chronic conditions. A systematic review evaluated the impact of disease management programs that contained two or more of those CCM components for diabetes, depression, heart failure and COPD (de Bruin et al., 2011). It found that, of the studies that reported changes in healthcare costs, 13 out of 21 showed a decrease in overall costs. Overall costs varied between -$16,996 (a system cost saving) and $3,305 (an increase in system cost) per patient per year (2007 prices). The results suggest that the effect is most positive for disease management programs for patients with heart failure and least positive for patients with depression. The study found no correlation between particular components of the program, or the number of components, and the overall cost saving associated with the program. It concluded that the evidence for proving that disease management programs saved money was still inconclusive and that further economic evaluations were required.

Other studies have looked at specific interventions that have been introduced by primary care to help improve care for those with chronic diseases and, ultimately, reduce the cost to the system of the patient. Some of the key interventions that have been found to be cost saving are explored below.

1.3.2.2.1 Patient Education

Pieber et al. (1995) found, in a study of diabetic patients participating in a structured education and treatment program in rural Austria, that programme patients had lower health care costs after six months compared with a control group.

At a staff-model health maintenance organisation (HMO), children who had asthma were offered a single educational session. The group showed a 40% reduction in emergency department visits (Greineder et al., 1999).

Whereas traditional patient education offers information and technical skills, self-management education teaches problem-solving skills. A central concept in self-management is self-efficacy – confidence to carry out behaviour necessary to reach a desired goal. Self-efficacy is enhanced when patients succeed in solving patient-identified problems. Evidence from controlled clinical trials suggests that programs teaching self-management skills are more effective in improving clinical outcomes for arthritis and adult asthma than information-only patient education. In some circumstances, self-management education improves outcomes and reduces costs (Bodenheimer et al., 2002a).

The Expert Patients Programme (EPP) was launched by England's Department of Health in 2001 with the aim of establishing lay-led self-management programmes in the NHS. An evaluation by Rogers et al. (2006) of the pilot programme found that the intervention was cost-effective compared to a control due to improvements in health outcomes and there being little difference in costs. Total costs in both groups were similar as the increased patient costs together with the cost of delivering the intervention was offset by reductions in resource use. The costs to the NHS were substantially lower in the intervention group, supporting the hypothesis that enhancing self care reduces resource use elsewhere.

Rich et al. (1995) demonstrated in a randomised controlled trial that a nurse-directed program of patient education, with post-hospital telephone and home visit follow-up (self-management support combined with delivery system redesign in the CCM terminology), was associated with a 56% reduction in hospital readmissions for congestive heart failure (CHF) and a significant improvement in quality-of-life scores compared with controls. Within a 90-day period, the overall cost of care was $460 less per patient in the treatment group. Stewart et al. (1999) showed that using a similar, but less intensive, intervention led to a 52% reduction in hospital costs for the intervention group during an 18-month period, resulting in overall savings. Cline et al. (1998) found similar cost reductions with a program of self-management support and a nurse directed CHF clinic.

Bolton et al. (1991) demonstrated that adult asthma patients given self-management support made fewer emergency department visits throughout a 12-month period compared with a usual care group, with the $85-per-person cost for the educational sessions offset by the $628-per-person reduction in emergency department charges.

Compared with usual care, a home-based health education program for low-income children previously hospitalised with asthma saved $11 for each dollar spent to deliver the health education (Clark NM, 1986). For children without a recent hospitalisation, costs for the two groups were the same.

However, in three other studies (Wilson et al., 1993, Bailey et al., 1990, Vojta CL, 1999), self-management support interventions did reduce health care use but the control groups showed similar reductions. In a study with a longer follow-up period, Kauppinen et al. (2001) found no significant reduction in health care costs after 5 years for adult asthma patients given intensive patient education throughout a one-year period. And Lahdensuo et al. (1998) found that for patients with mild to moderately severe asthma health care costs were actually higher for the group receiving a self-management program than for a usual care group.

This last result illustrates the challenges associated with patient education programmes. They are likely to increase patient awareness and improved health status. However, this may also lead to increased healthcare utilisation, at least in the short and medium term. The question for evaluation is the extent to which longer term specialist costs are averted by the intervention, an area that is by its nature difficult to assess empirically.

Bury et al. (2005) conducted a systematic review of 19 studies on lay-led self-management education programmes for chronic illnesses including chronic heart failure, lung disease, stroke, or arthritis. In self-management programmes, sufferers of these illnesses formed support groups to foster self-efficacy for the care and management of fellow individuals. Out of the 19 studies considered by Bury and colleagues, only two studies were found relevant, and these found that lay-led self-management programmes were effective in reducing hospitalisation. However, the authors commented that the utility of lay-led self-management was dependent on other care components.

Newman et al. (2004) conducted a systematic review of self-management educational interventions for type 2 diabetes, asthma and arthritis. The authors reported that self-management education was beneficial in reducing hospitalisations for the management of asthma. However, reduced hospitalisations was not one of the outcomes for the management and control of diabetes or arthritis.

Lorig et al. (2001) found self-management education by peer-educators was effective in the short term, but that the reduction in hospitalisations was not statistically significant after 2 years of the programme. The authors concluded that self-management education by peer-educators may be effective for reducing ACSC admissions when it is provided with other programmes, but the effects may be short term.

1.3.2.2.2 Enhanced Access

One of the reasons for unnecessary use of specialist emergency care is the poor access to primary care, especially out of normal office hours. In Australia, Hamitton (2007) found that patients report that GP accessibility is by far the strongest factor in the decision to attend the emergency department rather than a GP practice. Cowling et al. (2013) found that general practices providing more timely access to primary care had fewer self-referred A&E visits per registered patient and Cowling et al. (2014) found that 26.5% of unplanned A&E attendances in England in 2012/13 were preceded by the attending patient being unable to obtain a general practice appointment or one that was sufficiently convenient.

Increased access to GP services may therefore prevent some of these patients attending the emergency department. Advanced access, open access or same-day scheduling, as it is varyingly known, where practices offer patients same-day appointments, is described by Murray and Berwick (2003) and proposed as a potential method for reducing waits and improving primary care access.

However, the evidence is again equivocal. In a study of CHF patients discharged from nine Veterans Affairs hospitals, Oddone et al. (1999) compared usual care with an intervention including patient education, nurse telephone follow-up and enhanced access to primary care. The number of hospital readmissions did not differ between the two groups and the number of outpatient visits was actually higher in the intervention group.

1.3.2.2.3 Cluster visits

An important constraint to the delivery of complex healthcare, especially amongst elderly patients, is the need to coordinate consultations with a range of healthcare professionals. Care may be suboptimal, and resources wasted, if patients are unable or unwilling to make all the necessary visits. Primary care is the obvious setting in which such coordination can take place. Kaiser Permanente studied the impact of co-locating a multidisciplinary team so that each relevant member can meet the patient during a single visit (Sadur et al., 1999). The six-month program for diabetes care resulted in reduced hospital and outpatient use compared with usual care. The multidisciplinary outpatient diabetes care management was delivered by a diabetes nurse educator, a psychologist, a nutritionist and a pharmacist in cluster visits.

However, a study looking at a similar setup for CHF patients found that it returned no overall cost reductions compared with usual care (Riegel et al., 2000). Interestingly, although the intervention led to increased costs for class I patients (those with the mildest symptoms), it did create savings for class II patients (those with moderate symptoms). This suggests that better patient selection may make this a more cost-effective intervention.

1.3.2.2.4 Case management

Primary care is also an obvious setting in which 'case management' of patients with complex medical needs can be organised, with the intention of improving health status and reducing the need for emergency care. At a staff-model health maintenance organisation (HMO), children who had asthma were enrolled in a nurse case-management program. The group had 73% fewer emergency department visits and 84% fewer hospitalisations, with savings greatly exceeding programme costs (Greineder et al., 1999).

Stewart et al. (2002) calculated that it would be cost-effective to introduce a specialist nurse-mediated, post-discharge management service for heart failure for the whole population (of the UK). The authors suggest that such a service would not only improve quality of life and reduce admissions in patients with congestive heart failure, but also reduce costs.

Domurat (1999) looked at an intervention aimed at high-risk diabetes patients from Kaiser Permanente in which the patients were intensively managed by a team that offered planned diabetes visits, telephone contacts and group educational sessions. The study found that patients in the intensive program stayed half as long in the hospital as those in the control group. One of the findings of the study was that patients discharged from the intensive-management program may revert to their pre-program status, which suggests that ongoing case management is needed and that the continuing costs need to be balanced against the savings elsewhere.

Johansson et al. (2001) evaluated the effect of an individual support intervention on the utilisation of specialist care among cancer patients. They found that the intervention reduced the number of admissions and the length of stay (LOS) after adjustment for weight loss and psychological distress, but only for older patients (those aged 70 or older). The intervention included intensified primary healthcare comprising of extended information from specialist clinics, education and supervision in cancer care for general practitioners and home-care nurses.

1.3.2.2.5 Improved glycaemic control

Improved glycaemic control is seen as a core component of managing diabetes patients. In contrast with programs for CHF and asthma, which might be expected to produce cost savings almost immediately through reduced hospital and emergency department use, programs that improve diabetic glycaemic control might be expected to show savings only in the long-term through reduced vascular complications. However, some studies have shown that improved diabetes care can lead to cost reductions even in the short run. Wagner et al. (2001b) compared two groups of diabetic patients throughout one year and found the organisation was saving between $685 and $950 per patient annually for the group with improved HbA1c levels. The savings resulted from fewer hospital admissions, emergency department visits and physician consultations. Savings were statistically significant only for patients in the improved group whose baseline HbA1c level was 10% or above. Measuring HbA1c is a way to measure blood glucose levels – an important indicator for diabetics. For non-diabetics a usual reading would be in the range 4.0-5.9%. For people with diabetes an HbA1c level of 6.5% is considered good control. However, this study did not take into account the cost of the intervention and, therefore, overall cost-effectiveness could not be assessed. In a similar

vein, Testa and Simonson (1998) showed that improved glycaemic control of type 2 diabetes was associated with short-term reductions in hospital stay.

1.3.2.2.6 Pharmacist provided patient education and monitoring

It is likely that pharmacists can fulfil some of the primary care roles described above. Munroe et al. (1997) found that total health care costs dropped for diabetic patients enrolled in a program in which specially trained pharmacists provided patient education, monitoring and feedback to physicians, when compared with a control group. Further, pharmacists are well placed to bring down the number of adverse drug events. Schnipper et al. (2006) found that pharmacist counselling at discharge and a follow-up phone call 3-5 days later led to a reduction in preventable adverse drug events from 11% of patients in the control group to one percent in the intervention group. Gillespie et al. (2009) found that ward-based pharmacists led to a 16% reduction in hospital visits and a 47% reduction in emergency department visits. Drug-related readmissions were reduced by 80%. After inclusion of the intervention costs, the total cost per patient in the intervention group was $230 lower than in the control group.

1.3.2.2.7 Telehealth

"Telehealth" typically includes telemonitoring and telecare/telecounselling. Telemonitoring is transmitting information about clinical indicators, such as blood pressure, over a telephone or modem. Telecare/telecounselling involves provision of healthcare consultations over a telephone, videoconference, or via the internet. Pare et al. (2007) conducted a systematic review of 65 studies that evaluated the effectiveness of telemonitoring in the management of four types of chronic illnesses: cardiovascular diseases, diabetes, hypertension, and pulmonary diseases. Telemonitoring was associated with significantly reduced hospitalisations for cardiovascular and pulmonary illnesses but nothing was reported about hospitalisations in this study relating to hypertension and diabetes. Hersh et al. (2001) conducted a large systematic review of 25 trials and 2333 patients. This study compared telecare and two aspects of telemonitoring (blood sugar monitoring, automated patient monitoring) versus usual patient care for all hospital admissions, and found that the strongest evidence for efficacy of teleheath interventions in clinical outcomes is in applications of home-based telecare in chronic disease management, and in the management of hypertension and HIV infection. The review did not find telemonitor-based interventions reduced ACSC admissions. The results suggest, therefore, that the effectiveness of telehealth applications for reducing ACSC admissions for all or multiple causes is uncertain, and are fraught with issues with research methods.

However, there are several individual studies indicating the effectiveness of telemonitoring in reducing hospitalisations from chronic heart failure in elderly patients. Welch et al. (2000) conducted a large multi-centre randomised controlled trial of a telephone appointment and follow-up programme in three United States Veterans Affairs (VA) medical centres. More than 2000 calls were made to patients who were suffering from a range of chronic diseases (n = 512; mean age 68) and the providers had access to the same information during 'telephone visits' as 'in clinic' visits (or 'usual care'). The authors reported that the telephone care intervention had little effect, and, over 24 months, there was no change in the rate of re-admissions (0.5 intervention vs. 0.5 control). Welch and colleagues concluded that instead of providing a way to maintain contact with patients without requiring them to appear in clinic, telephone appointments appeared to become simply an additional service. Lattimer et al. (2000) trialled a programme of telephone consultation by specially trained nurses using decision support software in an out-of-hours general practice setting. Lattimer and colleagues randomised 14492 adults and children enrolled in a GP cooperative across 55 medical centres in the UK, to receive telephone consultation or usual care. The authors reported that, at 12-month follow-up, the nurse service was associated with reduced admission to hospital for both adults and children, but this did not reach statistical significance.

1.3.2.3 Reducing the intensity of specialist utilisation

Once access to specialist care has been secured, the intensity of use, and therefore the costs of that care, might be highly dependent on the organisation and capacity of primary care. The cost-effectiveness for an entire episode of care will often depend on the integration of specialist, primary and social care. In particular, with a well-functioning system of primary care, it might be feasible to discharge a patient from hospital sooner than would otherwise be the case, without increased risk to the patient's health. To this end, some aspects of rehabilitation might be undertaken in a community rather than hospital setting, and primary care might implement monitoring systems that increase the potential for telemedicine and initiatives such as 'hospital at home'.

A systematic review found that the effectiveness of simple outreach programmes (where specialists see patients in a primary care setting) was uncertain (Bazian, 2005). However, 'enhanced' outreach (entailing intense involvement of specialists in primary care) was associated with improvements in appropriateness of care, symptoms, patient satisfaction and concordance. The study could not identify which elements of the intervention caused the improvements in care. In particular, the mental health studies identified in the review examined a wide-ranging and intensive attempt to improve care. The shift of the psychiatrist from the hospital to the community was only one part of the intervention and was not considered the most important by the investigators. The authors

suggest it may be that a thorough programme of patient and primary care clinician education, without specialist clinical contact, would have had similar benefits and that this approach would still enable primary care clinicians to provide appropriate care for a wider range of patients, some of whom might otherwise have been referred to secondary care, without compromising the availability of clinicians in secondary settings. They concluded that this approach might cost less, be more efficient and lead to better care than full outreach. The study did not, however, look at system cost and the authors do not speculate on whether they believe the interventions saved money overall.

A similar scheme, one of a number called Hospital at Home, which sought to reduce the number of people requiring inpatient care by treating them at home, was found to save expenditure (Jones et al., 1999). Hospital at Home can provide an alternative to inpatient care in two ways—early discharge of patients from hospital or avoidance of admission.

Patel et al. (2004) evaluated the costs of stroke care in three different settings – stroke unit, stroke team and domiciliary stroke care – and found that, over a 12 month period, domiciliary care was the cheapest setting. The incremental cost between domiciliary care and stroke unit care was £64,097 per quality-adjusted life year gained, leading the authors to conclude that cost perspectives are important when stroke services are evaluated and that the improved health outcomes in the stroke unit come at a higher cost (currently in excess of the usual threshold for accepting new technologies in England).

One reason for unnecessary specialist costs may be that a patient's home circumstances make early discharge from hospital infeasible (for example, if there is no caregiver at home), leading to so-called 'blocked' hospital beds. This outcome is particularly likely to arise in systems where hospital and social care are delivered by separate agencies. In England and Wales, the health services have the power to fine local governments a daily tariff for delays in discharge caused by local social care failures. In an alternative model, local hospital and social care services were encouraged to work collaboratively by applying for special grants to improve community services. A study in 2007 found that almost two thirds of hospitals opted not to charge the local governments, but instead opted to work collaboratively (McCoy et al., 2007). The study found no improvement in delayed discharge bed days, beyond what the authors deemed to be a long-term trend of reduction.

Holmas et al. (2010) studied the effects of fining owners of long-term care institutions in Norway who prolong hospital LOS, driving hospital costs upwards and causing bed-blocking. They found that areas that introduced fines for 'bed blocking' actually had higher LOS than areas that did not. The

authors propose that this is due to the fines 'crowding out' the intrinsic motivation that the long-term care institutions already had for bringing down LOS.

Steventon et al. (2012a) looked at two interventions requiring higher levels of primary care – intermediate care and integrated care. They compared outcomes to a control group. The intermediate care intervention aimed to support older people following discharge from the local general hospital. Multispecialty teams visited the wards of the hospital on a daily basis, coordinating the discharge of patients into the care of community-based generic health workers who performed health tasks such as monitoring blood pressure and testing blood and urine. The integrated care intervention involved care management for older people. Multidisciplinary teams were established. Patients could be referred to the teams for support for social care needs by general medical practitioners or, after assessment, by the local authority. The study found that the intermediate care group had a higher number of unscheduled admissions into hospital and the integrated care group showed no difference. Both interventions led to higher rates of mortality than seen in their matched control groups.

Casas et al. (2006) showed that a standardised integrated care intervention, based on shared care arrangements among different levels of the system with support of information technologies, effectively prevents hospitalisations for exacerbations in chronic obstructive pulmonary disease patients. After 12 months' follow-up, the intervention showed a lower hospitalisation rate (1.5 versus 2.1) and a higher percentage of patients without re-admissions (49% versus 31%). The study did not differentiate between COPD admissions more generally and ACS COPD admissions. The intervention involved 4 key components. Firstly, it involved a comprehensive assessment of the patient at discharge, including severity of the respiratory disease; evaluation of comorbid conditions; and analysis of requirements in terms of social support. Secondly, an educational programme on self-management of the disease was administered at discharge, as described below. Thirdly, agreement on an individually tailored care plan following international guidelines was shared across the system via interaction between the specialised nurse, case manager and the primary care team. Fourthly, accessibility of the specialised nurse to patients/carers and primary care professionals during the follow-up period was ensured through an ICT platform including a web-based call centre.

Kruis et al. (2013) performed a systematic review on an intervention approach called integrated disease management (IDM). IDM was introduced as a way of improving quality and efficiency of care. IDM interventions are aimed at reducing symptoms and avoiding fragmentation of care, while containing costs. There is no consensus in the literature about the definition of IDM, but Schrijvers (2009) proposes a definition: "Disease management consists of a group of coherent interventions

designed to prevent or manage one or more chronic conditions using a systematic, multidisciplinary approach and potentially employing multiple treatment modalities. The goal of chronic disease management is to identify persons at risk for one or more chronic conditions, to promote self-management by patients and to address the illness or conditions with maximum clinical outcome, effectiveness and efficiency regardless of treatment setting(s) or typical reimbursement patterns". Kruis et al. (2013) found that people who participated in an IDM program had better quality of life and improved their exercise tolerance after 12months. Furthermore, in participants treated with such a program, the number of hospital admissions related to exacerbations decreased, and the total number of hospital days was reduced by three days.

Finally, Jacklin et al. (2003) looked at an intervention called virtual outreach, in which a "teleconsultation" (real-time consultations in which doctors and patients are separated geographically but communicate through the use of videoconferencing) are used instead of a normal outpatient visit. The authors found that over a six-month period costs were greater for the virtual outreach consultations than conventional outpatient appointments; the equipment used, which might be expected to reduce in cost over time, only accounted for some of this greater cost, with increased consultant and general practitioner time accounting for the rest. There was a saving to patients in terms of costs and time. However, this did not outweigh the additional cost of the intervention.

An alternative to specialists undertaking outreach services is the concept of general practitioners with special interests, under which general practitioners specialise in a particular area and are able to run the equivalent of a specialist clinic for relevant patients. Coast et al. (2005) looked at the cost of a general practitioner with special interest service for dermatology and found that it was more costly than traditional hospital outpatient care.

1.3.2.4 A note on intervention characteristics

It is important to note that choosing which patients participate in an intervention can have a large impact on whether the intervention is cost saving or not. As noted by Russell (2009), careful choices about frequency, groups to target and component costs can increase the likelihood that interventions will be highly cost-effective or even cost saving. Illness severity may also play an important role. Risk-stratifying chronic illness and targeting interventions where they are most effective may be a cost-effective strategy.

It is also worth noting that the extent to which interventions were 'well delivered' is hard to judge from the studies mentioned. This is likely to have an impact on the interventions' effectiveness and

so could explain why there are mixed results even among similar interventions aimed at similar patient groups.

Interventions typically do not occur in isolation, and this is particularly the case once they become part of the normal care being delivered. (Lemmens et al., 2009) examined the effectiveness of multiple interventions as compared to single interventions or usual care on health outcomes and health care utilisation within the context of integrated disease management in asthma and COPD. Their systematic review included 36 studies. 17 of the 36 studies targeted double interventions (patient-related and organizational interventions). 19 of the 36 studies performed triple interventions (patient-related, professional-directed and organisational interventions). They were heterogeneous in terms of (combinations of) interventions, outcomes measured, study design and setting. Pooled data showed that the studied disease management programmes significantly improved quality of life on several domains. Patients within triple intervention programmes had less chance of at least one hospital admission compared with usual care. Clearly some interventions can therefore be complementary to each other, and indeed may not be effective at all on their own. It is therefore important to understand what other interventions are taking place wherever possible.

1.4 How is primary care incentivised to reduce admissions?

Many of the papers that looked at interventions that reduce hospital admissions point to 'environmental' factors that are deemed necessary (though not on their own sufficient) for interventions to be successful (Bodenheimer et al., 2002b). In particular, any method of paying the primary care practice or practitioner will create incentives and therefore have a potential impact on behaviour. The role of incentives is considered under two headings: the implicit incentives for use of specialist care inherent in any payment mechanism, and the explicit incentives to reduce the use of specialist care embodied in what are known as 'pay for performance' (P4P) payment mechanisms.

1.4.1 Implicit incentives

Implicit incentives for GPs in relation to specialist care depend on the details of the payment scheme. For example, if a practice receives an annual capitation payment or salary to look after a registered patient population, the practice may not have a direct interest in maintaining the health of that population, and may indeed have an incentive to shift the costs of care onto other providers, such as specialists and hospitals. In the extreme, a practice might encourage patients to use emergency care inappropriately or delay intervention until hospital treatment becomes necessary. Clearly such incentives can be moderated by the natural desire of clinicians to promote the health of their patients and by appropriate performance monitoring and other regulatory devices. For

example, rates of emergency admissions amongst elderly patients, or risk-adjusted avoidable hospital admissions, might be published. To be fully effective, such instruments may require implementation of other reforms, such as the ability of patients to easily change their GP.

The tendency for practices to encourage 'overuse' of specialist care can be countered by asking practices to manage a capitation budget for their population, from which they must purchase specialist care and other services for their patients. Under this system of 'budget responsibility', practices have an incentive to scrutinise the need for specialist care more critically, in order to adhere to their budget. They may then seek to delay or refuse some specialist referrals, or to treat some patients in a less costly primary care setting.

The strength of incentives under budget responsibility depends heavily on how 'hard' the budget constraint is made, and how much of any surplus the practice is able to retain. For example, recent attempts in England to implement 'Practice Based Commissioning' have been largely ineffective. One of the contributory reasons has been that in many localities the budgets given to general practices have been notional, with few sanctions for overspending or rewards for under spending (Audit Commission, 1996).

Between 1990 and 1998 the English NHS experimented with a scheme known as GP fundholding, under which GPs could elect to assume responsibility for a budget that covered routine non-emergency hospital treatments and pharmaceutical spending. Experiments of a similar design have been attempted elsewhere (Thorlby et al., 2011). The budgets for fundholders were quite soft in the sense that GPs' income was not directly at risk and surpluses had to be spent on some aspect of patient services. Deficits had few concrete adverse implications for many practices and were often guaranteed by the paying health authority (Audit Commission, 1996).

Dusheiko et al. (2006) studied hospital use by English practices before and after the abolition of fundholding in 1998. They estimated that fundholders made 4.9% less use of the relevant non-emergency hospital treatments than their non-fundholding counterparts, a difference that quickly disappeared after abolition. A crucial question however is whether the reduction in utilisation had any adverse impact on patients' health, an issue that researchers have been unable to address definitively. More generally, to be fully effective, any system of budget responsibility requires that health outcomes are monitored to ensure that expenditure control is not being secured at the expense of population health.

A further important issue under any system of budget responsibility for primary care is the level of risk inherent in healthcare budgets for small population groups, such as practice populations.

Martin et al. (1998) estimate that under the prevailing budget-setting regime, there was a 1 in 3 chance that annual expenditure of a typical fundholding practice (10,000 patients) would vary more than 10% from the budget. Although some of this variation might be due to clinical practice or weaknesses in the budget-setting process (and therefore amenable to improvement), some is due to the inherent stochastic nature of the need for health services, and is therefore completely beyond the control of the practice. Therefore very careful risk management (perhaps in the form of cost-sharing, stop-loss arrangements or removal of responsibility for high cost patients) is needed to avoid exposing practices to very high levels of budgetary risk.

Other implicit incentives relevant to specialist care may arise from the nature of the market in which primary care operates. For example, within a gatekeeping system patients may be able to choose their general practitioner. This might encourage more parsimonious use of specialist care if GP income depends on attracting patients and patients perceive unnecessary use of specialist care to be a signal of poor GP quality. On the other hand, GPs might compete on their willingness to offer patients easy access to secondary care, in which case a perversely high use of specialist care might arise. Assuming patients choose their GP partly on the basis of perceived quality, much will depend on the performance information made available to patients and how it is presented and explained.

1.4.2 Explicit incentives

Under P4P arrangements, clinicians or practices receive a payment for meeting certain structural, process, outcomes or other performance criteria. The common feature is that the activity or result being rewarded should either be a direct measure of patient benefit (in the form of improved health or patient experience) or some action that is known (from research evidence) to lead to improved health. Measures of patient benefit might include risk-adjusted mortality rates. Close proxies for population health, such as levels of blood pressure, have also been used. Process measures, such as adherence to clinical guidelines, are in common use. The most widespread mechanisms are direct payments for specific preventive measures, such as screening, immunisation and vaccination. However, health systems are increasingly seeking to reward broader indications of good healthcare delivery or health outcomes.

In 2004 the NHS in the United Kingdom introduced a pay-for-performance contract for family practitioners. This scheme, known as the Quality and Outcomes Framework (QOF), increased existing income according to performance with respect to about 150 quality indicators, including clinical care for 10 chronic diseases, the organisation of care and the patient experience. Practices

are rewarded according to the aggregate score achieved across these indicators, with up to 20% of practice income contingent on reported performance (Dusheiko et al., 2006).

Downing et al. (2007) found that higher QOF clinical domain scores were generally associated with lower hospital admission rates. There have since been several studies of QOF attainment in particular disease areas. For example, Shohet et al. (2007) found, after adjusting for practice population deprivation status, that there was a significant inverse association between the proportion of epilepsy-treated seizure-free patients (calculated using a QOF indicator) and the proportion of epilepsy-treated patients with at least one epilepsy-related emergency hospitalisation. For every one percent increase in the proportion of seizure-free epilepsy-treated patients, there was a 0.43% reduction in the number of patients with at least one epilepsy-related emergency hospitalisation.

Dusheiko et al. (2011) found that a 10% improvement (judged by the practices QOF score) in the general practice quality of stroke care between 2004/5 and 2007/8 reduced 2007/8 hospital expenditure by about £130 million in England. The cost savings were found to be mainly due to reductions in emergency admissions and outpatient visits, rather than to lower costs for patients treated in hospital or to reductions in elective admissions. In contrast, they found little evidence of savings arising in other specialities. In the same vein, Bankart et al. (2011a) found that there was no association between aggregate QOF scores and emergency admission rates.

In a paper looking at the introduction of a P4P scheme for primary care in Australia, Scott et al. (2009) examined the impact the scheme had on the number of HbA1c tests ordered. It found that the incentive program had a positive effect on quality of care in diabetes management. The magnitude of the effect was approximately a 20 percentage point increase in the probability of ordering an HbA1c test since the reform was introduced. The subsequent impact on hospital admissions and other use of specialist care was not reported.

Mullen et al. (2010) studied physician medical groups contracting with a large network HMO in the US to compare clinical quality before and after the implementation of two P4P programs. The first was a quality incentive program (QIP), which paid quarterly bonuses to medical groups performing at or above the 75th percentile from the preceding year on one or more of five clinical quality measures. One year after the QIP went into effect, the HMO joined forces with five other health plans in a coordinated P4P program sponsored by California's Integrated Healthcare Association (IHA), a non-profit coalition of health plans, physician groups, hospitals, and purchasers. Five of the six measures selected by the IHA were also targets of the original QIP program. The clinical service

measures rewarded by the program included cervical cancer screening, breast cancer screening, and HbA1c testing for diabetics. They did not find any association with readmissions or avoidable hospitalisations. The authors concluded that the P4P initiative resulted neither in major improvement in quality nor notable disruption in care. In particular, although some rewarded measures may have improved in response to the program, they did not find any evidence of positive 'spillovers' to other aspects of care. For instance, they noted that providers that made improvements to their IT to improve outcomes that were rewarded, such as automated reminders for appointments, did not appear to make the natural extension to use these IT improvements to increase performance on other measures if there was no obvious return, even when the cost was small.

Lester et al. (2010) looked at the introduction and then removal of a P4P program for patients from Kaiser Permanente. The program offered financial incentives based on yearly assessment of patient level glycaemic control (HbA1c <8 percent), screening for diabetic retinopathy, control of hypertension (systolic blood pressure <140 mm Hg) and screening for cervical cancer. The payment attached to each indicator was directed to its relatively large medical care facilities rather than to individual doctors, and doctors' income was not affected by the incentives. The study focused on two indicators; screening for diabetic retinopathy and screening for cervical cancer. The incentives for the two types of screening were removed during the study period. During the five consecutive years when financial incentives were attached to screening for diabetic retinopathy (1999-2003), the rate rose from 84.9% to 88.1%. This was followed by four years without incentives when the rate fell year on year to 80.5%. During the two initial years when financial incentives were attached to cervical cancer screening (1999-2000), the screening rate rose slightly, from 77.4% to 78.0%. During the next five years when financial incentives were removed, screening rates fell year on year to 74.3%. Incentives were then reattached for two years (2006-7) and screening rates began to increase. Across the 35 facilities, the removal of incentives was associated with a decrease in performance of about three percent per year on average for screening for diabetic retinopathy and about 1.6% per year for cervical cancer screening. The authors concluded that removing facility directed financial incentives from clinical indicators may mean that performance levels decline.

The academic literature has hitherto been cautious about the effectiveness of P4P programmes. Most schemes have been small scale and tentative, and researchers have struggled to find a material impact. However there has been some success at encouraging desired behaviour. And there is growing recognition that the provider payment mechanism is a crucial area for future experimentation. However, it is worth noting that any P4P scheme is open to creating perverse and

unintended consequences and systems are likely to be susceptible to gaming (Gravelle et al., 2009), so careful experimentation, audit and review will always be necessary.

1.5 The gap left to be filled by future research

To date there has been a surprising lack of research into which interventions are effective at reducing ACSC admissions (with the exception of some disease-specific areas, such as diabetes). Most of the studies found in the literature review evaluated interventions on the basis of whether they improved observed process measures (such as compliance with a particular clinical guideline). Few considered specific outcomes and fewer still considered whether they prevented admission into secondary care. There is a need to properly understand the impact that different interventions have on admissions rates for ACSCs. Whether an intervention in the primary care setting reduced admissions into hospital, in particular for ACSCs, is in many cases an afterthought. This leaves researchers evaluating data retrospectively to understand what effect the intervention had on the broader healthcare demands of the patient.

Some characteristics have been identified that impact on rate of admission for ACSCs, such as continuity of care with a general practitioner (greater continuity associated with lower admission rates) or the number of general practitioners within the practice (single-handed practices having higher admission rates), but the evidence is again limited, likely due to an historical lack of quality data in this area. By combining data on primary care from many different sources, this research will aim to evaluate a greater number of primary care characteristics than has been possible in previous research.

Where interventions or characteristics have been identified they are typically taken in isolation. While this allows a clearer understanding of their specific impact, it may not accurately reflect their use in a real-life situation, nor give a true view of the impact they will have when combined together. By modelling for the many patient and population attributes and the practice characteristics and quality, this research will aim to give a more detailed understanding of both the direct impact of interventions, as well as the specific conditions under which they appear to be applicable.

Though international research is a valuable guide, it cannot be known what other health system characteristics might be impacting upon rates (e.g. existing programmes that have been established for a different reason) and therefore whether results shown elsewhere in the world are truly transferable to the English healthcare setting. Based solely on data from practices in England, this research should either add further evidence that international results apply in England or that, due

to differing system conditions, they are not transferrable. This should be useful in particular for policy makers in England.

Moreover, although ACSCs are defined by the fact that they are conditions for which admission into secondary care is thought to be avoidable through better primary care, there is no research looking at what proportion of ACSC admissions are actually avoidable for a given population (though there appears to be an acceptance that they are not all truly avoidable).

Previous research notes that in some international examples where primary care coverage is not complete, such as in the United States, admission rates for ACSCs are used as an indicator of the level of access to primary care available in a particular area, or to a particular population type. Conversely, in the UK, where access to primary care is free at the point of use, ACSC admission rates are broadly accepted to be a reflection of the quality of primary care delivered. However, little work appears to have been done on the implications of using the ACSC admission rate as a performance metric, nor the extent to which the quality reflected in the ACSC admission rate is improvable by those working in the general practice. This research will attempt to fill this gap by understanding the extent to which an improved GP practice could reduce admissions and by considering how much of existing variation is due to factors outside the control of general practice, and therefore should not be included in a future performance metric.

There has recently – e.g. (Blunt, 2013) and (Naylor et al., 2013) – been a lot of interest in ACSCs in the UK, particularly among the policy think tanks, however this has not yet translated into academic research.

The research in this thesis will aim to fill some of the gaps identified in the academic literature, building on existing work and hopefully creating a solid foundation for future work by other researchers in this important area. The next section explains the structure of the thesis and gives an overview of the questions that each section will explore.

1.6 An Overview of Thesis Chapters

This thesis aims to answer a series of questions, namely: How do we predict ACSC admission rates, at the practice level, and what is associated with varying rates? How much can ACSC admission rates be improved? What interventions are reducing ACSC admission rates? Could ACSC admission rates be used as a performance metric for judging practice performance?

Below is a brief overview of the key objectives for each chapter of this thesis:

Chapter 1 introduces the thesis, gives the reader an understanding of why the work carried out in the rest of the thesis is important and, through a review of the academic literature, sets out the current state of knowledge in the study of how better primary care can lead to a reduction in avoidable admissions into hospital.

Chapter 2 sets out the hypotheses that the thesis tests and where this thesis aims to add to the academic literature.

Chapter 3 provides an overview of the methods used and data collected in each of the later chapters. Chapters 5 to 8 describe the data, methods and statistical techniques used in them in more detail, but where these chapters share many of the same features and data, they are discussed more generally in this chapter.

Chapter 4 presents some descriptive statistics that formed part of the original investigative analyses used by the author, including exploring the trends and potential reasons for variation in emergency and ACSC admission rates. This helps to build a useful understanding of why later hypotheses are tested and why they are important.

Chapter 5 seeks to model admission rates for ACSCs at the practice level using multiple linear regression and to understand what factors are associated with varying rates. To do this it builds three separate models. The first model uses just the population characteristics (for instance the prevalence of asthma in the population). The second model adds the GP practice characteristics that reflect a quantity of resource (for instance the number of GPs per head of population). Finally the third model adds to the second the GP practice characteristics that reflect the quality of the care provided (for instance the practice's QOF score).

Chapter 6 builds on the work in chapter 5 to create a condition-specific model, again at the GP practice level. It illustrates this process for four conditions (specifically asthma, COPD, diabetes and hypertension) and then shows how these separate models can be combined, using seemingly unrelated linear regression, to create an overarching model for all ACSCs.

Chapter 7 examines the question of whether, given the accuracy of the models created in chapters 5 and 6, the rate of admission for ACSCs, with a suitable adjustment based on how a practice performs verses some predicted rate, could be used as a metric for measuring how well practices, or groups of practices, are performing. It does this by first examining the size of the population that would be required to ensure that a given metric is suitably accurate and reflective of the quality (or lack of quality) of the practice(s) concerned, and not some random effect. It then looks at how much inefficiency exists within the system (i.e. how much could GP practices potentially improve if they

improved their efficiency to the levels of the better performing practices). It does this first using corrected ordinary least squares and then using stochastic frontier analysis.

Chapter 8 looks at four interventions taking place within the healthcare system (Patient advice and liaison service (PALS); Weight loss support groups; Information and support for diabetes; Information and support for mental health) and uses propensity score matching to examine the impact they have had on ACSC admission rates.

Chapter 9 concludes with a discussion of the thesis findings, why they are important to policy makers and how they fill important gaps in the academic literature. It then goes on to identify potential areas for future academic research in the area.

2 Hypothesis and Aims

This thesis has four key aims. The first is to model the admission rate for ACSCs into secondary care at the practice level. In doing so it aims to understand the factors related to varying rates. The hypothesis being tested is that there is an underlying level of morbidity M_i within the population of practice i given by the relationship $M_i = f(x_i, P_i)$, where x_i is a set of population characteristics and P_i is the quality of preventive care. The level of ACSC admissions A_i is then determined by the equation $A_i = g(y_i, M_i, Z_i)$, where y_i is a (potentially different) set of population characteristics and Z_i is a set of practice characteristics reflecting the quantity and quality of care available to patients. Substituting the first into the second yields a single equation: $A_i = g(w_i, Q_i)$, where w_i is a set of exogenous population characteristics and Q_i a set of practice characteristics (both resource and quality). In principle, Q_i may be determined in part by previous levels of ACSC admissions, and so might be considered endogenous. At this stage practice characteristics Q_i are treated as exogenous. This paper will test the validity of this model.

The second aim is to show that individual ACSC rates of admission into secondary care can be modelled, and understand how these factors vary from those associated with the all-ACSC admission rate. That is, it hypothesises that a given condition specific rate of admission $C_i = h(v_i, R_i)$, where v_i is a set of exogenous population characteristics and R_i a set of practice characteristics (both resource and quality).

The third aim is to evaluate the potential for using (an adjusted version of) ACSC admission rate as a metric to gauge the performance of a practice, or group of practices, and further to understand how much the practice(s) could improve by. The hypothesis is that practices will need to be grouped together to make such a metric meaningful and that there is likely to be inefficiency in the system that could be reduced to improve (i.e. lower) rates of admission.

The fourth aim is to identify interventions that are taking place in the health service that reduce ACSC admissions and to evaluate the extent of their impact. The hypothesis is that activities that are 'external' to practices can still have an impact on ACSC admissions.

3 Materials and Methods

What follows is an overview of the methods that will be used in each of the later chapters as well as the data that has been collected and linked. Chapters 5 to 8, in which the significant analysis has been conducted, each contain a 'methods' section that describes in more detail the data, methods and statistical techniques used within them. Where they share many of the same features and data they will be discussed more generally in this chapter. All analysis was either carried out using the statistical package Stata or Microsoft's Excel.

3.1 Literature review

To create the introduction a literature review was completed. The published peer-reviewed literature was searched using the Cochrane Library, Medline (Pubmed) and Google Scholar databases. The questions that the literature review sought to answer were: what are ambulatory care sensitive conditions; what affects the rates of admission for ambulatory care sensitive conditions; how are admissions for ambulatory care sensitive conditions reduced; and what incentives exist to encourage primary care to reduce admissions for ambulatory care sensitive conditions. The key search terms used were: "Ambulatory care sensitive conditions", "ACSC", "primary care reducing the cost of secondary care", "primary care interventions", "disease management programs", "long-term condition programmes", "primary care characteristics associated with reduced hospital admissions", "primary care ACSC", "asthma", "copd", "diabetes", "hypertension", "interventions" and combinations thereof where appropriate.

Studies were selected using a two-stage process. First, titles and abstracts (where available) identified from the search strategy were scanned and included or excluded as appropriate. Second, the full text articles were retrieved for the remaining studies and were included in the literature review if they were both relevant to the questions being asked and they were not excluded for any of the following reasons: non-English language; inappropriate study design; interventions were not intended to reduce hospital admissions and no reference was made to admission rates as an outcome indicator; or no control group result was given.

The reference lists of key papers were searched to identify any peer-reviewed evidence that may have been missed in the literature search. And, as a final check for completeness, advice was sought from experts in the field for paper recommendations.

To ensure all reviewed papers were from reputable and reliable sources, for any papers from unrecognised journals an assessment was made of the relevant journal and the paper authors, so as to ensure that the paper was of sufficient quality to be included.

Once all papers had been reviewed, results were grouped by type or area covered and a critical assessment was made by the author as to the strength of the evidence in that area. This is presented in the first chapter of this thesis and gives a complete and detailed analysis of the research evidence to date.

3.2 Study setting and data sources

This study uses existing data sources (typically administrative databases) to conduct quantitative analyses to answer a series of questions. The study examines general practices in England and data is combined from many sources (see below) to create a master data set that has the general practice as its base unit. The data covers the population for the whole of England that are registered to a GP practice. This is thought to cover the vast majority of the population. The homeless and travelling community make up most of the population not registered with a general practice.

Practices were excluded from the analysis if they had fewer than 500 patients registered on their list or less than 200 patients per GP headcount, both of which were taken as indicators that the practice was either very new or closing down. Practices were also excluded if they had not returned QOF data in more than one of the years included in the study. 7339 practices out of 7892 (93%) had complete data sets and were included in the analysis.

Data was stored on an encrypted hard-drive on a secure computer using a Stata database. Patient level data (from the HES dataset) was aggregated to the level of GP practice, such that no patient-identifiable information was being used or stored.

The datasets used for the analyses are outlined in detail below. All are either publicly available on the web or can be accessed with permission from the Health and Social Care Information Centre.

3.2.1 Hospital Episode Statistics

Hospital Episode Statistics (HES) was the key dataset used in the analyses. Other datasets are listed below in section 3.8. HES is a dataset containing details of all admissions to NHS hospitals in England. The data include clinical information about diagnoses (made in hospital) and operations performed; information about the patient, such as their age, gender and ethnic category; administrative information such as date of admission and discharge; and geographic information

such as where the patient was treated and where they were referred from. The data are made up of finished consultant episodes (FCEs) as its basic unit. That is the episode of care for which a named consultant has responsibility for the patient until they are either passed to another consultant or discharged. For this work the author had access to HES inpatient data for FCEs that finished between 1st April 2005 and 31st March 2011. This data was obtained from the Health and Social Care Information Centre. Each episode contains some additional information that relates to the 'spell' of which it is a part. A spell here describes the period from admission to discharge and each episode within a spell includes the admission and discharge dates. Because there are typically many episodes within a spell (or the period from admission to discharge) the first episode within the spell was used as a proxy for the admission, to avoid double counting.

In the Chapter 4 analyses that examine how emergency admission rates and ACSC admission rates vary over time (sections 4.1 and 4.2), the complete HES dataset is used and the data runs from 1st April 2005 until 31st March 2011. This analysis appeared to indicate an issue with the 2005/6 data (perhaps due to a change in the way admissions are coded). Therefore, in the later longitudinal analysis that examined the seasonality of ACSC admissions, the data are restricted to exclude the 2005/6 data as a precaution (i.e. the seasonality data runs from 1st April 2006 until 31st March 2011). To avoid including an incomplete week, the data were further restricted for the day-of-week analysis to run from 1st April 2006 until 26th March 2011. In all cross-sectional analyses the data used runs from 1st April 2010 until March 2011 (the most recent year for which data was available at the time of extraction).

3.2.2 Other data sets used

Table 3.1 below gives an overview of the data sources used throughout this thesis.

Table 3.1 – Sources of data used

Data	**Source**
Number of admissions for all emergency admissions and ACSCs during 2005/6-2010/11 by GP practice	Hospital Episode Statistics (for admissions between April 2005 and March 2011)
Practice list size	Attribution Dataset (2011)
Age-sex breakdown of the practice's list (Eighteen 5-year intervals for each sex)	Attribution Dataset (2011)

Number of GPs (headcount) within practice	The Information Centre for health and social care (Data as at 30 September 2010)
Percentage of ACSC admissions that were referred from A&E, Outpatients, GP practice, Bed Bureau or Other	Hospital Episode Statistics (for admissions between April 2010 and March 2011)
Quality and Outcomes Framework (QOF) for April 2010 – March 2011, England (74 indicators)	The Information Centre for Health and Social Care (April 2010 – March 2011)
Quality and Outcomes Framework (QOF) Exception Reporting for April 2010 – March 2011, England (71 indicators)	The Information Centre for Health and Social Care (April 2010 – March 2011)
Results of a GP patient survey 2010-2011 (9 domains)	Results of GP Patient Survey April 2010-March 2011. GP Practices in England. Department of Health, GP patient survey
Estimated ethnic breakdown of the practice's list (April 2005 – March 2006)	East of England Public Health Observatory - Practice ethnicity data for disease prevalence modelling (April 2005 – March 2006) Based on data provided by the Healthcare Commission (now CQC)
Practice's PCT	Hospital Episode Statistics (for admissions between April 2010 and March 2011)
Practice's SHA	Hospital Episode Statistics (for admissions between April 2010 and March 2011)
General Practice's cluster type	General Practice Classification Groups. Yorkshire and Humber Public Health Observatory (published March 1st 2011)
QOF Disease Prevalence - Quality and Outcomes Framework (QOF) for April 2010 to March 2011, England - Numbers of patients on QOF disease registers	The Information Centre for Health and Social Care (April 2010 – March 2011)
GP practice's deprivation score (IMD, IDACI and IDAOPI)	Developed by The network of Public Health Observatories, they apply LSOA level deprivation data proportionally to ADS practice populations. Indices of Deprivation 2010, Department for Communities and Local Government; Attribution Dataset (2011)
Level of technology in use (5 indicators)	Electronic Prescription Service (Data Date: 15/03/2012), Organisation Data Service (Data Date: 6/03/2012), Connecting for Health (Data

	Date: 31/01/2012)
Number of persons on list who are nursing home patients	Exeter (NHAIS) System (Data as at 30 September 2010)
Location data for NHS Services	NHS Choices Website Extract (Data received on 15/01/13)
Longitude and latitude data by postcode	Government Postcodes Website (http://data.gov.uk/apps/uk-postcodes)
Practice's CCG	Organisation Data Service (ODS) (Extracted April 2011)

3.3 Statistical analyses

3.3.1 Descriptive statistics

The number of emergency admissions was calculated from HES data by looking at first episodes only, picking an admission type that indicated that it was an emergency admission and removing any episodes not complete at the end of the data year (as these will appear in another year's data). To get the number of emergency admissions for the year, the date of admission was examined and assigned to a financial year. This exercise was then repeated for all admissions to work out the proportion of all admissions that were emergency admissions. Mid-year population estimates from ONS were used to create the rate of emergency admissions. Similarly the date of admission was used to assign a week to each admission and to create the weekly admissions over time graph.

Emergency length of stay (LOS) was calculated by averaging over all emergency admission spells (for which there was data available). Bed utilisation was calculated by multiplying the average LOS by the number of admissions (including those where LOS was not known). The same analysis was repeated for ACSC admissions. These were selected from among all emergency admissions by using the primary diagnosis code provided in the HES data. The codes used are those designated by Purdy et al. (2009). More detail is given in the introduction to justify this choice of coding from among those available.

Having assigned an ACSC type (or none) to each admission, the cost to commissioners of each episode was calculated using the PbR tariff for 2010/11. For each episode, the healthcare resource group (HRG) code provided was used to lookup the associated non-elective spell tariff. Where LOS exceeded the long stay trim-point, the long stay tariff multiplied by the excess LOS was added on.

Note that this (intentionally) ignores the 'market forces factor' which is applied to the PbR tariff to adjust for the different staffing costs in different parts of the country.

3.3.1.1 Mapping

To perform the mapping analysis, the middle layer super output area (MSOA) was used as the base unit for the data. There are 6,781 MSOAs in England, all with a minimum population of 5000. The choice of MSOA as the geographical unit was made for practical reasons. The HES data from which the number of ACSC admissions was calculated contained three geographical fields relating to where the patient resides: a shortened (4 letter) postcode; the middle layer super output area (MSOA); and a lower super output area (LSOA). The LSOA is a more granular version of the MSOA (there being 32,842 LSOAs in England). Population figures were readily available from ONS for either the LSOA or the MSOA. The MSOA was considered sufficiently granular however to provide the detail needed; the additional computational complexity required to process LSOAs was not necessary.

The rate for each MSOA was taken as the number of admissions for ACSCs during 2010/11 divided by the population of the MSOA in mid-2010, as provided by the Office for National Statistics (ONS). The cost map was then done similarly, using the cost of each admission and summing over all admissions from the MSOA.

The age-sex standardised admission ratio is calculated as follows. The numerator is the crude number of admissions for the MSOA (as described above). The denominator is then each age-sex category admission rate at the national level, multiplied by the population of the corresponding age-sex category at the MSOA level, summed over all the age-sex categories.

3.3.1.2 Day-of-Week and Seasonal Analyses

To understand how the day of week affected ACSC admission rates, all emergency admissions were extracted from the HES dataset between 1st April 2006 and 26th March 2010 inclusive. These dates were chosen to include as many weeks as possible from the available data, whilst excluding data for 2005/6 which looked to have a data-issue when examining the trends in emergency admissions, and ensuring that only complete weeks (Saturday to Friday) were included. This ensured there were the same number of Mondays as Tuesdays in the dataset, and so on.

The emergency admissions were then split into ACSC admissions and non-ACSC emergency admissions. For each day of the week, for each week in the dataset, the percentage of the total admissions (either ACSC or non-ACSC emergency) that occurred during the given day was calculated.

For each day of the week in turn, a t-test was then used to compare the proportion of ACSC admissions that had occurred versus the proportion of non-ACSC emergency admissions.

For the seasonality analysis, the number of ACSC admissions that occurred in each month of the year was calculated for the years 2007, 2008 and 2009. This was then normalised to a 30-day month by dividing the admission number by the number of days in the given month and multiplying by 30. Analysis of variance (ANOVA) was then performed on these standardised admission rates per month for each ACS condition and for all the conditions combined. A t-test comparison between each month and all other months was then performed (for each condition) using the Bonferroni method to correct for multiple comparisons, to determine which months, if any, were statistically significantly higher or lower than other months.

3.3.2 Multiple Linear Regression

To carry out the multiple linear regression modelling a new dataset was created. This new dataset had the general practice as its base unit. HES contains a field 'gpprac', which contains a code which defines the practice of the patient's registered GP. To create the dataset for the multiple linear regression analysis this code was used to link data on the number of admissions for ACSCS (from HES) to others from other datasets (described in section 3.8)

Multiple linear regression analysis was used to predict a dependent variable given a set of explanatory (independent) variables. Multiple linear regression was used to build the models in chapters 5 and 6.

3.3.2.1 Model development

As described in the 'Hypothesis and Aims' section, the basis of the model in chapter 5 is that the number of admissions for ACSCs (A_i) for a practice population i can be described by the following equation:

$$A_i = g(w_i, Q_i)$$

where w_i is a set of exogenous population characteristics and Q_i is a set of practice characteristics.

To create this model, data was sought at the general practice level that would provide an indicator within the domains of population and practice characteristics (both resource and quality).
Having built the dataset, the regression was performed using the Stata "regress" command. All of the variables are listed in Appendix I along with their descriptive statistics. To begin with, all the

independent variables were included for each model. The least significant term was then removed until all variables remaining had a p-value of less than 1%. The tests described below were then run and any necessary adjustments to the model were made. The regression was then re-run, repeating the process above on any terms whose p-value had increased above 1%.

A similar process was followed for the condition-specific models in chapter 6, except that a 5% significance level was used, due to the reduced number of variables involved.

3.3.2.2 Model specification tests

In order to ensure that the regression's results were valid, it needed to be true that the assumptions on which it was based were valid. For each of the models therefore, the following set of tests was used to ensure that the assumptions required for linear regression held; where they did not, mitigating action was taken.

Multicollinearity. To ensure that two or more variables were not near perfect linear combinations of one another the "vif" command in Stata was used, where a VIF value of greater than 10 means that the variable could be considered as a linear combination of other independent variables and therefore warrant further investigation. Where this was the case the variable with the highest VIF value was removed. The "vif" command was re-run until all the variables had a VIF value less than 10.

Linearity. The relationship between dependent and independent variables should be linear for regression to be valid. To test for linearity the "acprplot" command in Stata was used to plot an augmented partial residual plot. The option "lowess lsopts(bwidth(1))" was used to create a lowess smoothing with a bandwidth of 1. This was performed for each of the independent variables. If the two lines were fairly close then it was assumed that the linearity assumption was holding; otherwise a transformation was performed (typically a log transformation) of the independent variable and re-tested.

Homoscedasticity. There should be constant variance of the errors versus the predicted values created by the model. If the model is well-fitted there should be no pattern to the residuals plotted against the fitted values. Each of the models displayed a clustering when examined in this way. However, previous research has shown that for datasets with a large sample size the predictive power of the model remains good (Dixon et al., 2009) (Dunn et al., 2003) (Ellis and McGuire, 2007). To counteract some of the impact of this, the 'robust' option was used with the regression, to produce robust standard errors.

Normality of the error distribution. To test the normality of the residuals the regression analysis was used with the "predict" command to create the residuals. The "kdensity" command was then used with a normal density overlaid and the two resulting lines compared.

3.3.3 Corrected Ordinary Least Squares

Corrected ordinary least squares (COLS) is used to estimate the efficiency within a system. There are two key steps. The first is to use multiple linear regression to obtain an estimate of the slope parameters and an estimate of the intercept parameter. The approach to doing this was broadly the same as described in the section above entitled 'multiple linear regression' except that the practice characteristics related to quality that were included in the previous models were not included in this regression, as elements of quality would be picked up in the 'efficiency' estimate created by COLS.

The second step is to shift (or "correct") the intercept so that the estimated frontier bounds the data from below. It does this by adjusting the intercept by the minimum residual from the regression, that is the frontier will go through this minimum data point, on the assumption that this is the 'best practice' and highest efficiency possible within the system. A proof of the consistency of the COLS estimator appears in (Greene, 1980). The difference between this 'efficient' frontier and the actual values was deemed to be the inefficiency within the system. To provide further estimates – on the basis that this may be an optimistic assumption – the analysis provided also gives the results for a shift to the 1%, 5% and 10% lowest residuals.

3.3.4 Stochastic Frontier Analysis

Stochastic frontier analysis (SFA) was developed by Aigner et al. (1977). SFA is also used to give an estimate of the efficiency within a system. SFA uses regression analysis to estimate a conventional cost function, with the difference being that efficiency is measured using the residuals from the estimated equation where the error term is divided into two elements: a symmetric and a one-sided component.

The symmetric component accounts for random variations due statistical noise and it is assumed to be normally distributed. The one-sided component is non-negative and reflects technical inefficiency relative to the stochastic frontier – being zero if it were on the frontier (i.e. no inefficiency) and greater than zero otherwise. The distribution of the one-sided component has to be assumed before carrying out the analysis. Following the advice of Jacobs (2001) a half-normal distribution was assumed. The Stata function 'sfcross' was used to conduct the SFA. As for COLS, the inefficiency estimate given by the SFA (i.e. the proportion of the residual due to inefficiency) was divided by the actual rate (the dependent variable) to give a percentage inefficiency.

3.3.5 Propensity Score Matching

Propensity score matching allows the evaluation of an intervention by creating two groups – one for the treated and one for the non-treated – that are similar in all relevant pre-treatment characteristics. That being done, differences in the outcomes between the two well-selected groups are attributed to the intervention. If there were only a single (or couple of) pre-treatment characteristic(s) of relevance it is easy to see how such a matching could be performed. However, to enable many characteristics X to be matched, Rosenbaum and Rubin (1983) suggest the use of so-called balancing scores b(X), i.e. functions of the relevant observed covariates X such that the conditional distribution of X given b(X) is independent of assignment into treatment or non-treatment. Propensity score matching, as its name suggests, uses the propensity score (i.e. the probability of participating in the intervention treatment given observed characteristics X) to perform the balancing.

To perform the propensity score matching, the Stata module 'psmatch2' developed by Leuven and Sianesi (2003) was used. The configuration for each matching was determined individually to ensure that the mean bias (determined using the Stata function 'pstest') was less than 5%, the level which Caliendo and Kopeinig (2008) suggest is sufficient for most empirical studies. All of the tests use a matching within a given caliper, without replacement. A probit model is used to estimate the propensity score. The dependent variable is the binary treated/not-treated flag for the given intervention, the outcome is the condition-specific rate of admission and the independent variables are those described in the models in chapter 6 and the second and third order polynomials of those variables where indicated.

4 Descriptive statistics

4.1 Emergency admission trends in England

4.1.1 Is the number of emergency hospital admissions increasing?

The first aim of this chapter is to understand what trends, if any, there have been in emergency admissions. The NHS Data Model and Dictionary (Service, 2012) defines an emergency admission as "when admission is unpredictable and at short notice because of clinical need" and this is the definition used throughout this paper. Table 4.1 shows the number of emergency admissions each financial year from 2005/6 until 2010/11. It shows the number of emergency admissions increasing by 36% over the five-year period. Figure 4.1 shows these emergency admissions by the week in which they occurred from April 2005 until March 2011. There appears to be a 'jump' in the number of emergency admissions at the interface between the 2005/6 data and the 2006/7 data. There are many potential reasons for this, the most likely being a change in coding practice between the two financial years. If future analyses look further at data over time, they should revisit this discrepancy and potentially consider not using data from 2005/6. Despite this, there is a clear upwards trend over the period, though there is significant fluctuation throughout the year.

Table 4.1 – Emergency admissions[1]

	Total Emergency Admissions	% of all admissions	Rate of emergency admissions (per 1000 population)
2005/6	3,844,593	34.35%	76.2
2006/7	4,693,277	33.64%	92.5
2007/8	4,754,947	32.67%	93.0
2008/9	5,007,487	32.68%	97.3
2009/10	5,174,144	32.71%	99.9
2010/11	5,235,012	32.37%	100.2

The number of emergency admissions is increasing over time, but only in line with the number of admissions overall. If anything, emergency admissions are reducing slightly as a percentage of overall admissions. The total number of admissions would be expected to rise as the population size increases and ages. Interestingly the number of admissions per person is also increasing. This is

[1] Total emergency admissions were calculated directly from HES data by the author, but closely match those given by The King's Fund (Purdy, 2010) and others

likely to be due to there being a greater proportion of older people in the population, who are more likely to require emergency admission.

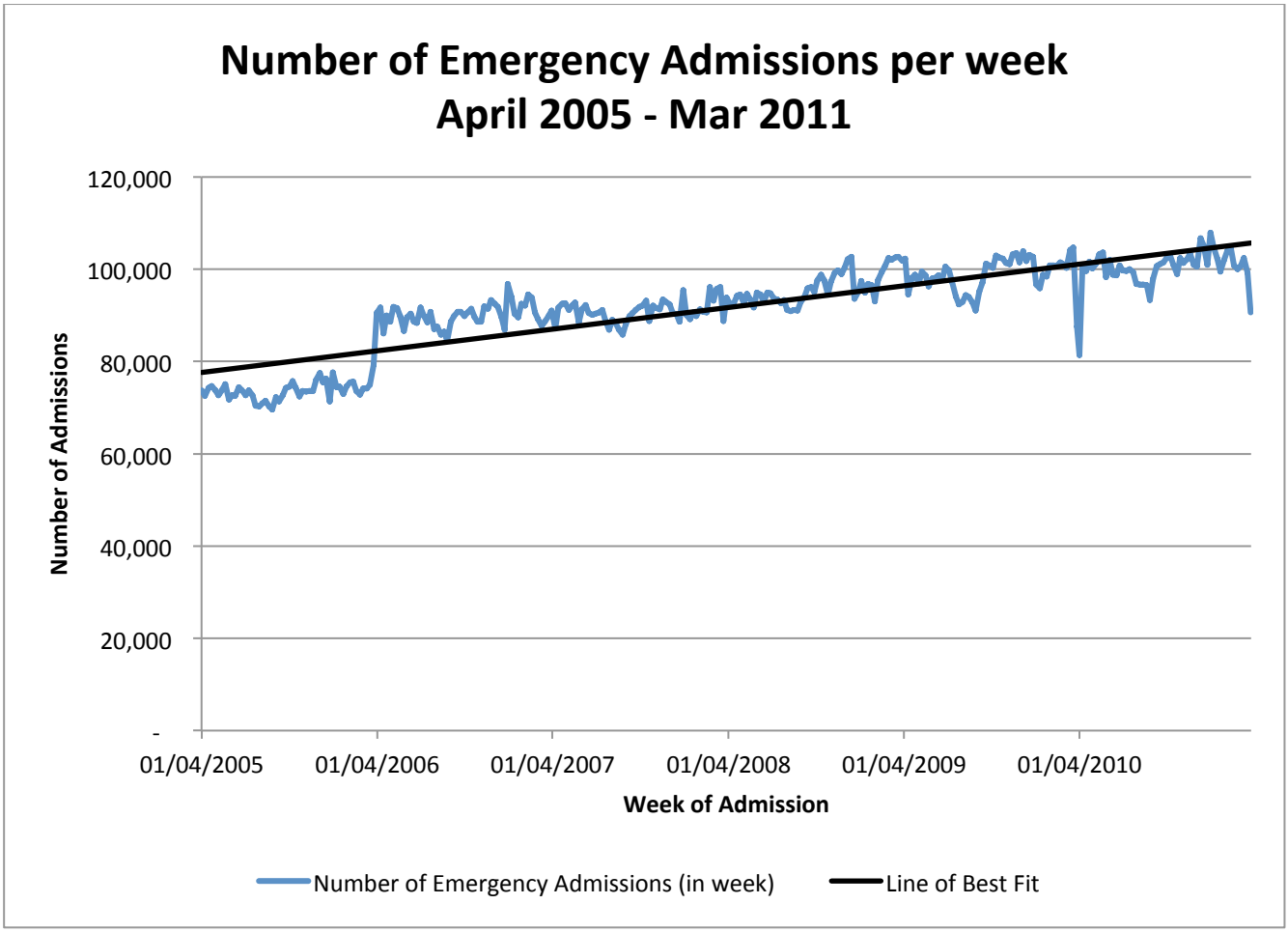


Figure 4.1 – Emergency admissions per week, from April 2005 to Mar 2011

4.1.2 Is overall emergency bed demand increasing?

The number of admissions is increasing. However bed utilisation is made up from the number of admissions multiplied by the length of time the patient is admitted (their LOS). Even though the number of admissions is increasing, if LOS were decreasing sufficiently over time, there could still be a reduction in bed utilisation. Table 4.2 shows the average LOS for emergency admissions that occurred during each financial year.

Table 4.2 – Emergency admissions LOS

	Average length of stay (LOS) in days for emergency admissions
2005/6	4.92
2006/7	4.28
2007/8	3.97
2008/9	3.70
2009/10	3.42
2010/11	2.92

This, necessarily, does not include all the admissions from part 4.1.1 as those admissions for which the data did not include a date of discharge have been excluded. A substantial decrease in LOS appears to have been achieved over the five-year period. However, the data is biased as admissions with long LOSs in earlier years are more likely to be included than those in later years; for instance a one-year LOS admitted in Feb 2006 would be included, but a one-year LOS from Feb 2011 would not (as they had not been discharged at the time the data was cut). To try and account for this bias, the average LOS for each year was calculated for admissions that were also discharged that year (see Table 4.3). This will give a lower average LOS for each year; however it should bias each year equally and therefore make longitudinal comparisons more meaningful.

Table 4.3 – Emergency admissions LOS II

	Average length of stay (LOS) in days for patients discharged within year
2005/6	4.01
2006/7	3.75
2007/8	3.49
2008/9	3.30
2009/10	3.10
2010/11	2.92

The average LOS is again seen reducing year on year. This figure combined with the number of emergency admissions shows that the total bed utilisation each year fluctuates significantly (see Table 4.4). There does not appear to be the same rising trend as seen with emergency admission numbers alone.

Table 4.4 – Bed utilisation for emergency admissions

	Total bed utilisation for emergency admissions (bed days)	% of all bed days for all admissions
2005/6	15,431,523	60.4%
2006/7	17,606,308	61.4%
2007/8	16,605,273	61.2%
2008/9	16,525,583	61.5%
2009/10	16,041,285	61.3%
2010/11	15,285,680	60.9%

This suggests that, although the number of emergency admissions is rising, the bed days required to deal with them is not consistently rising, with bed utilisation for emergency admissions at similar levels in 2010/11 to those in 2005/6. Bed capacity within hospitals, which is typically not very flexible in terms of accepting both emergency and non-emergency patients, may be limiting the number of beds that are being used for emergency admissions.

4.2 ACSC admission trends

Policy makers are most interested in the admissions to hospital that can be avoided. As mentioned in the introduction, there are a group of conditions – called ambulatory care sensitive conditions (ACSCs) – that are thought to be preventable if primary care is of high enough quality. Figure 4.2 shows the number of ACSC admissions per week, over the six year period. And Table 4.5 shows the number of ACSC admission per year, and how this relates to all emergency admissions and all admissions respectively. It shows admissions increasing by 36% over the period from 2005/6 to 2010/11. Interestingly this is the same percentage increase as that seen in the overall level of emergency admissions.

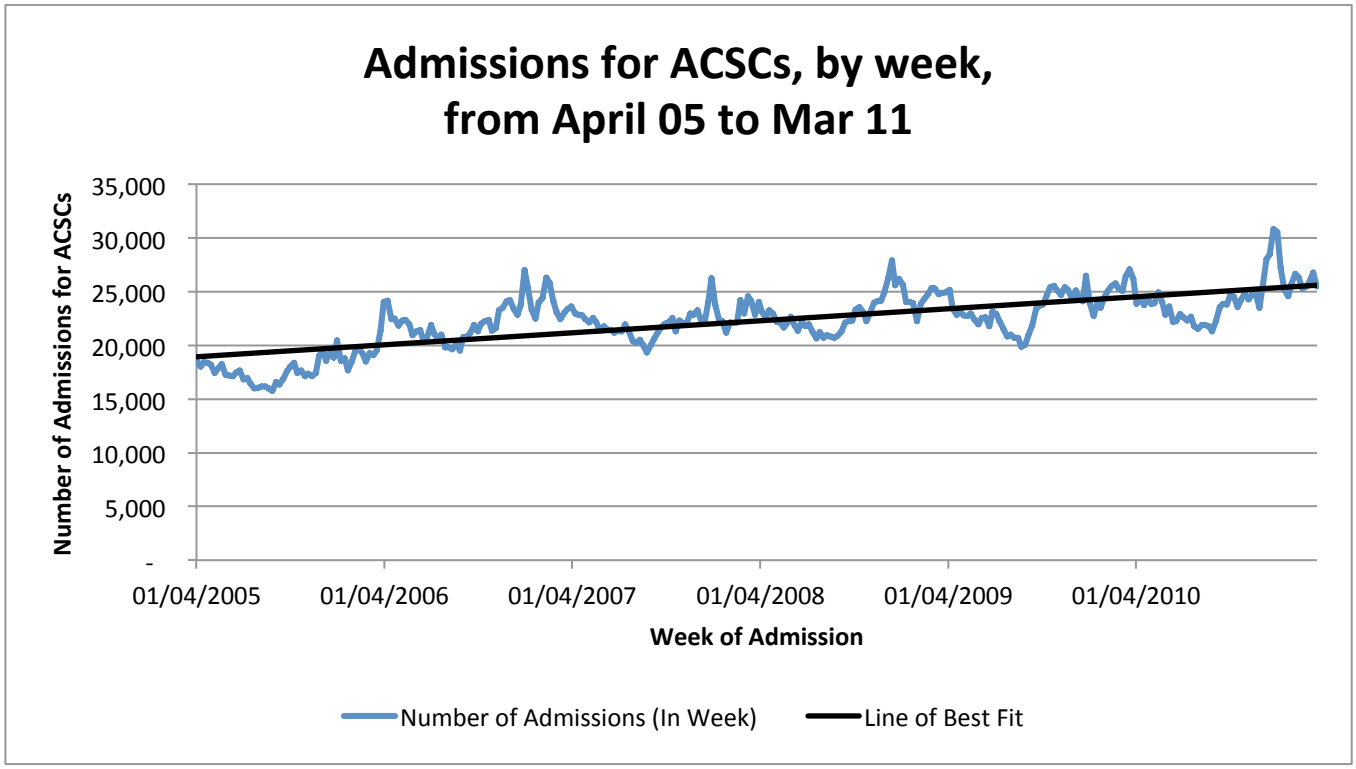


Figure 4.2 – ACSC admissions per week, from April 2005 to Mar 2011

Table 4.5 – ACSC admissions by year and relative to other admissions

	Number of ACSC Admissions	% of all emergency admissions	% of all admissions
2005/6	935,089	24.3%	8.4%
2006/7	1,167,943	24.9%	8.4%
2007/8	1,157,906	24.4%	8.0%
2008/9	1,206,664	24.1%	7.9%
2009/10	1,229,305	23.8%	7.8%
2010/11	1,269,513	24.3%	7.8%

Compared against emergency admissions generally, the number of ACSC admissions as a proportion of emergency admissions stays very similar over the six years – 24.3% of emergency admissions are for ACSCs ±0.6% for all six years.

Table 4.6 gives a breakdown of these ACSC admissions by disease type, showing the number of admissions and the associated cost. Cost is based on the HRG tariff (for 2006/7) and is, therefore, how much the PCT paid the hospital, rather than the true cost to the hospital of providing the care. The table shows that the total cost of ACSC admissions in 2010/11 was £2,154,821,132 or 7.1% of the £30,553,526,625 (Health, 2011) spent on all inpatient treatment in England in 2010/11.

Table 4.6 – Cost of ACSC admissions in England during 2010/11

ACSC Type	Number of Admissions	Cost of Admissions (2010/11)
Angina	302,739	£339,570,056
Asthma	58,141	£61,480,964
Cellulitis	86,624	£158,278,944
Chronic obstructive pulmonary disease	113,197	£256,132,289
Congestive heartfailure	51,810	£144,889,325
Convulsions and epilepsy	73,550	£99,296,175
Dehydration and gastroenteritis	125,135	£187,653,847
Dental conditions	9,470	£11,530,811
Diabetes complications	22,135	£47,757,134
Ear, nose and throat infections	86,617	£57,400,217
Gangrene	1,407	£5,469,844
Hypertension	6,057	£9,070,834
Influenza and pneumonia	148,736	£368,632,712
Iron deficiency anaemia	14,117	£29,529,671
Nutritional deficiency	119	£283,339
Other vaccine-preventable diseases	847	£1,208,471
Pelvic inflammatory disease	4,347	£7,434,762
Perforated / bleeding ulcer	26,103	£43,046,013
Pyelonephritis	138,362	£326,155,724
All ACSCs	**1,269,513**	**£2,154,821,132**

4.3 Mapping the variation in ACSC admissions across the country

The above analysis shows that the number of ACSC admissions varies throughout the year. The rate of ACSC admissions for a given population also varies by GP practice. Figure 4.3 shows the variation by GP practice in 2010/11 for all GP practices in England.

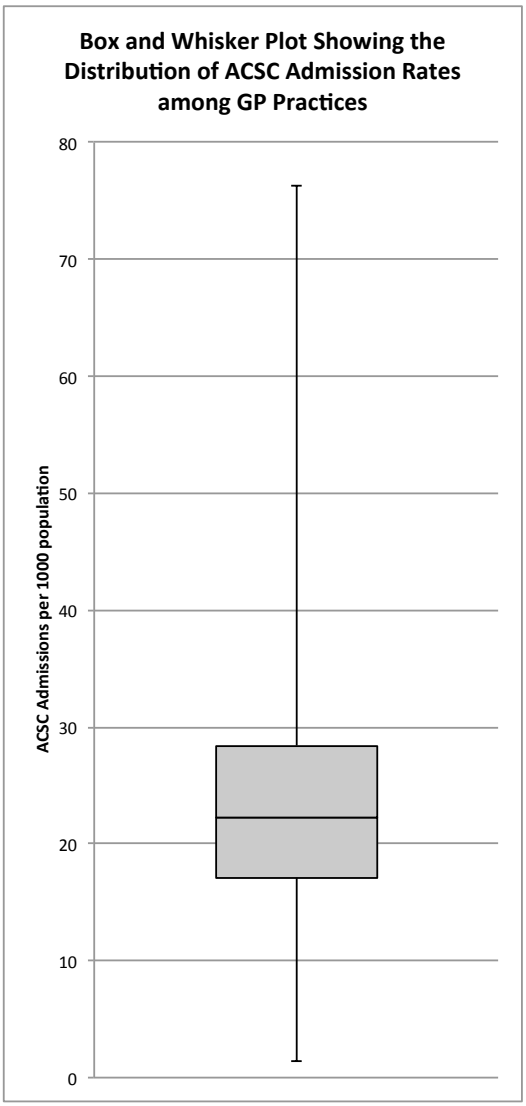


Figure 4.3 – Box and Whisker Plot showing Variation in ACSC admission rates by GP practice

The mean rate of ACSC admissions per 1000 persons across the practices was 23.05. As shown in Figure 4.3, the minimum was 1.38, the lower quartile was 17.02, the median was 22.19, the upper quartile was 28.42 and the maximum was 76.25.

As noted previously, some of this variation will be explainable by known and observable factors. To examine the potential causes of this variation, the crude admission rate was plotted on a map of England. Rather than use GP practice as the base-unit for this analysis, a geographic area unit, namely the middle layer super output area (MSOA), was used. There are 6,781 MSOAs in England, all with a minimum population of 5000. The rate for each MSOA was taken as the number of admissions for ACSCs during 2010/11, divided by the population of the MSOA in mid-2010, as

provided by the Office for National Statistics (ONS). Figure 4.4 plots this crude admission rate for each MSOA.

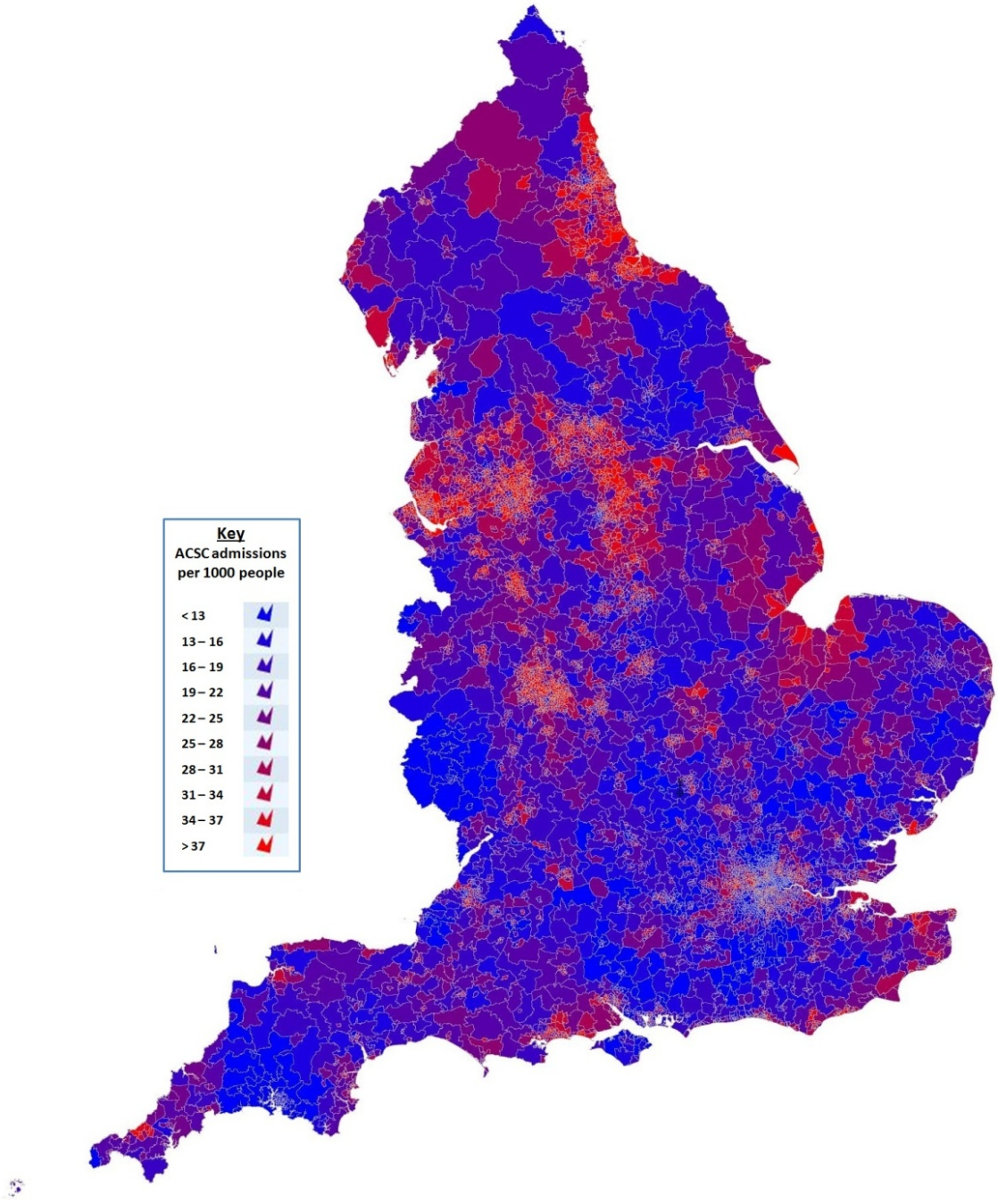


Figure 4.4 – ACSC admission rate per 1000 people, by MSOA

Figure 4.4 appears to indicate clustering of areas with similar admission rates. Instead of showing the rate of ACSC admissions Figure 4.5 (below) shows the cost of those admissions per 1000 people.

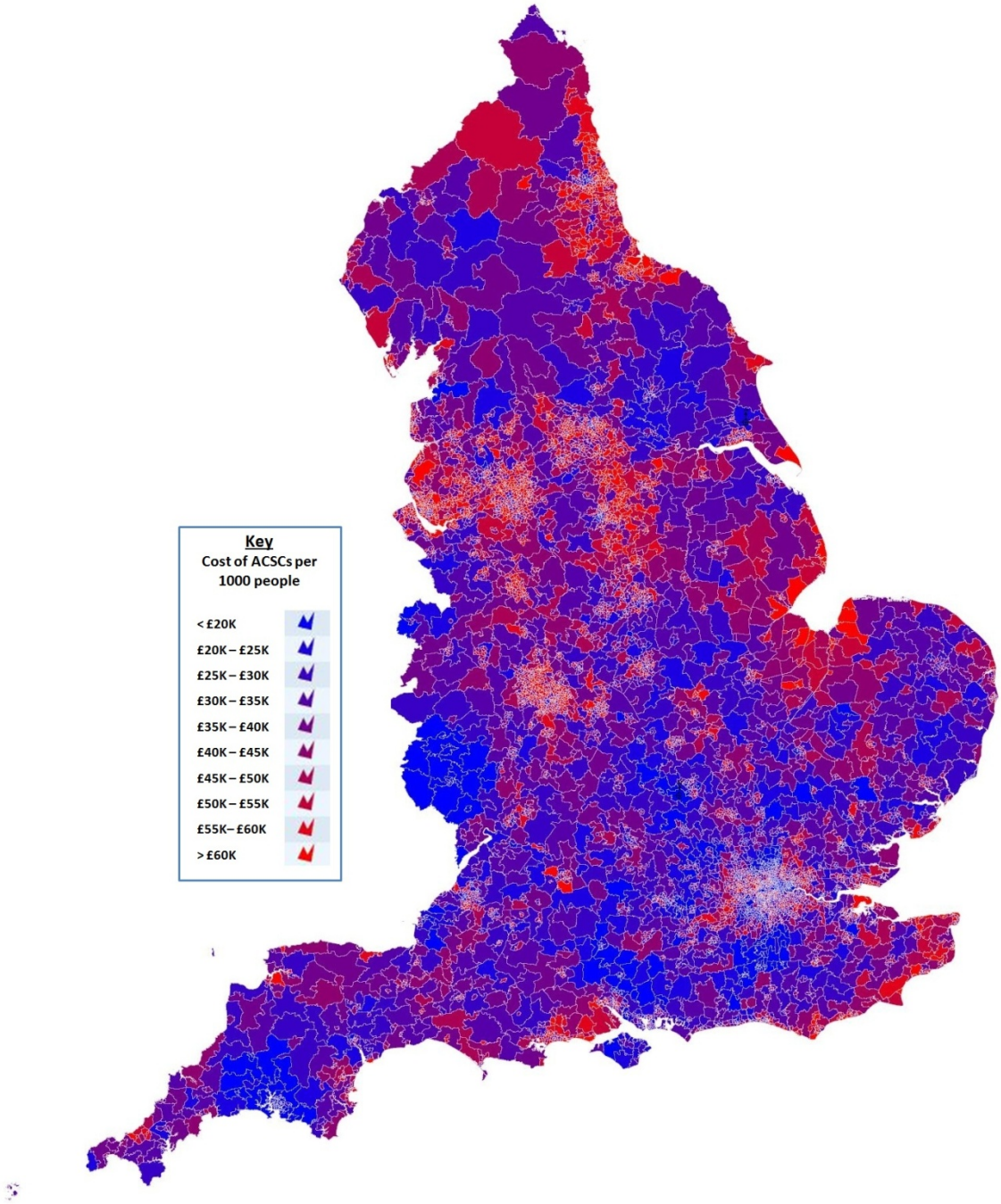


Figure 4.5 – Cost of ACSC admissions per 1000 people, by MSOA

This again shows a significant clustering, this time of high-cost regions. It also suggests that urban areas are likely to have higher rates and costs of admissions than rural areas. In order to investigate

this hypothesis further, the crude admission rate used in Figure 4.4 was adjusted to take account of the age and sex distribution of each MSOA. Table 4.7 gives the age-sex rate for ACSC admissions across the whole of England for 10/11. Each cell gives the number of ACSC admissions expected for each 1000 persons in that age and sex group.

Table 4.7 – ACSC admission rate per 1000 people for different age-sex bands

	Age Band								
	0 - 9	**10 - 19**	**20 - 29**	**30 - 39**	**40 - 49**	**50 - 59**	**60 - 69**	**70 - 79**	**80+**
Male	65.20	13.86	16.51	20.22	31.05	45.15	68.79	133.68	268.97
Female	55.83	19.57	24.51	22.73	29.43	39.64	56.41	110.22	226.32

The age-sex standardised admission ratio is calculated as follows. The numerator is the crude rate of admission for the MSOA (as described above). The denominator is then each age-sex category admission rate at the national level, multiplied by the population of the corresponding age-sex category at the MSOA level, summed over all the age-sex categories. Having calculated the standardised admission ratio, the map was redrawn – see Figure 4.6.

The age-sex distribution (Table 4.7) is as we would expect, with the very young having a greater number of admissions and, within this 0-9 age group, boys being more susceptible to admission than girls. We then see a reduction in admission rates in the 10-19 category and a continuous increase in rates as we move to each consecutive age-bracket (with the exception of women aged 30-39 for which we see a small dip). Those aged 60 years and above are just over 4.5 times more likely to have an ACSC admission than those below 60.

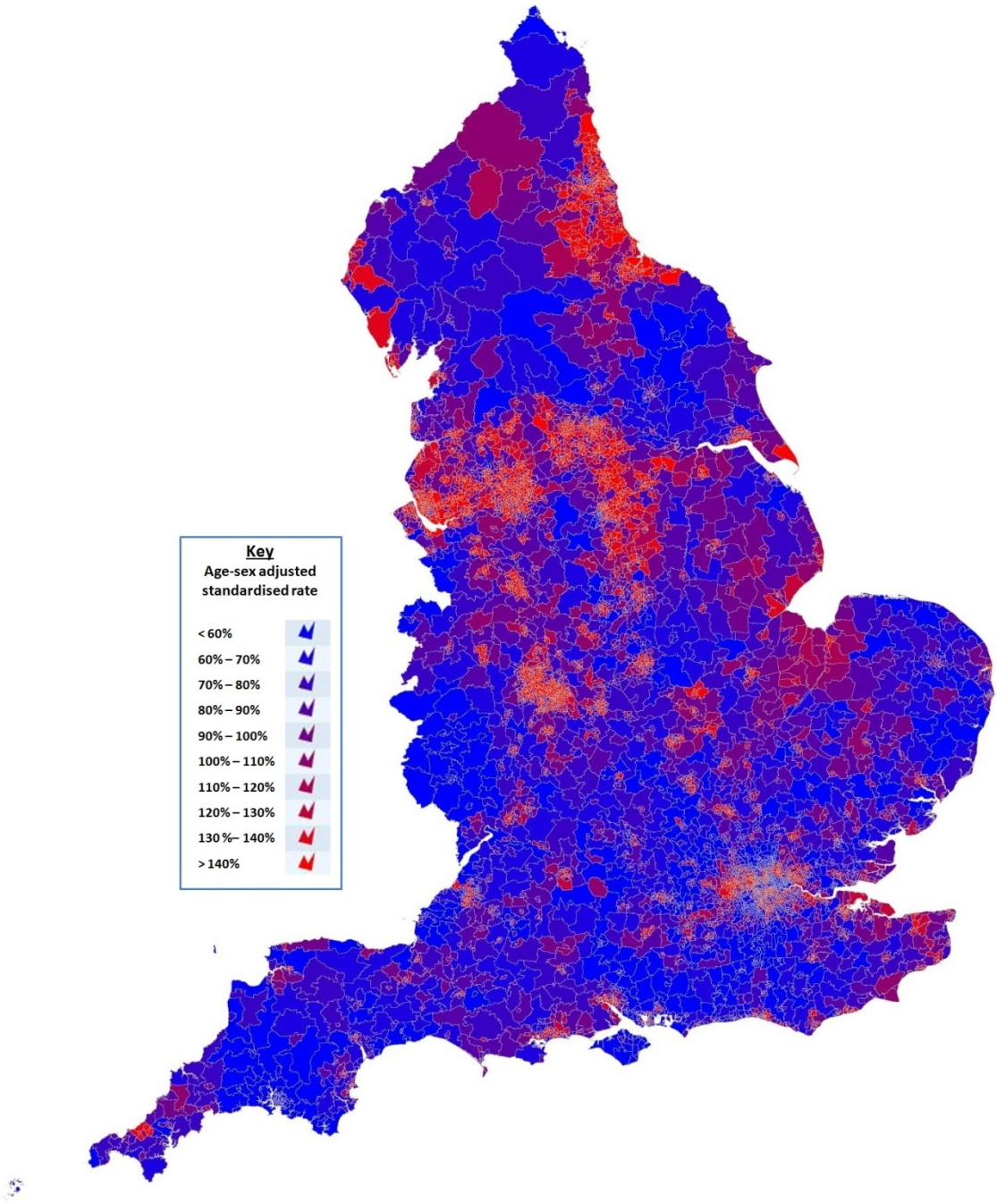


Figure 4.6 – Percentage difference between actual number of ACSC admissions and expected, based on area's age and sex profile, by MSOA

This map (Figure 4.6) shows that, having standardised for the age and sex of each of the MSOA level populations, the clustering of areas with higher than expected rates of admission for ACSC conditions is even more pronounced. It also indicates that smaller areas – likely to be largely urban areas – have generally higher levels of admissions (even after adjusting for the age and sex of their

populations) than do the larger areas – likely to be largely rural areas. In further statistical analyses a dummy variable will be used to measure the association between area type and ACSC admission rate.

4.4 Variation by area type

The Yorkshire and Humber Public Health Observatory (now part of Public Health England) developed a set of classification groups for general practices in England. The groupings classify practices by factors such as list size and composition, deprivation and the area's population density. Table 4.8 shows how the rates of admissions for ACSCs vary by grouping.

Table 4.8 – Average rates of admission for ACSCs by YHPHO groupings

Cluster Number	Description	Mean rate of admission (per 1000) for ACSCs	Std. Deviation	Number of Practices in Cluster
1	Practices with a smaller than average list size, a high percentage of the population aged under 15 years old and fewer aged 65 years or older. A very high proportion of the population from Asian ethnic groups and a higher than average proportion from Black ethnic groups and very high levels of deprivation.	24.85	10.27	357
2	High percentage under 15 years. Very high percentage of black population and higher than average Asian population. High deprivation	18.47	8.23	739
3	Practices with a high percentage of children (under 15 years old) and very high levels of deprivation.	31.24	9.25	910
4	Practices with a very low percentage of people under 15 years and a lower proportion of older people (65 years and older) and an above average proportion of the population from Asian and Black ethnic groups.	15.59	8.93	289
5	Practices with a higher percentage of older people (aged 65 years and older) with slightly higher levels of deprivation.	29.37	7.80	1142
6	Practices with an average proportion of the population in younger and older age groups and generally low deprivation.	19.73	6.70	1327
7	Located in towns or urban fringe settlements with low deprivation and few people from Asian and Black ethnic groups.	20.68	6.62	904

8	Practices with a high percentage of the population aged 65 years and older and low levels of deprivation.	25.03	7.58	499
9	Practices with large average list sizes, an average proportion of the population under 15 years old, a higher proportion aged 65 years and older and low levels of deprivation.	21.21	6.16	1382
10	Located in villages, hamlets and isolated settlements with a small average list size and a higher proportion of the population aged 65 years and older. Few people from Asian and Black ethnic groups and low levels of deprivation.	17.48	5.80	305

There is clearly large variation between different groupings (15.59-31.24), however due to the way the groupings are formed it is difficult to isolate the specific characteristics associated with differing rates.

There are similarly large variations between different Strategic Health Authorities (SHAs) as shown in Table 4.9 (16.70-32.15). Further analysis is needed to discover what is causing this variation. Different SHAs are likely to be serving very different populations but it could also be that something occurring at the SHA level, for instance a variation in funding levels, is causing a shift in admission rates.

Table 4.9 – Average rates of admission for ACSCs by Strategic Health Authority

Strategic Health Authority (SHA)	Mean rate of admission (per 1000) for ACSCs	Std. Deviation	Number of Practices in Cluster
North East SHA	32.15	8.96	382
North West SHA	29.89	8.47	1209
Yorkshire And The Humber SHA	27.90	8.44	775
East Midlands SHA	22.92	6.22	606
West Midlands SHA	26.13	7.82	922
East Of England SHA	19.79	5.75	764
London SHA	16.70	7.06	1425
South East Coast SHA	20.13	6.87	616
South Central SHA	17.51	5.58	490
South West SHA	20.00	6.24	712

4.5 Analysis of seasonal and day-of-week patterns of ACSC and emergency admission rates

It is known from previous studies (Blunt et al., 2010) that the time of year and day of week can have an impact on emergency admissions into hospital. To understand the impact of these factors on

ACSCs this study performs two analyses. The first compares the proportion of ACSC admissions on each day of the week with emergency admissions more generally. The second examines if the month of the year is typically associated with lower or higher rates of admission for ACSCs – both for all ACSCs combined and separately.

4.5.1 Day of Week

We know that emergency admission rates vary by day-of-week (Robinson, 2012). ACSC admissions are a subset of emergency admissions. It is, therefore, interesting to see how ACSC admissions vary by day-of-week and how this compares to how other emergency admissions vary by day-of-week.

Figure 4.7 shows the percentage of ACSC admissions that occur on each day of the week compared to emergency admissions not defined to be ACS. The percentages are averages over the period between 1st April 2006 and 26th March 2010.

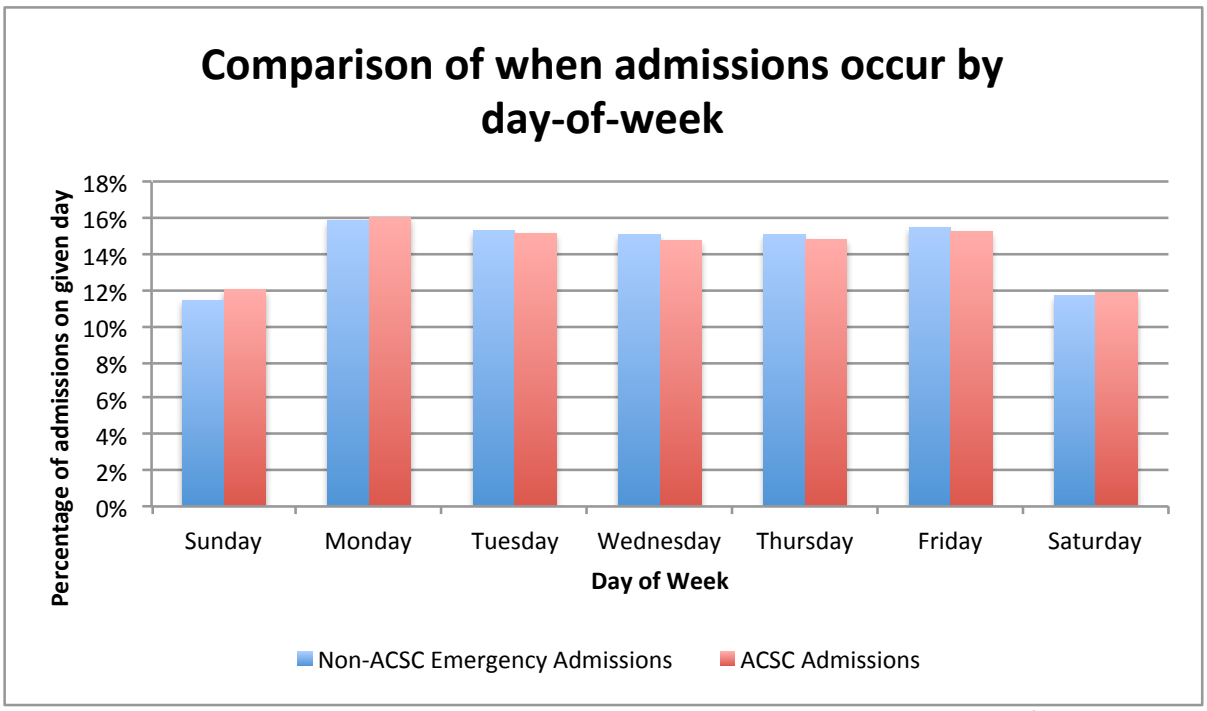


Figure 4.7 – Comparison of when admissions occur by day-of-week for ACSCs and non-ACSCs (1st April 2006 – 26th March 2010)

ACSC admissions appear to follow the overall pattern of non-ACSC emergency admissions with lower rates of admission at the weekend. T-tests were performed to assess whether the differences between admission percentages for ACSCs and non-ACSCSs for each day were significant.

The percentage of ACSC admissions was signifcantly (at 0.05) greater on Saturday, Sunday and Monday than for non-ACSC admissions, whereas they were significantly lower for Tuesday, Wednesday, Thursday and Friday.

The day of week has an impact on the expected rate of admission for ACSCs and, moreover, this subgroup is different to non-ACSC emergency admissions. Later analysis will focus on annual rates of admission, thereby neutralising the day-of-week effect, but researchers and policy-makers should be aware of the potential impact day of week can have when measuring and resourcing for ACSCs.

One potential reason for higher than expected admission rates for ACSCs at weekends might be that access to GP practices is restricted at weekends. Whereas during the week admission rates for ACSCs are managed by GP practices, at the weekend the patient has no choice but to attend hospital, which then goes on to admit them. The issue of practice access and its impact on ACSC admission rates will therefore be explored further later in this thesis.

4.5.2 Seasonality

To look for evidence of seasonality in the admission rates, the proportion of admissions for the given condition that took place in a given month was calculated. This was standardised (by dividing by the number of days in the month and multiplying by 30) to take account for the different lengths of months. An analysis of variance (ANOVA) was performed on these standardised admission rates per month for each ACS condition and for all the conditions combined. A t-test comparison between each month and all other months was then performed, using the Bonferroni method to correct for multiple comparisons, to determine which months, if any, were statistically significantly higher or lower than other months. Rates were deemed to be seasonal if the analysis of variance was significant at the 5% level and at least one month-to-month comparison was statistically significant at the 5% level.

Rates of admission for all ACSCs combined, Asthma, Cellulitis, Congestive heart failure, COPD, Dehydration and gastroenteritis, Diabetes complications, ENT infections, and Influenza and pneumonia were all found to be seasonal.

Rates of admission for Angina, Convulsions and epilepsy, Dental conditions, Gangrene, Hypertension, Iron deficiency anaemia, Nutritional deficiency, Other vaccine-preventable diseases, Pelvic inflammatory disease, Perforated/bleeding ulcer, and Pyelonephritis were not found to be seasonal.

Figure 4.8 shows the standardised proportions of admissions in each month for each condition over the 3 year period (2007-2009).

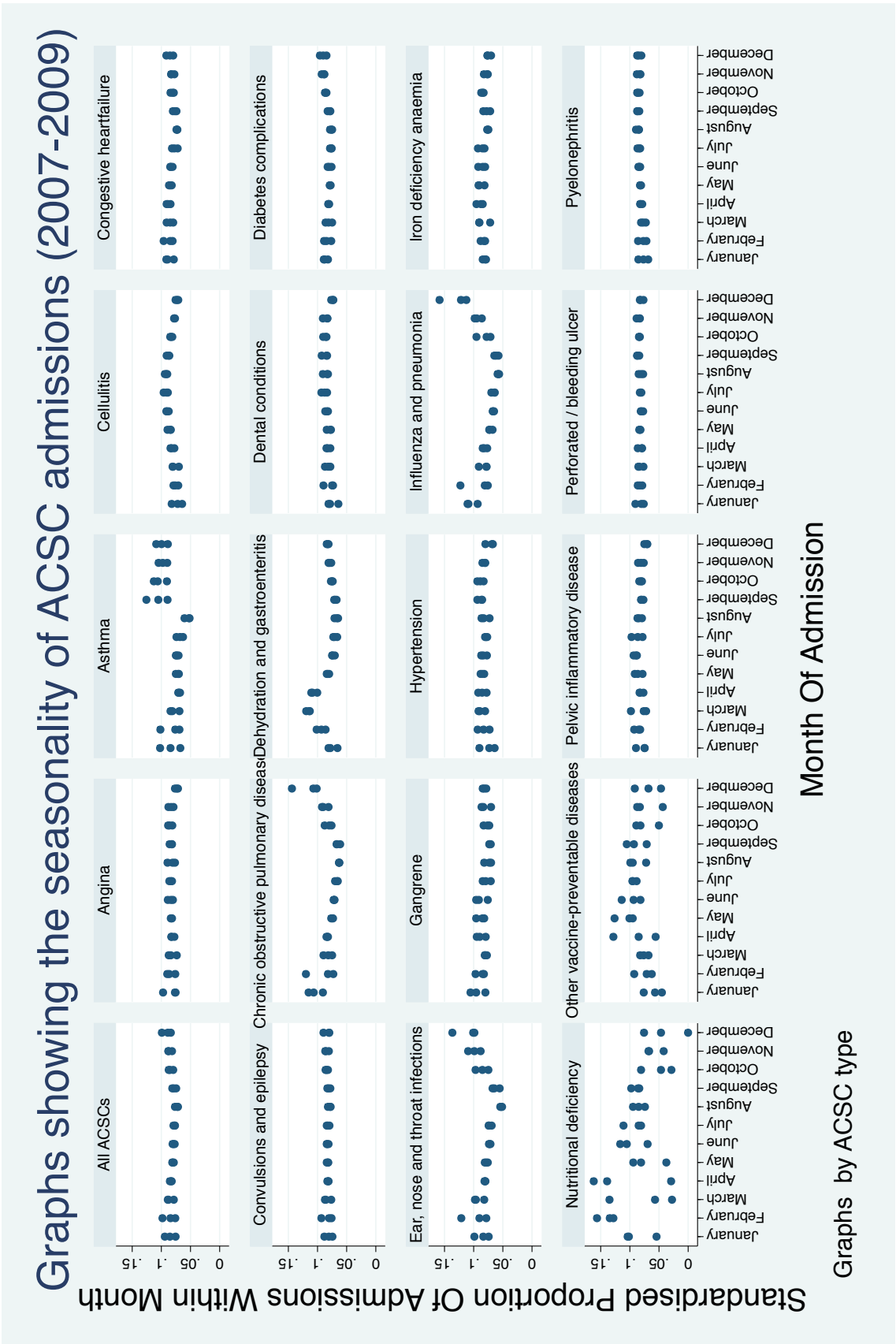


Figure 4.8 – Graphs showing the proportion of ACSC admissions by month

The month of the year appears to have an impact on many ACSCs. Later analysis will focus on annual rates of admission, thereby neutralising the seasonal effect, but researchers and policy-makers should be aware of the potential impact that the time of year can have when measuring and resourcing for particular ACSCs.

5 Modelling ACSC admission rates

5.1 Introduction

There are various reasons to model the rates of ACSC admission, but key amongst them is to enable prediction of expected rates, thereby giving an insight into the factors that affect rates and, once rates have been predicted, to understand which practices are doing well, given some set of conditions (such as a particular population profile). Comparing practices without allowing for such factors (that may well be out of the control of the practice) would lead to very misleading results. As noted in the introduction, being able to target interventions on those at highest risk of admission is necessary to ensure that the intervention is successful. Modelling expected rates is the first step to identifying risk factors for admission and therefore identification of particular patients on whom care/interventions could be focused to prevent admission.

This chapter aims to model the admission rate for ACSCs into secondary care at the practice level. In doing so it aims to understand the factors related to varying rates. The hypothesis being tested is that there is an underlying level of morbidity M_i within the population of practice i given by the relationship $M_i = f(x_i, P_i)$, where x_i is a set of population characteristics and P_i is the quality of preventive care. The level of ACSC admissions A_i is then determined by the equation $A_i = g(y_i, M_i, Z_i)$, where y_i is a (potentially different) set of population characteristics and Z_i is a set of practice characteristics reflecting the quantity and quality of care available to patients. Substituting the first into the second yields a single equation: $A_i = g(w_i, Q_i)$, where w_i is a set of exogenous population characteristics and Q_i a set of practice characteristics (both resource and quality). In principle, Q_i may be determined in part by previous levels of ACSC admissions, and so might be considered endogenous, however in this chapter practice characteristics Q_i are treated as exogenous.

As described in the introductory chapter, previous work has looked at the factors that might be associated with the rate of admissions at any given GP practice and therefore be included in w_i and Q_i. Patient characteristics, such as increased deprivation, advanced age, female gender, poor health, white ethnicity and smoking are all associated with higher rates of admissions. Practice characteristics, such as continuity of care with physician and being able to see a particular physician, higher staffing levels, being able to access the GP, being a larger practice and the practice being further away from the hospital are all associated with lower rates of admissions.

Multiple linear regression is widely used in the academic literature to develop models. Given a variable y and a number of variables $X_1, \ldots, X_p$ that may be related to y, multiple linear regression

analysis can be applied to quantify the strength of the relationship between y and X_j, to assess which X_j may have no relationship at all, and to identify which subsets of the X_j contain redundant information about y. Multiple linear regression will be used to test the hypothesis proposed above.

Of the three core aspects being modelled (i.e. population characteristics, practice characteristics (resource) and practice characteristics (quality)) the impact of population characteristics, such as deprivation rates and the age and sex of the population, on admission rates is best understood in the academic literature (Zhan et al. (2004), Downing et al. (2007), Calderon-Larranaga et al. (2011) and Bankart et al. (2011b)). There is less evidence for the impact practice-resource characteristics, such as practice list size or number of GPs, have on admission rates – and less still for the impact of practice-quality characteristics, such as those measured by the QOF. The model developed in this chapter will therefore follow a process of adding one aspect at a time, starting with population characteristics only and finishing with a model that incorporates population and practice (resource and quality) characteristics, allowing for a comparison between model results and those given in the academic literature.

5.2 Methods

To investigate the factors associated with varying levels of admission rates for ACSCs, a multiple linear regression of the data was performed, at the level of the GP practice. For each GP practice in England for which there was 2010/11 QOF data available (8245 practices), corresponding data were identified for each of the variables listed below. Refer to chapter 3 for further details on the source of each data set.

A single year of data was used to for the analysis for a range of reasons. Using data from multiple years would potentially give greater weight to any conclusions reached, however the author felt that, on balance, the advantages of using data from a single year outweighed the advantages of using data from multiple years. Using a single year of data reduced the complexity of the analysis and meant that findings will be easier to interpret. Focusing on a single year excludes the effect of changes over time, such as changes in policies, either at the national or local area level, allowing conclusions to be focused on the factors modelled. Analysis in later chapters builds on the work in this chapter and requires a single year approach. And finally, changes to the indicators that are included or not in the QOF (HSCIC, 2011) each year, as well as the methodology for their calculation, mean that making comparisons over multiple years would mean excluding many of these important indicators.

An age and sex standardised ratio of admissions for all ACSCs was used as the dependent variable in each model. To create this dependent variable, the actual number of ACSC admissions from the practice was divided by the expected number, based on the practice list's age and sex makeup. Each of the independent variables was then classified based on the three categories established in the hypothesis, namely population characteristics, resources and quality metrics. A complete list of the variables used and their descriptive statistics can be found in appendix I. An overview of the categorisations used in the models is shown below:

Dependent Variable:

- The age and sex standardised ratio of admissions for all ACSCs during 2010/11

Independent Variables:

Population Characteristics:

- The estimated ethnic breakdown of the practice's list
- GP practice's deprivation score (IMD, IDACI and IDAOPI)
- Percentage of persons on the practice's list who are nursing home patients
- Disease prevalence (based on QOF disease registers)
- The practice's PCT (dummy variable)
- The practice's SHA (dummy variable)

Practice Characteristics (Resource):

- The practice list size
- Number of GPs (headcount) within practice per 1000 persons on list
- The practice's cluster type (dummy variable)
- Level of technology in use in GP practice (5 indicators)

Practice Characteristics (Quality Metrics):

- QOF indicator results (74 indicators)
- The exception rate for QOF indicators (71)
- The percentages of patients admitted for ACSCs referred by A&E, GP, Outpatients, Bed Bureau or Other
- Results of a GP patient survey (9 domains – 5 access, 4 patient opinion)

5.2.1 Rationale for variable choice

The model stated in the introduction to the chapter sets out the expected categories of independent variable that this chapter seeks to test, namely: $A_i = g(w_i, Q_i)$, where w_i is a set of exogenous population characteristics and Q_i a set of practice characteristics (both resource and quality).

Under each category of metric, that is population characteristics, practice resource characteristics and practice quality characteristics, where data could be found (at the level of the GP practice) that was a good proxy for the category, it was included in the original specification for each model.

Where possible the specific indicator has been used, rather than an aggregate that may distort the interpretation that can be drawn from any results. Each individual QOF indicator has been included, therefore, so that the regression can test if there are specific indicators, representing particular clinical processes or interventions, that are impacting on ACSC admission rates. The QOF indicators are all intended to represent good clinical quality, it is therefore appropriate that all be included. To determine if overarching quality mattered more than specific interventions the aggregate QOF score for the practice was also included. Having included each of the QOF indicators it was important to include the respective exception rate for that indicator. Exception rates indicate that a given practice has excluded some of their patients from the relevant QOF indicator. This can be because the care prescribed by the QOF indicator is deemed clinically inappropriate or some other reason (no reason need be given). Without the exception rate, therefore, the exclusion of patients by GPs could lead to misleading results and so each exception rate will also be included.

Similarly, for the GP patient survey results, each of the questions was included so that results could be interpreted more accurately – for instance there is a difference between a patient reporting that access to their surgery is good and that they would recommend the practice to a friend.

This led to the development of three separate models.

5.2.2 Model 1

The first model used the population characteristics to predict the dependent variable. Variables that were not statistically significant at $P \leq 0.01$ were removed from the model (one at a time, largest first) until all terms were statistically significant.

To ensure the model was correctly specified, any terms that were found to be collinear with other terms were removed. The SHA dummy was found to be collinear with another term in the model, likely to be the PCT dummy as each SHA is broken up into a number of PCT areas. The SHA term was therefore removed from the final model. An augmented partial residual plot was used to identify

any terms that might not be linearly associated with the dependent variable. Mental health prevalence was found to be a better fit if it was log transformed. The log transformed version of this variable was therefore used in the model. A robust option that produces robust standard errors was used for the regression to counter the effect of possible hetroscedastistcity (i.e. a non-constant variance of the errors versus the predicted values). Finally, the error distribution of the model was checked to ensure it was normally distributed (see Appendix II) and found to be satisfactory.

5.2.3 Model 2

The second model used population and practice characteristics (resources) to predict the dependent variable, using the same method described above.

Again it was ensured that the model was correctly specified by removing the collinear SHA dummy. An augmented partial residual plot was used to identify any terms that might not be linearly associated with the dependent variable. The number of GPs per 1000 population and mental health prevalence were both found to be a better fit if they were log transformed. The log transformed versions of these variables were therefore used in the model. The robust option for the regression was again used to counter hetroscedastistcity. Finally, the error distribution of the model was checked to ensure it was normally distributed (see Appendix II) and found to be satisfactory.

5.2.4 Model 3

The third model used population and practice characteristics (resources) along with the quality metrics to predict the dependent variable, using the same method described above.

Again it was ensured that the model was correctly specified by removing the collinear SHA dummy. The percentage of ACSC referrals that came from a GP was also found to be collinear and thus removed. An augmented partial residual plot was used to identify any terms that might not be linearly associated with the dependent variable. The number of GPs per 1000 population, mental health prevalence and the exception report for QOF indicator 6 for asthma were all found to be a better fit if they were log transformed. The log transformed versions of these variables were therefore used in the model. The robust option for the regression was again used to counter hetroscedastistcity. Finally, the error distribution of the model was checked to ensure it was normally distributed (see Appendix II) and found to be satisfactory.

5.3 Results

5.3.1 Model 1

The regression results for model 1 are presented in Table 5.1.

Table 5.1 – Regression results for Model 1

Number of obs	7892
F(152, 7739)	106.92
Prob > F	0
R-squared	0.6983
Root MSE	0.2157

	Coef.	Robust Std. Err.	t	P>t	Beta
Ethnicity Asian (proportion of list)	0.00246	0.00032	7.59	0.000	0.09301
IDACI Deprivation Score	0.01488	0.00047	31.63	0.000	0.46402
Coronary Heart Disease Prevalence (QOF Registry)	2.34137	0.56225	4.16	0.000	0.07057
Hypertension Prevalence (QOF Registry)	-0.71645	0.13205	-5.43	0.000	-0.06457
COPD Prevalence (QOF Registry)	4.55472	0.61378	7.42	0.000	0.09887
Cancer Prevalence (QOF Registry)	-2.51076	0.69143	-3.63	0.000	-0.03878
Mental Health Prevalence (QOF Registry) (Log transformed)	0.07573	0.01091	6.94	0.000	0.08620
Asthma Prevalence (QOF Registry)	2.41882	0.31521	7.67	0.000	0.08316
Dementia Prevalence (QOF Registry)	4.36785	0.82990	5.26	0.000	0.04132
Atrial Fibrillation Prevalence (QOF Registry)	-4.75624	0.90408	-5.26	0.000	-0.07496

Table 5.1 shows the statistically significant regression results, excluding dummy variables for clarity, for model 1. The model accounts for 69.8% of the variation in the standardised ACSC admission ratio. It shows that there is an association between a higher standardised ACSC admission ratio and increases in: the proportion of the list of Asian ethnicity; the IDACI deprivation score of the practice's area; the prevalence of coronary heart disease within the practice population; the prevalence of COPD within the practice population; the prevalence of mental health issues within the practice population (variable log transformed); the prevalence of asthma within the practice population; and the prevalence of dementia within the practice population. It further shows that there is an association between a lower standardised ACSC admission ratio and increases in: the prevalence of hypertension within the practice population; the prevalence of cancer within the practice population; and the prevalence of atrial fibrillation within the practice population.

The 'Beta' result given in the final column shows the 'beta coefficients' (i.e. the regression coefficients obtained by first standardising all variables to have a mean of 0 and a standard deviation of 1). They therefore show how much the standardised admission ratio would change in the model if the given variable were varied by one standard deviation. This allows for a helpful way to compare changes in variables.

5.3.2 Model 2

The results for model two are presented in Table 5.2.

Table 5.2 – Regression results for Model 2

Number of obs	7852
F(152, 7739)	105.43
Prob > F	0
R-squared	0.7042
Root MSE	0.2137

	Coef.	Robust Std. Err.	t	P>t	Beta
Ethnicity Asian (proportion of list)	0.00338	0.00052	6.55	0.000	0.12783
Dementia Prevalence (QOF Registry)	4.37080	0.82218	5.32	0.000	0.04130
IMD Deprivation Score	0.01464	0.00064	22.97	0.000	0.45701
Atrial Fibrillation Prevalence (QOF Registry)	-3.76098	0.90487	-4.16	0.000	-0.05937
GP Headcount per 1000 population (Log transformed)	0.05278	0.01149	4.59	0.000	0.04787
Coronary Heart Disease Prevalence (QOF Registry)	2.82204	0.56377	5.01	0.000	0.08517
Hypertension Prevalence (QOF Registry)	-0.71576	0.13026	-5.49	0.000	-0.06457
COPD Prevalence (QOF Registry)	4.36526	0.60470	7.22	0.000	0.09473
Mental Health Prevalence (QOF Registry) (Log transformed)	0.06639	0.01098	6.05	0.000	0.07561
Asthma Prevalence (QOF Registry)	2.14574	0.33866	6.34	0.000	0.07383
Heart Failure due to LVD Prevalence (QOF Registry)	-4.63452	1.31643	-3.52	0.000	-0.02904

Table 5.2 shows the statistically significant regression results, excluding dummy variables for clarity, for model 2. The model accounts for 70.4% of the variation in the standardised ACSC admission ratio. It shows that there is an association between a higher standardised ACSC admission ratio and increases in: the proportion of the list of Asian ethnicity; the prevalence of dementia within the practice population; the IMD deprivation score of the practice's area; the number of GPs (FTE) per 1000 population on the practice's list (variable log transformed); the prevalence of coronary heart disease within the practice population; the prevalence of COPD within the practice population; the prevalence of mental health issues within the practice population (variable log transformed); and the prevalence of asthma within the practice population. It further shows that there is an association between a lower standardised ACSC admission ratio and increases in: the prevalence of atrial fibrillation within the practice population; the prevalence of hypertension within the practice population; and the prevalence of heart failure due to left ventricular dysfunction (LVD) within the practice population.

5.3.3 Model 3

The results for model three are presented in Table 5.3.

Table 5.3 – Regression results for Model 3

Number of obs	7339
F(152, 7739)	99.64
Prob > F	0
R-squared	0.7299
Root MSE	0.2007

	Coef.	Robust Std. Err.	t	P>t	Beta
Ethnicity Asian (proportion of list)	0.00279	0.00055	5.04	0.000	0.10413
IMD Deprivation Score	0.01265	0.00058	21.63	0.000	0.40157
Proportion of list in a nursing home	0.00233	0.00047	4.94	0.000	0.03741
GP Headcount per 1000 population (Log transformed)	0.04874	0.01180	4.13	0.000	0.04423
Coronary Heart Disease Prevalence (QOF Registry)	2.65327	0.56434	4.7	0.000	0.08077
Hypertension Prevalence (QOF Registry)	-0.62167	0.13839	-4.49	0.000	-0.05600
COPD Prevalence (QOF Registry)	4.64634	0.58657	7.92	0.000	0.10154
Mental Health Prevalence (QOF Registry) (Log transformed)	0.04388	0.00910	4.82	0.000	0.04998
Asthma Prevalence (QOF Registry)	2.17373	0.31063	7	0.000	0.07414
Survey - able to see preferred GP	-0.00097	0.00022	-4.49	0.000	-0.03845
Survey - satisfied with phone access	-0.00078	0.00019	-4.03	0.000	-0.03331
QOF Score mh09 exception rate	-0.08448	0.02161	-3.91	0.000	-0.02635
Atrial Fibrillation Prevalence (QOF Registry)	-3.46598	0.89517	-3.87	0.000	-0.05503
Proportion of referrals via A&E	0.08722	0.03130	2.79	0.005	0.04016
QOF Score dm25	-0.28642	0.06401	-4.47	0.000	-0.03928
Survey - would you recommend practice	-0.00124	0.00040	-3.1	0.002	-0.03374
QOF Score dm25 exception rate	0.45906	0.08774	5.23	0.000	0.05770
QOF Score asthma06 exception rate (Log transformed)	0.01040	0.00244	4.26	0.000	0.03095
QOF Score hf04 exception rate	0.06734	0.01544	4.36	0.000	0.03207
QOF Score dm22 exception rate	-0.67746	0.14383	-4.71	0.000	-0.03946
QOF Score epilep08	-0.09215	0.02647	-3.48	0.001	-0.03199

Table 5.3 shows the statistically significant regression results, excluding dummy variables for clarity, for model 3. The model accounts for 73.0% of the variation in the standardised ACSC admission ratio. It shows that there is an association between a higher standardised ACSC admission ratio and increases in: the proportion of the list of Asian ethnicity; the IMD deprivation score of the practice's area; the proportion of the practice list in a nursing home; the number of GPs (FTE) per 1000 population on the practice's log list (variable log transformed); the prevalence of coronary heart disease within the practice population; the prevalence of COPD within the practice population; the prevalence of mental health issues within the practice population (variable log transformed); the prevalence of asthma within the practice population; the proportion of ACSC admissions that were referred from A&E; the practice's QOF exception rate for indicator dm25 (i.e. the percentage of patients with diabetes in whom the last HbA1c is 9 or less, or equivalent test/reference range depending on local laboratory, in the previous 15 months); the practice's QOF exception rate for

indicator asthma06 (i.e. the percentage of patients with asthma who have had an asthma review in the previous15 months) (variable log transformed); and the practice's QOF exception rate for indicator hf04 (i.e. the percentage of patients with a current diagnosis of heart failure due to LVD who are currently treated with an ACE inhibitor or Angiotensin Receptor Blocker, who are additionally treated with a beta-blocker licensed for heart failure, or recorded as intolerant to, or having a contraindication to, beta-blockers.

It further shows that there is an association between a lower standardised ACSC admission ratio and increases in: the prevalence of hypertension within the practice population; the proportion of general practice survey respondents who were able to see their preferred GP (of those that wanted to see a particular GP); the proportion of general practice survey respondents that were satisfied with phone access (to their GP practice); the practice's QOF exception rate for indicator mh09 (i.e. the percentage of patients with schizophrenia, bipolar affective disorder and other psychoses with a review recorded in the preceding 15 months. In the review there should be evidence that the patient has been offered routine health promotion and prevention advice appropriate to their age, gender and health status); the prevalence of atrial fibrillation within the practice population; the practice's QOF indicator dm25 (i.e. the percentage of patients with diabetes in whom the last HbA1c is 9 or less, or equivalent test/reference range depending on local laboratory, in the previous 15 months); the proportion of general practice survey respondents that would recommend their practice to 'someone who has just moved to the local area'; the practice's QOF exception rate for indicator dm22 (i.e. the percentage of patients with diabetes who have a record of estimated glomerular filtration rate (eGFR) or serum creatinine testing in the previous 15 months); and the practice's QOF indicator epilep08 (i.e. the percentage of patients age 18 and over on drug treatment for epilepsy who have been seizure-free for the last 12 months recorded in the previous 15 months).

5.4 Discussion

Differing amounts of variation were accounted for by each of the models, ranging from 69.8% in the most simple (model 1), to 73% in the most complex (model 3). That is, in the third model, 27% of the variation in the GP practice admission rates for ACSCs is still unexplained. It is worth noting that 93% of the GP practices which had all the data available to create model 1 also had sufficient data to cover all the areas required to create model 3. One would therefore need to consider the use of the model before determining which is the most appropriate.

5.4.1 Model 1

The first model aimed to model ACSC admission rates by considering the characteristics of the populations registered to the practices' respective lists.

A greater proportion of the registered population being of Asian ethnic origin was associated with a higher number of ACSC admissions. No other ethnicity category was found to have an association with ACSC admission rates. Previous research by Bankart et al. (2011b) (noted in the introduction), looking at all emergency admissions, has shown an association between white ethnicity and increased numbers of emergency admissions. This suggests that Asian people are particularly susceptible to the sub-category of emergency admissions classed as ACSCs, or that they are underserved by primary care. Further work could examine which of these factors is the more important. The association remained significant in the second and third models.

A higher score on the income deprivation affecting children index (IDACI) was associated with higher rates of ACSC admissions. This is as would be expected, though it is interesting that this particular deprivation score is significant, but not others. In later models this is replaced by the more general IMD deprivation score.

Higher coronary heart disease prevalence, as indicated by the practice's disease register, is associated with higher rates of ACSC admissions, as we would expect. Coronary heart disease is associated with angina and we would therefore expect increased prevalence to lead to more admissions for the condition (which is one of the ACSCs). Similarly, COPD and Asthma, which both showed a higher prevalence as indicated by the practice's disease register, were associated with increased rates of admissions. All three prevalence variables are still significant in the third model.

Cancer prevalence is surprising because increased prevalence appears to be associated with lower rates of admissions, whereas we might expect the opposite. However, the term loses statistical significance in the second and third models and it may therefore be that the model is picking up some 'side-effect'.

Interestingly, increased Mental Health prevalence and Dementia prevalence are both associated with higher rates of admission for ACSCs despite none of the ACSCs being directly related to mental health. This would suggest that mental health plays an important indirect role in influencing ACSC admissions. Possible reasons might include mental health patients being less susceptible to normal primary care interventions aimed at managing patients or that the patients are less compliant with routines set up by their primary care physician, such as medicine regiments. This is an area that will

require further work to determine whether there is anything that can be done to reduce ACSC admissions among those with mental health problems. Mental health prevalence remains significant in the second and third models, whereas dementia prevalence loses significance in the third.

Increased hypertension prevalence and atrial fibrillation prevalence stand out as being associated with lower rates of admissions and also still being statistically significant in the second and third models. We would expect that increased atrial fibrillation prevalence would indicate a higher risk of stroke and congestive heart failure in the population; however, it could be that the higher prevalence rate actually indicates that the practice has a better knowledge of their population (atrial fibrillation is detected using an electrocardiogram) and that, having known about it, they are able, and do, give treatment (typically medication) for it. A further investigation into this area might look at the prescribing habits of GPs to determine if primary care medication is in fact bringing down the rates of ACSC admissions. Similarly, increased hypertension prevalence would indicate an increased risk factor (high blood pressure) among the population, but again, it could be that the higher prevalence rate actually indicates that the practice has better knowledge of their population and therefore offers appropriate and necessary treatment.

In all three models the PCT dummy was significant and made it into the parsimonious version of the model. In the first model it accounted for 22.81% of the variation. This implies that there are PCT-wide factors affecting the number of admissions for ACSCs. It is unclear what these are, but they could include overall funding levels or the effect of secondary care.

5.4.2 Model 2

The second model added practice characteristic variables to the variables used in the existing model.

The IMD deprivation score is statistically significant in the second and third models, whereas the IDACI score loses significance.

The number of GPs per 1000 registered list population was associated with higher rates of admissions for ACSCs in both the second and third models. This is a surprising result and contradicts results from other research such as by Zhan et al. (2004) that suggests a greater number of GPs per capita should be associated with fewer admissions. Although we would typically think that more GPs should mean fewer admissions, it could be that areas that have greater need also have a greater number of GPs per capita and so we are picking up this effect (that is, the number of GPs per 1000 people could be endogenous).

Heart failure due to left ventricular dysfunction (LVD) prevalence is surprising because increased prevalence appears to be associated with lower rates of admissions, whereas we would expect the opposite. However, the term loses its statistical significance in the third model and it may therefore be that we are picking up some 'side-effect'.

The second and third models include a dummy variable for the practice's area type (cluster), as defined by the Yorkshire and Humber Public Health Observatory, as well as a dummy variable for PCT. In the second model the cluster type accounted for 0.43% of the variation and the PCT accounted for 21.71% of the variation. This suggests that some of the variables that have been added to the model were previously being picked up within the PCT variable in the first model.

5.4.3 Model 3

The third model added the quality metric variables to the variables used in the previous model.

The PCT dummy and cluster type dummy were again in the model. In this third model, the cluster type accounted for 0.41% of the variation, whereas the practice's PCT accounted for 18.98% of the variation. Again we see the percentage of variation accounted for by the PCT dummy variable reducing as other variables are introduced. This will be due to the effects previously attributed to the PCT dummy being accounted for by the new variables. In future models the expectation would be that by adding further variables, such as funding level, the percentage of variation accounted for by the practice's PCT would be reduced still further.

A higher proportion of nursing home patients on the practice's list was associated with a greater number of ACSC admissions. This could point to these patients being sicker than the rest of the population, even after adjusting for age and sex, or it could indicate that nursing homes are less good at preventing admissions for ACSCs.

An increase in the proportion of ACSC admissions that were referred from A&E was associated with more ACSC admissions. This suggests that for practices that are doing less well at reducing ACSC admissions, it is A&E departments which are detecting the need for admission, as would be expected.

The model finds two QOF indicators to be significantly associated with ACSC admission rates. The first relates to the percentage of patients with epilepsy who are on treatment and who have been seizure-free for the last twelve months. The second is the percentage of patients with diabetes who had an HbA1c level of 9 or less in their last test. Higher levels of each indictor are associated with

lower levels of ACSC admissions, as would be hoped, as they should both measure a reduction in a risk factor for an ACSC.

The model also finds five QOF exception reports to be significantly associated with ACSC admission rates. 'Exceptions', made for a variety of reasons, exempt a patient from a QOF indicator; they are excluded from both the numerator and denominator of the particular QOF calculation. We would therefore typically expect exceptions to be associated in the opposite direction to the QOF indicator to which they relate. Two of the associations are therefore surprising. Increases in the number of exceptions for the following were all associated with lower rates of ACSC admissions: the percentage of patients with a selection of mental disorders who had a review in the last fifteen months along with advice; and the percentage of patients with diabetes who had a test (glomerular filtration rate) in the last fifteen months. It is unclear why this should be true and further investigation is required. The three remaining QOF exception reports which are significant are all associated with higher admission rates as they increase. They are the percentage of patients with a diagnosis of heart failure due to LVD who are currently being treated by particular drugs; the percentage of patients with asthma who have had an asthma review in the previous fifteen months; and the exception report associated with the diabetes QOF indicator mentioned as significant previously (an HbA1c level of 9 or less). In all cases we would expect the actual indicator to lower risk factors and therefore the exception is likely to mean un-lowered risk factors.

Finally, three survey results were significant and all were associated with lower admission rates for ACSCs. They were: the percentage of patients who report being able to see their preferred GP; the percentage who would recommend the practice; and the percentage satisfied with phone access. Previous research has shown an association between continuity of GP and reduced levels of admissions, but not that the patient's choice specifically is important.

This would appear to suggest that patients' views of their GP practice reflect the quality of care being provided. However, care is needed in interpreting these results as other explanations are possible. For example, it could be that GPs in practices where the patients are engaged and positive (such as those from high socio-economic groups) have better relationships with their patients which leads to better care being delivered. Or it could be that patients who are already able to self-manage their condition are better able to access the GP services and care they need and therefore have a better experience of that care than they otherwise would. Further work is needed to understand whether a causal link exists and to ensure that practices that care for patients from low socio-economic groups are not penalised further for factors outside their control.

5.4.4 Strengths and Weaknesses

5.4.4.1 Data

Many of the data sets used are well understood and some, such as Hospital Episode Statistics (HES) that the admissions data was pulled from, have been used by many other healthcare researchers. The data being analysed is formed from linking previously unconnected data sets. This means new and interesting associations can be found, but it does also mean that the complete dataset is 'untested' by existing academic research. Some of the datasets are drawn from different time periods, and represent proxies for the data for the same time period. This could be causing variation – though no obvious issues were found – and if more time-accurate data became available in the future it would be better to switch. Coding quality within the HES dataset is thought to be good (and improving) but all datasets potentially suffer from issues with their recording and coding. In particular, issues with the coding within a particular practice could create inconsistency and affect results.

An advantage of using existing routinely collected datasets is that this work could be replicated in future years or on data from different years without too much hardship. It also means that the marginal cost of data collection is minimal.

The large number of data points, covering all practices in England which submit data for QOF indicators, means that any conclusions drawn from the research should be widely applicable across England. However, choosing only practices with valid QOF scores could skew results towards the (presumably better) practices that return the indicators.

The models developed consider the prevalence of conditions within the population (such as asthma or hypertension) but not the prevalence of multi-morbidity within the population (such as the proportion of people who have both asthma and hypertension). This is because the relevant data to consider multi-morbidity was not available. However, as patient level data sets become available, this would be a useful addition to the models created in this chapter.

Further datasets that give a broader view of practices' characteristics, in particular quality indicators, would likely improve the accuracy of the model. However, given available data, the model created appears to give a reasonable level of accuracy.

5.4.4.2 Techniques and Approach

The method used (i.e. multiple linear regression) is well understood and used extensively in the literature. The outcomes of regression models have been well corroborated by other methods.

Multiple linear regression will only ever show associations between the independent variables and the dependent variable, and does not imply that one *causes* the other. This means that the model is good for predicting rates but researchers need to be careful not to suggest that changing one of the independent variables will change the dependent variable. It does however give strong evidence for areas that could be investigated further to try and prove causality.

There could be variables and factors that influence admission rates that are not being captured by the model. To be valid, regression models should account for all factors. In reality, however, they are limited by the availability of data.

There are constraints on the model which is only valid within the range of the variables within it. For example, the percentage of the list population of Asian ethnicity must be within the 0 - 97.07% range. However, there may be constraints on variables that are not taken into account by the model, for instance smoking rates (which are not in the model) are within some range within all the practice populations. Smoking rates are highly likely to have an impact on the population's health. Should smoking rates change over time and shift out of the existing range the model may cease to be accurate.

5.4.4.3 Design

The regression uses a single year of data, rather than multiple years. Using data from multiple years may have allowed the identification of factors that are associated with varying ACSC admission rates but that do not have an impact over the shorter term. This is potentially true for prevention activities, such as smoking cessation, as well as disease management programmes where the care being provided is slow to have an effect on the patient. Future research using larger, multi-year datasets ought to be able to identify such factors and would provide a valuable addition to this analysis.

The regression uses cross-sectional data, rather than longitudinal. A longitudinal model may be able to allow stronger assertions to be made as it is easier to account for particular factors, such as population characteristics, as most of the population being observed in each area will remain constant. It would also allow for predictions to be made of how changes in variables in a given year affect rates in a later year. It also gives the data more richness that may show the data has a different meaning to that previously thought. For example, the IMD deprivation score gives a view on the proportion of the population that are of low socio-economic status. However, it may be that what really matters is the proportion of the population that have been of a low socio-economic

status for the last five years and that those that are transitory do not impact admission rates and are distorting the model.

Finally, the model does not distinguish between 100 asthma admissions at one practice and 100 diabetes admissions at another, as they are grouped together within the dependent variable. Using disease-specific quality indicators in this model may, therefore, be misleading. Should the model be used in the future to determine if particular changes affected admission rates, the researcher would need to be conscious that condition-specific interventions may not show any impact due to 'overcrowding' of admissions for other conditions. The next chapter will aim to eliminate this issue by creating condition-specific models.

6 Modelling condition-specific rates

6.1 Introduction

This chapter builds on the work done in chapter 5 to model admissions for all ACSCs combined, and aims to show that individual ACSC rates of admission into secondary care can be modelled and lead to understanding how these factors vary from those associated with the all-ACSC admission rate. That is, it hypothesises a given condition specific rate of admission $C_i = h(v_i, R_i)$, where v_i is a set of exogenous population characteristics and R_i a set of practice characteristics (both resource and quality).

A concern with modelling the overall rate of ACSC admissions is that some conditions which have a larger proportion of emergency admissions might 'drown out' some other conditions and, in particular, interventions aimed at reducing those conditions and quality metrics measuring their impact would not be picked up. The essential problem is to attribute variations to the practice as opposed to 'need'. Moving to the level of a specific condition should allow a greater focus on practice characteristics as the population factors are better understood for specific conditions, rather than the ACS group of conditions as a whole. To identify the factors associated with particular conditions, multiple linear regression will be used with a given condition admission rate as the dependent variable.

Four conditions will be considered: asthma, hypertension, chronic obstructive pulmonary disease and diabetes. These specific conditions were chosen because they are all conditions that have a mapping to an indicator in the QOF clinical domain. The QOF data, as shown in the previous chapter, is expected to be an important indicator of a practice's quality and, because this is a key element to the model, only those conditions that have this mapping were included in the analysis. Future analyses seeking to model other conditions would need to identify an appropriate proxy for a practice's clinical quality for the respective condition.

A potential issue which should be borne in mind when interpreting the results in this chapter is whether the approach of picking a given condition, and looking just at the admissions that have been coded as being for that condition, will comprehensively reflect all the relevant admissions for that condition. For instance, hypertension in the population might lead to "direct" admissions for hypertension that are coded as such. However, hypertension might also lead to other "indirect" admissions that are coded as being for a different condition but that are nonetheless affected by the hypertension condition. This second, "indirect" admissions group will not be picked up by the

condition-specific models created in this chapter (nor indeed would they have been picked up by the all-ACSC admission model unless the "indirect" admission condition happened to be an ACSC).

The previous chapter demonstrated that population and practice (resource and quality) should all be included in any model and therefore each condition-specific model will use variables representing each aspect but, where possible, specific to the condition being examined.

Judging individual practices based on their performance against a condition-specific indicator is likely to be misleading due to the small numbers of admissions involved. However, it is important to consider each condition separately to avoid the 'drowning out' mentioned above. To get around these two issues the conditions will first be modelled separately and then combined together using an econometric technique known as seemingly unrelated regression (SUR).

A seemingly unrelated regression (SUR) system comprises several individual relationships that are linked by the fact that their disturbances are correlated because of common unobservable factors. This is likely to be true of modelling admission rates for different conditions as any shocks to practices, such as unexpected sickness in an area, are likely to impact across the range of conditions. SUR uses this fact to create more efficient coefficient estimates. SUR was first developed by Zellner (1962). It has since been used extensively in the literature. A recent example in healthcare is given by Adam et al. (2014) who use SUR to identify the determinants of variability of ward-level costs in a Chinese hospital. For SUR to be applicable each of the individual equations must satisfy the classical assumptions associated with the linear regression model separately, as set out in chapter five. Estimating the models separately however ignores the correlation between the disturbances of different equations, which can be exploited by joint estimation (Baltagi, 2008).

A short overview of each of the four conditions considered is given below:

6.1.1 Asthma

Asthma is a common long-term condition that can cause a cough, wheezing, and breathlessness. Asthma is caused by inflammation of the airways. These are the small tubes, called bronchi, which carry air in and out of the lungs. In asthma sufferers, the bronchi will be inflamed and more sensitive than normal. Coming into contact with something that irritates the lungs, known as a trigger, such as animal fur or tobacco smoke, can cause airways to become narrow, the muscles around them to tighten and an increase in the production of sticky mucus. There are around 5.4 million people with Asthma in the UK (AsthmaUK, 2014). In 2010/11 there were 58,141 emergency admissions in England for asthma deemed ambulatory care sensitive, costing just over £61m.

Previous studies have found some interventions that reduce asthma admission rates and emergency care more generally. Greineder et al. (1999) demonstrated that by offering children a single education session they were able to reduce emergency department visits by 40% in the US. Similarly Bolton et al. (1991) have demonstrated that adult asthma patients given self-management support made fewer emergency department visits throughout a 12-month period compared with a usual care group. However, in a study with a longer follow-up period, Kauppinen et al. (2001) found no significant reduction in health care costs after 5 years for adult asthma patients given intensive patient education throughout a one-year period. And Lahdensuo et al. (1998) found that for patients with mild to moderately severe asthma health care costs were actually higher for the group receiving a self-management program than for a usual care group.

Newman et al. (2004) conducted a systematic review of self-management educational interventions for asthma. The authors reported that self-management education was beneficial for the management of asthma in reducing hospitalisations.

Greineder et al. (1999) showed that, at a staff-model health maintenance organisation (HMO) in the US, children enrolled in a nurse case-management program for asthma had 73% fewer emergency department visits and 84% fewer hospitalisations.

Age and sex are known to impact on asthma admissions. There is a much higher rate of admission for prepubertal males than females. However, there is a higher incidence of asthma admissions for adult females than adult male asthmatic patients (Skobeloff et al., 1992). Asthma patients are more likely to have comorbidities than a similar non-asthmatic matched population (Soriano et al., 2005).

6.1.2 Chronic Obstructive Pulmonary Disease (COPD)

COPD is a general term that is used to describe a number of conditions including chronic bronchitis and emphysema. COPD is an incurable, but largely preventable disease, which leads to damaged airways in the lungs, causing them to become narrower and making it harder for air to get in and out. There are an estimated 3.7 million people with COPD in the UK, though some 2.8 million of these are thought to be undiagnosed and therefore unaware they have the disease. In 2010/11 there were 113,197 emergency admissions in England for COPD deemed ambulatory care sensitive, costing just over £256m. The most important risk factor for COPD is smoking, followed by other aspects of social deprivation, diet and occupational exposure to dust (Foundation, 2007). COPD patients are also more likely to have comorbidities than a similar matched population that do not have COPD (Soriano et al., 2005).

Bury et al. (2005) found that lay-led self-management programmes were effective in reducing hospitalisation for lung disease, but the authors commented that the utility of lay-led self-management was dependent on other care components.

Pare et al. (2007) conducted a systematic review that evaluated the effectiveness of telemonitoring in the management of chronic illnesses. Telemonitoring was found to be associated with significantly reduced hospitalisations for pulmonary illnesses.

6.1.3 Diabetes

Diabetes mellitus, also known simply as diabetes, is a group of metabolic diseases in which there are high blood sugar levels over a prolonged period. Diabetes is due to either the pancreas not producing insulin (Type 1), or the cells of the body not responding properly to the insulin produced (Type 2). Untreated, diabetes can lead to complications, including heart disease, stroke, kidney failure, foot ulcers and damage to the eyes (WHO, 2013). There are an estimated 3.2 million people with Type 1 and Type 2 diabetes in the UK (DiabetesUK, 2014). In 2010/11 there were 22,135 emergency admissions in England for diabetes deemed ambulatory care sensitive, costing just under £48m.

Previous work assessing interventions for those with diabetes has identified a number of potentially positive results. In a study of diabetic patients participating in a structured education and treatment program in rural Austria, Pieber et al. (1995) found that programme patients had lower health care costs after six months compared with a control group. However, Newman et al. (2004) conducted a systematic review of self-management educational interventions for type 2 diabetes and reported that self-management education was not beneficial for the management of diabetes.

Kaiser Permanente studied the impact of co-locating a multidisciplinary team so that each relevant member of the team could meet with the diabetic patient during a single visit (Sadur et al., 1999). Care was delivered by a diabetes nurse educator, a psychologist, a nutritionist and a pharmacist. They found the diabetes care delivered in this way resulted in reduced hospital and outpatient use compared with usual care.

Domurat (1999) looked at an intervention aimed at high-risk diabetes patients in which the patients were intensively managed by a team that offered planned diabetes visits, telephone contacts and group educational sessions. The study found that patients in the intensive program stayed half as long in hospital as those in the control group.

Improved glycaemic control is seen as a core component of managing diabetes patients. Wagner et al. (2001b) compared two groups of diabetic patients throughout one year and found the organisation was saving between $685 and $950 per patient annually for the group with improved HbA1c levels. (Measuring HbA1c is a way to measure blood glucose levels – an important indicator for diabetics. For non-diabetics a usual reading would be in the range 4.0-5.9%. For people with diabetes an HbA1c level of 6.5% is considered good control.) The savings resulted from fewer hospital admissions, emergency department visits and physician consultations. Savings were statistically significant only for patients in the improved group whose baseline HbA1c level was 10% or above.

6.1.4 Hypertension

Hypertension is defined as a persistent raised blood pressure of 140/90mmHg or more. Hypertension is symptomless, but it is a major risk factor for a number of other potentially fatal conditions, such as coronary heart disease, stroke, congestive heart failure and chronic kidney disease. Age, gender and ethnicity are known, un-modifiable risk factors. For any given age up to 65 years, women tend to have a lower blood pressure than men. After 65 years, this trend is reversed. Hypertension is known to be more prevalent in black Caribbean men and women, and less prevalent in Bangladeshi men and women. Modifiable risk factors include high salt intake, obesity, physical inactivity, high alcohol consumption and diabetes (Maryon-Davis and Stewart, 2005). In the UK 31% of men and 27% of women have hypertension (HSCIC, 2013). In 2010/11 there were 6,057 emergency admissions in England for hypertension deemed ambulatory care sensitive, costing just over £9m.

Hersh et al. (2001) conducted a systematic review that compared telecare and automated patient monitoring versus usual patient care for all hospital admissions and found that the strongest evidence of efficacy of telemedicine in clinical outcomes was in the applications of home-based telemedicine in the management of hypertension.

6.2 Methods

To investigate what factors are associated with varying levels of admission rates for ACSCs, a multiple linear regression of the data was performed at the level of the GP practice. For each GP practice in England for which there was 2010/11 QOF data available (8245 practices), corresponding data were identified for each of the variables listed below. (Refer to chapter 3 for further details on the source of each data set.)

The dependent variable for each model, based on the specific condition, will not be age-sex adjusted, as it was in the previous chapter, and instead will be the unadjusted rate of admission for the specific condition. This is because the number of admissions per practice, at the condition level, is sometimes zero and, in particular, an expected rate of zero (based on the age-sex of the list population) would cause an issue as the denominator in the standardised ratio. Instead the expected rate (based on the age-sex breakdown of the population) will be included as an independent variable.

The dependent variable in each model is calculated (as in the previous chapter) by taking the number of first episodes for the condition (ICD10 codes for each condition given below) for each GP practice during the 2010/11 financial year, divided by the number of persons on the GP's list, multiplied by one thousand.

Each of the condition-specific models picks out the components of the final model (model 3) in the previous chapter that were most relevant to the condition. In particular, only QOF results related to the condition being considered were included and prevalence estimates (from practice disease registries) for the particular condition (rather than all conditions they hold data for). As well as the prevalence of the specific condition (where available) the prevalence of mental health conditions was also included, as mental health was found in the previous chapter to be associated with admission rates (despite no particular ACSC being for mental health). Each regression also included a dummy variable for the practice's PCT and their cluster type, which has been omitted from the outputs for clarity.

Statistical significance within the regression model was judged at the five percent level – higher than the one percent used in the previous chapter – on the basis that there were fewer variables being included in the model in the first place.

To ensure each condition-specific model was correctly specified, any terms that were found to be collinear with other terms were removed. An augmented partial residual plot was used to identify any terms that might not be linearly associated with the dependent variable. Finally, the error distribution of the model was checked to ensure it was normally distributed.

6.2.1 Asthma Model

The prevalence of asthma within the practice population was included in the model. As well as the QOF indicators directly related to asthma, the QOF indicators related to smoking were also included,

due to the known connection between smoking and respiratory issues (Calderon-Larranaga et al., 2011). The asthma model regression was performed on the following model:

Dependent Variable:

- The rate of ACS asthma admissions during 2010/11 (admissions per 1000 persons on GP's list)[2]

Independent Variables:

Population Characteristics:

- The expected ACS asthma admission rate given the practice's age and sex breakdown, based on the rates seen nationally
- The estimated ethnic breakdown of the practice's list
- GP practice's deprivation score (IMD, IDACI and IDAOPI)
- Percentage of persons on the practice's list who are nursing home patients
- Asthma prevalence (based on QOF disease register)
- Mental Health prevalence (based on QOF disease register)
- The practice's PCT (dummy variable)

Practice Characteristics (Resource):

- The practice list size
- Number of GPs (headcount) within practice per 1000 persons on list
- The practice's cluster type (dummy variable)
- Level of technology in use in GP practice (5 indicators)

Practice Characteristics (Quality Metrics):

- QOF indicator results related to Asthma (full description in Appendix I)
    - Smoke03, Smoke04
    - Asthma03, Asthma 06, Asthma08
- The exception rate for QOF indicators related to Asthma (full description in Appendix I)
    - Smoke03, Smoke04
    - Asthma03, Asthma 06, Asthma08
- The total QOF points attained by the practice
- Results of a GP patient survey (9 domains – 5 access, 4 patient opinion)

[2] ACS asthma admissions are defined as those with a diagnosis code equal to J45 or J46. This follows the coding practice suggested by Purdy et al. (2009).

6.2.2 Chronic Obstructive Pulmonary Disease (COPD) Model

The prevalence of COPD within the practice population was included in the model. As well as the QOF indicators directly related to COPD, the QOF indicators related to smoking were also included, due to the known connection between smoking and respiratory issues (Calderon-Larranaga et al., 2011). The COPD model regression was performed on the following model:

Dependent Variable:

- The rate of ACS COPD admissions during 2010/11 (admissions per 1000 persons on GP's list)[3]

Independent Variables:

Population Characteristics:

- The expected ACS COPD admission rate given the practice's age and sex breakdown, based on the rates seen nationally
- The estimated ethnic breakdown of the practice's list
- GP practice's deprivation score (IMD, IDACI and IDAOPI)
- Percentage of persons on the practice's list who are nursing home patients
- COPD prevalence (based on QOF disease register)
- Mental Health prevalence (based on QOF disease register)
- The practice's PCT (dummy variable)

Practice Characteristics (Resource):

- The practice list size
- Number of GPs (headcount) within practice per 1000 persons on list
- The practice's cluster type (dummy variable)
- Level of technology in use in GP practice (5 indicators)

Practice Characteristics (Quality Metrics):

- QOF indicator results related to COPD (full description in Appendix I)
    - Smoke03, Smoke04
    - COPD08, COPD10, COPD12, COPD13
- The exception rate for QOF indicators related to COPD (full description in Appendix I)
    - Smoke03, Smoke04
    - COPD08, COPD10, COPD12, COPD13
- The total QOF points attained by the practice
- Results of a GP patient survey (9 domains – 5 access, 4 patient opinion)

[3] ACS COPD admissions are defined as those with a diagnosis code equal to J20, J41, J42, J43, J47, J44 or J40. This follows the coding practice suggested by Purdy et al. (2009).

6.2.3 Diabetes Model

No diabetes prevalence estimate exists within the QOF registry data so no estimate is included. However all diabetes QOF indicators were included. The diabetes model regression was performed on the following model:

Dependent Variable:

- The rate of ACS diabetes admissions during 2010/11 (admissions per 1000 persons on GP's list)[4]

Independent Variables:

Population Characteristics:

- The expected ACS diabetes admission rate given the practice's age and sex breakdown, based on the rates seen nationally
- The estimated ethnic breakdown of the practice's list
- GP practice's deprivation score (IMD, IDACI and IDAOPI)
- Percentage of persons on the practice's list who are nursing home patients
- Mental Health prevalence (based on QOF disease register)
- The practice's PCT (dummy variable)

Practice Characteristics (Resource):

- The practice list size
- Number of GPs (headcount) within practice per 1000 persons on list
- The practice's cluster type (dummy variable)
- Level of technology in use in GP practice (5 indicators)

Practice Characteristics (Quality Metrics):

- QOF indicator results related to Diabetes (full description in Appendix I)
    - DM02, DM05, DM09, DM10, DM11, DM12, DM13, DM15, DM16, DM17, DM18, DM21, DM22, DM23, DM24, DM25
- The exception rate for QOF indicators related to Diabetes (full description in Appendix I)
    - DM02, DM05, DM09, DM10, DM11, DM12, DM13, DM15, DM16, DM17, DM18, DM21, DM22, DM23, DM24, DM25
- The total QOF points attained by the practice
- Results of a GP patient survey (9 domains – 5 access, 4 patient opinion)

[4] ACS diabetes admissions are defined as those with a diagnosis code equal to E100, E101, E102, E103, E104, E105, E106, E107, E108, E110, E111, E112, E113, E114, E115, E116, E117, E118, E120, E121, E122, E123, E124, E125, E126, E127, E128, E13 or E14. This follows the coding practice suggested by Purdy et al. (2009).

6.2.4 Hypertension Model

The QOF indicators directly related to hypertension and the hypertension prevalence estimates were included. The hypertension model regression was performed on the following model:

Dependent Variable:

- The rate of ACS hypertension admissions during 2010/11 (admissions per 1000 persons on GP's list)[5]

Independent Variables:

Population Characteristics:

- The expected ACS hypertension admission rate given the practice's age and sex breakdown, based on the rates seen nationally
- The estimated ethnic breakdown of the practice's list
- GP practice's deprivation score (IMD, IDACI and IDAOPI)
- Percentage of persons on the practice's list who are nursing home patients
- Hypertension prevalence (based on QOF disease register)
- Mental Health prevalence (based on QOF disease register)
- The practice's PCT (dummy variable)

Practice Characteristics (Resource):

- The practice list size
- Number of GPs (headcount) within practice per 1000 persons on list
- The practice's cluster type (dummy variable)
- Level of technology in use in GP practice (5 indicators)

Practice Characteristics (Quality Metrics):

- QOF indicator results related to Hypertension (full description in Appendix I)
    - BP04, BP05
- The exception rate for QOF indicators related to Hypertension (full description in Appendix I)
    - BP04, BP05
- The total QOF points attained by the practice
- Results of a GP patient survey (9 domains – 5 access, 4 patient opinion)

[5] ACS hypertension admissions are defined as those with a diagnosis code equal to I10 or I119. This follows the coding practice suggested by Purdy et al. (2009).

6.2.5 Condition-specific models combined

To combine the four condition-specific models, seemingly unrelated regression (SUR) was used. SUR was developed by Zellner (1962) and is a generalisation of a linear regression model that consists of several regression equations, each having its own dependent variable and potentially different sets of exogenous explanatory variables. Each equation is a valid linear regression on its own and can be estimated separately. Such estimates are consistent but not generally as efficient as the SUR method. SUR was used on the outputs of the regression models developed in parts 6.3.1-4. The Stata function 'sureg' was used to perform the SUR analysis.

6.3 Results

6.3.1 Asthma Model

The multiple linear regression of the model described above at the five percent statistical significance level gave the following results:

Table 6.1 – Regression results from Asthma model

	SS	df	MS
Model	2351.32	170	13.831
Residual	3791.76	7682	0.494
Total	6143.08	7852	0.782

Number of obs	7853
F(168, 7669)	28.02
Prob > F	0
R-squared	0.3828
Adj R-squared	0.3691
Root MSE	0.7026

	Coef.	Std. Err.	t	P>t	Beta
Expected Asthma Rate (by age-sex of pop)	1.28947	0.18527	6.96	0.000	0.10756
Ethnicity Black (proportion of list)	-0.01483	0.00266	-5.57	0.000	-0.12140
Ethnicity Mixed (proportion of list)	-0.01882	0.00205	-9.16	0.000	-0.16757
Ethnicity Other (proportion of list)	-0.01928	0.00518	-3.73	0.000	-0.06685
Ethnicity White (proportion of list)	-0.01618	0.00135	-12.02	0.000	-0.43146
IMD Deprivation Score	0.01809	0.00143	12.67	0.000	0.24822
GP Headcount per 1000 population	0.09120	0.03018	3.02	0.003	0.02866
Asthma Prevalence (QOF Registry)	7.66472	0.72737	10.54	0.000	0.11591
QOF Score asthma06	-0.40154	0.10431	-3.85	0.000	-0.03597
Survey - satisfied with phone access	-0.00213	0.00054	-3.95	0.000	-0.03887

The model accounts for 38.3% of the variation in the ACS asthma rates. It finds the expected rate of asthma admissions (based on age and sex of the population) and the recorded prevalence of asthma for persons on the GP's list to be positively associated with higher rates of admission. A higher deprivation score (IMD – the index of multiple deprivation that covers a range of economic, social and housing issues into a single score) is associated with high rates of admissions. A higher proportion of the population having ethnicity Black, White, Mixed or 'Other' were all associated with lower admission rates. (Note the remaining ethnicities in this categorisation not associated with

lower admission rates were Asian and Irish). A higher score on the QOF indicator Asthma06 (i.e. the percentage of patients with asthma who have had an asthma review in the previous 15 months) and on the National GP Survey result (i.e. those satisfied with the phone access) were both associated with lower rates of admission. Finally, more full-time equivalent GPs per 1000 persons on the practice's list was associated with higher rates of admissions.

6.3.2 Chronic Obstructive Pulmonary Disease (COPD) Model

The multiple linear regression of the model described above at the five percent statistical significance level gave the following results:

Table 6.2 – Regression results from COPD model

	SS	df	MS
Model	10512.50	170	61.838
Residual	9674.67	7650	1.265
Total	20187.17	7820	2.581

Number of obs	7821
F(168, 7669)	48.9
Prob > F	0
R-squared	0.5208
Adj R-squared	0.5101
Root MSE	1.1246

	Coef.	Std. Err.	t	P>t	Beta
Expected COPD Rate (by age-sex of pop)	0.35207	0.04605	7.65	0.000	0.13022
Ethnicity Mixed (proportion of list)	0.01539	0.00321	4.8	0.000	0.07528
Ethnicity White (proportion of list)	0.01603	0.00194	8.28	0.000	0.23388
IMD Deprivation Score	0.03812	0.00526	7.24	0.000	0.28797
IDACI Deprivation Score	1.31830	0.49979	2.64	0.008	0.10344
Proportion of list in a nursing home	0.00706	0.00216	3.26	0.001	0.02826
COPD Prevalence (QOF Registry)	50.33964	2.49668	20.16	0.000	0.26339
QOF Score copd12 exception rate	0.23354	0.10355	2.26	0.024	0.01842
Survey - satisfied with phone access	-0.00229	0.00090	-2.54	0.011	-0.02299
Survey - would you recommend practice	-0.00772	0.00165	-4.67	0.000	-0.05094

The model accounts for 52.1% of the variation in the ACS COPD rates. It finds the expected rate of COPD admissions (based on age and sex of the population) and the recorded prevalence of COPD for persons on the GP's list to be positively associated with higher rates of admission. Higher deprivation scores IMD (the Index of Multiple Deprivation that covers a range of economic, social and housing issues into a single score) and IDACI (Income Deprivation Affecting Children) are associated with high rates of admissions. A higher proportion of the population having ethnicity White and Mixed were associated with higher admission rates. A higher proportion of the practice's population being in a nursing home was associated with higher admission rates. A higher exception rate on the QOF indicator COPD12 (i.e. the percentage of patients exempted from the indicator 'The percentage of all patients with COPD diagnosed after 1 April in previous year in whom the diagnosis has been confirmed by post bronchodilator spirometry') was associated with higher admission rates.

On the National GP Survey results, those satisfied with the phone access and those who would recommend their practice were both associated with lower rates of admission.

6.3.3 Diabetes Model

The multiple linear regression of the model described above at the five percent statistical significance level gave the following results:

Table 6.3 – Regression results from Diabetes model

	SS	df	MS
Model	176.50	168	1.051
Residual	1242.90	7669	0.162
Total	1419.39	7837	0.181

Number of obs	7838
F(168, 7669)	6.48
Prob > F	0
R-squared	0.1243
Adj R-squared	0.1052
Root MSE	0.4026

	Coef.	Std. Err.	t	P>t	Beta
Ethnicity Black (proportion of list)	0.00433	0.00147	2.95	0.003	0.07319
Ethnicity White (proportion of list)	0.00250	0.00060	4.18	0.000	0.13834
IMD Deprivation Score	0.00725	0.00085	8.49	0.000	0.20690
GP Headcount per 1000 population	0.04967	0.01744	2.85	0.004	0.03246
Mental Health Prevalence (QOF Registry)	7.20215	1.39956	5.15	0.000	0.06796
QOF Score dm25	-0.47302	0.09734	-4.86	0.000	-0.06043
QOF Score dm24 exception rate	0.36899	0.08206	4.5	0.000	0.05503
Survey - would you recommend practice	-0.00180	0.00056	-3.22	0.001	-0.04496

The model accounts for 12.4% of the variation in the ACS diabetes rates. A higher deprivation score (IMD – The index of multiple deprivation that covers a range of economic, social and housing issues into a single score) is associated with high rates of admissions. A higher proportion of the population having ethnicity Black and White were associated with higher admission rates. A higher score on the QOF indicator DM25 (i.e. the percentage of patients with diabetes in whom the last HbA1c is 9 or less (or equivalent test/reference range depending on local laboratory) in the previous 15 months) and on the National GP Survey result (i.e. those that would recommend their practice) were both associated with lower rates of admission. The exception rate for the QOF indicator DM24 (i.e. the percentage of patients with diabetes in whom the last HbA1c is 8 or less (or equivalent test/reference range depending on local laboratory) in the previous 15 months) was associated with a higher rate of admissions. The recorded prevalence of mental health issues for persons on the GP's list was positively associated with higher rates. Finally, more full-time equivalent GPs per 1000 persons on the practice's list was associated with higher rates of admissions.

6.3.4 Hypertension Model

The multiple linear regression of the model described above at the five percent statistical significance level gave the following results:

Table 6.4 – Regression results from Hypertension model

	SS	df	MS
Model	19.39	164	0.118
Residual	211.64	7632	0.028
Total	231.03	7796	0.030

Number of obs	7797
F(168, 7669)	4.26
Prob > F	0
R-squared	0.0839
Adj R-squared	0.0642
Root MSE	0.1665

	Coef.	Std. Err.	t	P>t	Beta
Expected Hypertension Rate (by age-sex of pop)	0.97251	0.20650	4.71	0.000	0.10139
IDACI Deprivation Score	0.09300	0.03186	2.92	0.004	0.06819
Survey - able to see preferred GP	-0.00036	0.00014	-2.49	0.013	-0.03170
Survey - would you recommend practice	-0.00066	0.00024	-2.75	0.006	-0.04077

The model accounts for 8.4% of the variation in the ACS hypertension rates. It finds the expected rate of hypertension admissions (based on age and sex of the population) to be positively associated with higher rates. A higher deprivation score (IDACI – Income Deprivation Affecting Children Index) is associated with high rates of admissions. Finally, on the National GP Survey, two results were associated with lower rates: those that would recommend their practice and those that report being able to see their preferred GP.

6.3.5 Condition-specific models combined

It is unlikely that the error terms for each condition-specific regression are uncorrelated as the equations measure different components of the same practices. It would therefore be more efficient to estimate the equations as part of a seemingly unrelated regression (SUR) system. If the error terms are correlated then, because SUR estimates the equations jointly, it will produce a more efficient estimator. If the error terms were not correlated then there is no relation between the models and the results of SUR will be the same as regressing the models separately (as above). Doing so for the four conditions estimated so far gives the results shown in Table 6.5. Note that each model still contains a dummy variable for the practice's PCT and their cluster type that have again been omitted from the outputs for clarity (see Table 6.5).

Table 6.5 – Results of the seemingly unrelated regression

Equation	# of obs	df	Root MSE	R-squared	Chi-squared	Prob > F
ACS Asthma Admission Rate	7765	170	0.6925	0.3854	4865.27	0
ACS COPD Admission Rate	7765	170	1.1059	0.5237	8539.17	0
ACS Diabetes Admission Rate	7765	168	0.3955	0.1265	1123.28	0
ACS Hypertension Admission Rate	7765	164	0.1646	0.0830	701.24	0

	Coef.	Std. Err.	t	P>t	95% Confidence Interval	
ACS Asthma Admission Rate						
Expected Asthma Rate (by age-sex of pop)	1.30360	0.18448	7.07	0.000	0.94202	1.66518
Ethnicity Black (proportion of list)	-0.01383	0.00269	-5.14	0.000	-0.01911	-0.00855
Ethnicity Mixed (proportion of list)	-0.01859	0.00204	-9.11	0.000	-0.02259	-0.01459
Ethnicity Other (proportion of list)	-0.01695	0.00534	-3.17	0.002	-0.02741	-0.00648
Ethnicity White (proportion of list)	-0.01567	0.00134	-11.73	0.000	-0.01828	-0.01305
IMD Deprivation Score	0.01808	0.00142	12.77	0.000	0.01531	0.02085
GP Headcount per 1000 population	0.08603	0.02986	2.88	0.004	0.02751	0.14455
Asthma Prevalence (QOF Registry)	7.74963	0.72149	10.74	0.000	6.33553	9.16373
QOF Score asthma06	-0.40077	0.10323	-3.88	0.000	-0.60311	-0.19844
Survey - satisfied with phone access	-0.00214	0.00053	-4.00	0.000	-0.00318	-0.00109
ACS COPD Admission Rate						
Expected COPD Rate (by age-sex of pop)	0.34941	0.04541	7.69	0.000	0.26041	0.43841
Ethnicity Mixed (proportion of list)	0.01547	0.00315	4.91	0.000	0.00929	0.02165
Ethnicity White (proportion of list)	0.01667	0.00191	8.74	0.000	0.01293	0.02041
IMD Deprivation Score	0.04103	0.00517	7.94	0.000	0.03090	0.05117
IDACI Deprivation Score	1.01665	0.49062	2.07	0.038	0.05506	1.97824
Proportion of list in a nursing home	0.00720	0.00221	3.25	0.001	0.00286	0.01154
COPD Prevalence (QOF Registry)	50.11813	2.46758	20.31	0.000	45.28176	54.95450
QOF Score copd12 exception rate	0.25271	0.10201	2.48	0.013	0.05278	0.45264
Survey - satisfied with phone access	-0.00228	0.00089	-2.57	0.010	-0.00402	-0.00054
Survey - would you recommend practice	-0.00760	0.00164	-4.63	0.000	-0.01082	-0.00438
ACS Diabetes Admission Rate						
Ethnicity Black (proportion of list)	0.00498	0.00147	3.38	0.001	0.00210	0.00787
Ethnicity White (proportion of list)	0.00271	0.00059	4.58	0.000	0.00155	0.00388
IMD Deprivation Score	0.00751	0.00084	8.90	0.000	0.00586	0.00917
GP Headcount per 1000 population	0.04825	0.01723	2.80	0.005	0.01448	0.08202
Mental Health Prevalence (QOF Registry)	7.09846	1.39078	5.10	0.000	4.37258	9.82433
QOF Score dm25	-0.43907	0.09677	-4.54	0.000	-0.62874	-0.24940
QOF Score dm24 exception rate	0.36912	0.08173	4.52	0.000	0.20894	0.52929
Survey - would you recommend practice	-0.00187	0.00056	-3.36	0.001	-0.00295	-0.00078
ACS Hypertension Admission Rate						
Expected Hypertension Rate (by age-sex of pop)	0.94889	0.20890	4.54	0.000	0.53946	1.35832
IDACI Deprivation Score	0.09134	0.03160	2.89	0.004	0.02941	0.15327
Survey - able to see preferred GP	-0.00034	0.00014	-2.38	0.017	-0.00062	-0.00006
Survey - would you recommend practice	-0.00065	0.00024	-2.74	0.006	-0.00112	-0.00019

The SUR analysis does indeed lead to a closer fit with smaller standard errors in most cases. The coefficients are also slightly different to those given by regressing each equation individually. However, none of the signs of the coefficients change and so the results described above for each individual regression hold. Note that the SUR regression has been carried out over the subset of observations (practices) for which data was available for all four regressions. However, the loss of

data points (88 in the most extreme case) is unlikely to impact substantially on any findings, since this accounts for just over one percent of observations (practices).

6.4 Discussion

The amount of variation which can be accounted for by each model varies greatly, from just over 8 to 52%. These varying proportions are likely to be largely due to the varying numbers of total annual admissions for each condition; there were 113,197 admissions for COPD in 2010/11 with the model accounting for 52% of the practice-level variation; there were 58,141 admissions for asthma with the model accounting for 38.5% of the variation; there were 22,135 admissions for diabetes with the model accounting for 12.7% of the variation; and there were 6,057 admissions for hypertension with the model accounting for 8.3% of the variation. However, they could also reflect the different levels of understanding of risk factors for admission for each of the four conditions.

For each condition there are likely to be admissions that were caused by the condition, but for which the admission has not been picked up by the model because they are not coded as such. Hypertension, in particular, is likely to lead to admissions that would not be coded as hypertension, such as for stroke. It was not possible to include these admissions in the analysis (as not all stroke admissions will be caused by hypertension). It should be borne in mind, then, that not all admissions caused by conditions are being picked up. This could be another reason for the different amounts of variation accounted for by each of the models.

As expected from previous research in the area, population characteristics, such as deprivation, age and sex, are associated with varying rates of admissions in each of the condition models. More interestingly, QOF scores and general practice patient survey results are positively associated with lower rates of admission. The two QOF scores that are associated with lower rates both relate to an 'intervention' that is carried out within the GP practice – namely an asthma review and a test to ensure blood glucose levels for diabetics is being kept under control. Previous research by Campbell et al. (2007) used a longitudinal analysis over the period that QOF was introduced and found a statistically significant increase in the rate of improvement in clinical quality for diabetes and asthma (though the authors did not consider ACSC admission rates). The fact that differences in the attainment of these QOF scores reflect different levels of ACSC admissions suggests that either most practices improved with the introduction of QOF, raising quality across the board; or that good practices improved more than poorer ones, thereby bringing up the average. Either way, the result suggests that, for diabetes and asthma, the QOF result does reflect better practice quality.

GP headcount per 1000 population on the practice's list is associated with higher rates of admission for both asthma and diabetes. This unexpected result is likely due to GP headcount reflecting a level of investment in the relevant area, with sicker areas being given greater funding and therefore more doctors per head. If this is the case then there is likely an unobservable level of sickness within the population that is not being picked up by the models (except through the GP headcount per 1000 population). Future modellers should consider whether there is a variable, or proxy, that indicates sickness levels more generally within the population. Calderon-Larranaga et al. (2011) and Zhan et al. (2004) have previously shown that an increase in primary care provision leads to fewer admissions for ACSCs. However, these studies were both in countries where access to primary care is incomplete and therefore, as the authors note, representative of improved access to primary care, rather than improved provision in some other sense. The result that GP headcount per 1000 population is associated with higher rates of admissions for ACSCs would therefore appear to be indicative of something else, namely, as primary care reaches saturation (that is, as would be expected in England's tax funded system, patients do not face significant barriers to accessing care), a different influence is seen and the increasing number of GPs within a locality reflects the larger demand required by a sicker population. This is an interesting result and understanding the precise point at which GP headcount makes this switch from being associated with lower rates of admissions to being associated with higher rates of admissions should be an area for future research.

Mental health prevalence within the population was significant only for diabetes. One potential reason might be that diabetes typically requires more and stricter self-care (e.g. monitoring blood glucose levels) than the other three conditions, and that this self-care is harder for those with mental health issues. Previous research has found that those with a range of long-term conditions are more likely to experience mental health problems than the rest of the population (Naylor et al., 2012). It could be that the model is picking up this effect, but it is unclear why mental health prevalence is significant for diabetes but not the other conditions considered, other than the explanation offered above that diabetes requires more self-care than the other three conditions. Further work is required to understand this result in more detail.

Two of the survey results relate to access (i.e. satisfaction with phone access and being able to see preferred GP) and suggest that easier access to a GP practice may lead to fewer emergency admissions for these conditions, and that patients are well placed to provide accurate judgements in relation to accessibility. Much previous research has shown the importance of access in order to lower ACSC admission rates (Starfield et al., 2005b) (Ansari, 2007) (Leibowitz et al., 2003) (Wilson and Childs, 2006). However, none of these studies were based on patients' own perceptions of

access and this is therefore an important result showing that patients' judgements about practice accessibility appear accurate.

The final survey result relates to those that would recommend the practice, which is a reflection of the patient's general opinion about the quality of the practice. This was associated with lower rates of admission for three out of the four conditions. No previous research has shown patients' opinion of the quality of their practice being associated with lower ACSC admission rates.

These survey results, all of which are associated with lower rates of admissions, perhaps suggest that patients are (in aggregate) good at judging the quality of their practice. An alternative hypothesis is that good patient-doctor relationships (which are reflected in higher survey results) themselves lead to better compliance and more readiness to consult, thereby reducing admissions. Future work should examine this issue further and could examine the potential for using patient survey results to score practices and reward them for better results.

It is surprising that some factors are associated with different rates of admission for some conditions but not others. For instance, the proportion of the list in a nursing home is associated with higher rates of admission for COPD but not the other three conditions. If nursing home occupancy reflects a sickness within the population more widely, we would expect it to have a similar effect across all the conditions. The fact that it does not should be a cause for concern. Further work is required to investigate why COPD might be worse for nursing home patients verses other conditions, whether patients with COPD are more likely, verses other conditions, to be in a nursing, or whether the result for COPD is spurious. A similar issue applies to the factor GP headcount per person in population. If this in fact reflects a sickness level within the population that has led to more GPs being setup in the area, then we would expect it to apply to all conditions, when in fact it is only associated with higher rates for asthma and diabetes. Again, further work is needed to explain this result.

This chapter has shown how, for four of the nineteen ambulatory care sensitive conditions, models can be developed that predict the expected rates of admissions within a given practice. It has further shown how they can be combined to give estimates with a closer fit. The next chapter will look at the potential for ACSC admission rates to be used as a performance metric on which practices (or CCGs) could be judged. It will use the overarching model from chapter 5 that treats all ACSCs as equal. However it is likely that a more accurate, and rigorous, approach would be to develop a complete model using the process shown in this chapter for all nineteen conditions, should the necessary data become available to do so.

6.4.1 Strengths and Weaknesses

6.4.1.1 Data

The model created in this chapter uses much of the same data as the model in the previous chapter. It therefore has many of the same strengths and weaknesses as described in that chapter (see 5.4.4.1). However, the condition-specific models use the condition-specific admission rates as their dependent variable which, by their nature, rely on smaller numbers of admissions. This will make any coding errors or other omissions have a greater impact on the results (versus the all-condition rate).

QOF quality indicators used in the model, insofar as they reflect condition-specific quality, should be more likely to represent the practice's quality characteristics that affect the admission rate. This is an improvement on the model created in the previous chapter.

6.4.1.2 Techniques and Approach

Again, the main technique used (i.e. multiple linear regression) is the same as that used in the previous chapters and so the strengths and weaknesses associated with this method will be the same (see 5.4.4.2).

This chapter uses a further econometric technique (i.e. seemingly unrelated regression (SUR)) to combine the condition-specific models. SUR is used less than multiple linear regression in the healthcare literature. However, it has been used for many years and its requirements, assumptions and limitations are all well understood. The major advantage of SUR is that it uses more information and therefore results in more precise parameter estimates. The major disadvantages are that it requires more data and is sensitive to model specification errors. The opposite is true for single equation estimation. Having created the separate models it makes sense to reduce the errors through the use of SUR. It should be noted that constraints that apply to each individual condition-specific model will apply to the combined SUR model, however this should not create an onerous constraint. It should further be noted that there is a loss of observations when using SUR, as only observations that have sufficient data for all four condition-specific models are included. This loss, at just over one percent, should not create problems for the conclusions reached above, but if, for example, the aim were to create a comprehensive metric the fact that it does not cover all practices would need to be taken into account.

6.4.1.3 Design

As in chapter 5, the condition-specific models use a cross-sectional approach (rather than longitudinal). As well as the weaknesses described in 5.4.4.3, the condition-specific approach may highlight further issues with the cross-sectional method. In particular some of the variables related to quality may only have an impact on admission rates over a longer time-frame and so are not seen intra-year.

Admissions were designated to a given condition based on the coding practice suggested by Purdy et al. (2009), namely that the primary diagnosis should match one of the prescribed ICD10 codes. This is the accepted method. However, as noted by Gibbons et al. (2014) for diabetes admissions, this will not capture all the admissions for the condition. Indeed Gibbons et al. (2014) found that between January 2006 and December 2010 just 6.2% of admissions that listed diabetes as one of the diagnoses cited it as the primary diagnosis. As noted by the authors, reliance on the primary diagnosis likely underestimates the number of admissions due to diabetes. However, no better alternative is forthcoming and as such, for the time being, primary diagnosis was used, but interpretation of results should consider that admissions may be underreported.

Four of the 19 ACSC conditions were chosen to be modelled in this chapter. The models demonstrate a proof-of-concept for how all 19 could be modelled. To be able to model the remaining 15 conditions further data would be required. QOF data was used for the four conditions chosen to represent the quality of the practice. QOF data is not available for most of the other conditions and, therefore, further data that represented the quality of the practices' care with regard to the particular condition would need to be found before the other conditions could be modelled. Similarly prevalence scores do not exist for all the other conditions, so a suitable proxy for the rate of the condition within the population would also need to be found.

Were this further data to be found, the modelling process demonstrated in this chapter could be repeated for each remaining condition. These could then be combined using SUR (as demonstrated). The addition of further conditions should lead to a still closer fit and smaller standard errors.

Creating models for all the ACSCs separately and then combining would also allow a more complete comparison to be made between this method and that used in chapter five, which does not differentiate between the conditions.

7 ACSC admission rates as a performance metric

7.1 Introduction

This chapter will explore whether the admission rate for ACSCs for a given practice, or group of practices, could be the basis of a metric to be used to measure the practice(s) performance and whether the potential improvements in that rate would warrant attaching an incentive to encourage the practice(s) to improve. The hypothesis is that practices will need to be grouped together to make such a metric meaningful and that there is likely to be inefficiency in the system that could be reduced to improve (lower) rates of admission.

In England performance metrics already exist in primary care that provide financial rewards for practices that meet or exceed certain designated levels, most notably the Quality and Outcomes Framework (QOF) that was introduced in the UK in 2004 that rewards performance for a variety of clinical domains. No performance metric currently exists for a measure related to the number of admissions into secondary care – for ACSCs or other conditions.

The importance of identifying conditions that are amenable to primary care is discussed by Gibbons et al. (2012) who comment that measuring admission rates for ACSCs is a potentially useful indicator of primary care performance, and they conclude that a key question for future research is to understand what proportion of unplanned admissions is potentially preventable.

This chapter begins by looking at how large the population size used in a metric would need to be to be confident (within some probability range) that the metric was measuring changes in the quality of the GP practice and not random fluctuations, for instance those caused by unpredictable incidence and severity of illness in the practice's population.

Adapting the analysis of Martin et al. (1997) the components of the variability in ACSC admission rates can be partitioned into four components:

(1) an element that is due to patient or practice characteristics, which are captured by the model, such as the population's age, or the practice's location;
(2) an element that is due to patient or practice characteristics, which are *not* captured by the model, such as the level of out of hours support provided;
(3) an element that is due to clinical practice or practice 'quality';
(4) an element that is totally random, caused by unpredictable incidence and severity of illness

In this categorisation components (1) and (2) can be considered the systematic elements in the sense that they could, in principle, be predicted. In practice the model only incorporates (1). The

model used to predict expected ACSC admission rates can be judged by the extent to which it maximises (1) and minimises (2). The model should not seek to capture the variations that are due to clinical practice (3) as these are to be captured by the metric. And finally no model can compensate for the random element (4) though, as shown later in the chapter, this element becomes smaller as the population size being modelled is increased.

To identify how large the random element (4) is, a model is developed for the rate of admission for all ACSCs (using regression methods like those used in earlier chapters). This model gives an expected rate of admission for each practice. Two analyses illustrate the impact of population size on the size of the random element, and therefore indicate the size of population required to make such a metric viable. The first analysis looks at how the distribution of the difference between this expected rate and the actual rate of admission across practices varies as list size increases. This is followed by looking at how that difference distribution is reduced by increasing the population size that the metric is measured over by clustering practices together.

The second part of the chapter examines the extent to which ACSC admission rates could be reduced. Although ACSC admissions are defined by the fact that they should be avoidable through better primary care, it is reasonable to assume that, given current practice, not all are truly avoidable. Any performance metric based on ACSC admission rates would need to take into account what realistic improvements in an ACSC could be expected. Indeed, if the potential for improvement were not great enough, it may not justify the expense and effort to establish and monitor the performance metric.

Previous work examining the potential for savings from reducing ACSC admissions in England has typically made an assumption as to the proportion of admissions which could 'reasonably' be avoided. For instance, analysis by the NHS Institute assumed that practices had a reasonable chance of achieving the rate of admissions achieved by those practices in the top 25th percentile of (unadjusted) ACSC admission rates. This analysis, based on data from 2012/13, suggested a potential annual saving of £983 by reducing emergency admissions by around 522,000 (NHS-Institute, 2014).

Another non-econometric approach by Freund et al. (2013) used semi-structured interviews of physicians to estimate the proportion of a selection of ACSC admissions in Germany that were likely to be avoidable. It found that 41% of the admissions were deemed to be potentially avoidable and they classified the causes into 5 categories: system related (e.g. unavailability of ambulatory

services); physician related (e.g. suboptimal monitoring); medical (e.g. medication side effects); patient related (e.g. delayed help-seeking) and social (e.g. lack of social support).

Various econometric methods exist for estimating how much admission rates could be reduced if practice were improved from current levels i.e. if efficiency were improved in the less efficient practices to levels seen in more efficient practices. Efficiency here, as defined by (Farrell, 1957), refers to the maximum amount of output from a given input.

Much work has been done looking at the efficiency of healthcare organisations and systems (Hollingsworth, 2008, Hollingsworth, 2003, Hollingsworth and Maniadakis, 1999). However, most have focused on hospitals and secondary care. In England the most recent example in primary care is from Giuffrida and Gravelle (2001) who used data envelopment analysis (DEA) to estimate the efficiency of primary care. The unit of analysis used was the Family Health Service Authority (FHSA), which was, during the period of study, the administrative unit for primary care in England. At that time, there were 90 FHSAs, with average populations of around 560,000 people, served by around 290 GPs. The study found a technical efficiency of 98.4% and cost efficiency of 96.4%.

Two econometric methods will be used to estimate efficiency in this chapter. First, Corrected Ordinary Least Squares (COLS) will be used, before moving on to Stochastic Frontier Analysis (SFA).

COLS uses two steps to estimate the (in)efficiency within the system. The first step is to use ordinary least squares (OLS) to obtain an estimate of the slope parameters and an estimate of the intercept parameter (as has been done in previous chapters). In the second step the OLS intercept is shifted down ("corrected") to ensure that the estimated frontier bounds the data from below. It does this by adjusting the intercept by the minimum OLS residual, that is the frontier will go through this minimum data point, on the assumption that this is the 'best practice' and highest efficiency possible within the system.

A problem with COLS estimation is that the residual is interpreted as due to inefficiency alone, with there being no recognition of statistical error (Street, 2003). SFA has been developed to overcome this shortcoming by splitting the residual into two components, one of which represents the inefficiency and the other the random noise.

Since the pioneering work of Aigner et al. (1977), SFA has been widely used in productivity and efficiency studies to estimate production, cost and profit frontier models. However it is only more recently that the technique for efficiency measurement has been applied to the health sector, with Hofler and Folland providing one of the first applications in 1991 (Moshiri et al., 2010). It is now

widely used across a number of different settings within the general health sector, both in the US and Europe (Hollingsworth, 2008). However, the use of COLS and SFA is not without controversy and the work of Street (2003) and Newhouse (1994), among others, suggests that model specification can have large impacts on the results. In particular they warn that the results for any individual practice should be treated with extreme caution and they advise against ranking practices on the basis of efficiency analysis.

SFA uses regression analysis to estimate a conventional cost function, with the difference being that efficiency is measured using the residuals from the estimated equation where the error term is divided into two elements: a symmetric and a one-sided component.

The symmetric component accounts for random variations in the admission rate due statistical noise or due to factors outside the control of the practice (random equipment failure, measurement error, etc.) and it is assumed to be normally distributed (Neves, 2011).

The one-sided component is non-negative and reflects technical inefficiency relative to the stochastic frontier, being zero if it were on the frontier (i.e. no inefficiency) and greater than zero otherwise. The distribution has to be previously assumed before carrying out the analysis. A number of distributions are commonly used for the one-sided component including exponential, half-normal and gamma distributions. Jacobs (2001) suggests that the half-normal distribution is the most common. The one-sided component is therefore assumed to have a half-normal distribution in the following analysis.

7.2 Methods

To judge how much the random element (4) is reduced by increasing population size the standard deviation of the percentage difference between expected and actual rates of ACSC admissions is first examined for the whole population of practices and then how it varies by list size. For a normally distributed sample of size n and standard deviation s the standard error is s/√n. This result is used to calculate 95% confidence intervals for different sized populations, formed by clustering together groups of random practices.

To determine how efficient the system is, two econometric methods were used: first corrected ordinary least squares (COLS) and then stochastic frontier analysis (SFA). Both use an ordinary least squares (OLS) regression to create a model for predicting ACSC admission rates as a first step. As noted by Smith and Street (2005), a statistical model that satisfies traditional modelling criteria may not necessarily be fit for the purpose of inferring efficiencies of individual organizations. In

particular, more parsimonious models may overestimate the inefficiency in the system. Conversely, if no attention is paid to the parsimony criteria and all potential explanatory variables are included indiscriminately then, in the extreme, this might result in modelling the performance of all observations without error, leading to the conclusion that all are equally efficient. In the absence of set criteria for developing the model, Smith and Street go on to suggest that analysts should seek to develop realistic and theoretically cogent models and, furthermore, that analyst leave a careful audit of the technical choices they have made.

With this in mind, the following specification, based on the categorisations used in previous chapters, was used to create the model. Note the model was chosen to only include those features that the practice does not have direct control over. That is, it does not include quality indicators, as these will be picked up in the 'efficiency' element of the analyses. A one percent statistical significance level was used to create the model.

Dependent Variable:

- The rate of all ACSC admissions during 2010/11 (admissions per 1000 persons on GP's list)

Independent Variables:

- The expected ACSC admission rate given the practice's age and sex breakdown, based on the rates seen nationally
- The estimated ethnic breakdown of the practice's list
- GP practice's deprivation score (IMD, IDACI and IDAOPI)
- Percentage of persons on the practice's list who are nursing home patients
- Prevalence (based on QOF disease register) of: Coronary heart disease, stroke or transient ischaemic attack; hypertension, chronic obstructive pulmonary disease, hypothyroidism, cancer, mental health conditions, asthma, heart failure, heart failure due to lvd, palliative care, dementia, atrial fibrillation, cardiovascular disease
- The practice's PCT (dummy variable)
- The practice list size
- The practice's cluster type (dummy variable)

Once the regression was performed, tests were carried out following the same method described in chapter 5, to ensure the model was correctly specified. Any terms that were found to be collinear with other terms were removed. An augmented partial residual plot was used to identify any terms

that might not be linearly associated with the dependent variable. Finally, the error distribution of the model was checked to ensure it was normally distributed.

Where the variable predicted by the regression was less than zero, they were adjusted to be zero (as negative rates are impossible in real-life). Practices are seeking to minimise their admission rates, so a cost frontier was used for both COLS and SFA. COLS typically adjusts the regression frontier to the minimum residual level. This result is given, along with adjustments that shift the frontier to the 1%, 5% and 10% smallest residuals.

SFA was then used, with a cost frontier, to give a further estimate of the efficiency within the system. SFA gives an estimate for the proportion of the residual that is due to inefficiency. Taking this estimate as a proportion of the actual rate of admission (i.e. the dependent variable in the regression) gives the percentage inefficiency that exists for any given practice. The average of this was then taken to give the figure for average inefficiency. To calculate the number of admissions that would be avoided if this inefficiency were removed, the number of admissions that were 'inefficient' for each practice was calculated by taking the proportion of the residual that was due to inefficiency and multiplying by the practices' list size. This was then used to calculate the percentage of the total ACSC admissions for the practices that the SFA was calculated over. This percentage was then used on the total ACSC admissions for all practices (on the basis that practices that did not have sufficient data for the SFA would, on average, be as inefficient as those that did).

7.3 Results

A metric that sought to judge the performance of a practice, with regard to their ACSC admission rate, would do so based on the extent to which they beat, or missed, some expected rate of admission, based on factors known about the practice that they were deemed to have no or little control over, such as disease prevalence. However, this is only valid if component (2) is minimised (i.e. the model being used to adjust rates is as accurate as possible) and component (4) is not so large, in comparison to the assumed 'quality' effect, that the metric is no better than random.

Across all practices the percentage difference between predicted and actual ACSC admission rates has a standard deviation of 25.25. Assuming normal distribution, 95% of the practices will lie within 1.96 standard deviations of the mean. This suggests that 95% of practices will have a predicted rate that is within the range ±49.5% of the actual rate.

Examining how the accuracy of predicted ACSC rates vary as list size increases illustrates that, broadly, the larger the practice population the greater the accuracy of the prediction. Figure 7.1

plots the residual from the regression model divided by the actual ACSC admission rate (as a percentage) for each practice, against the practice's list size. The standard deviation of this residual over actual admission rate is 25.89 for practices with lists of fewer than 10,000 persons; 22.77 for practices with lists of between 10,000 and 20,000 persons; 16.32 for practices with lists of between 20,000 and 30,000 persons; and 37.30 for practices with more than 30,000 persons.

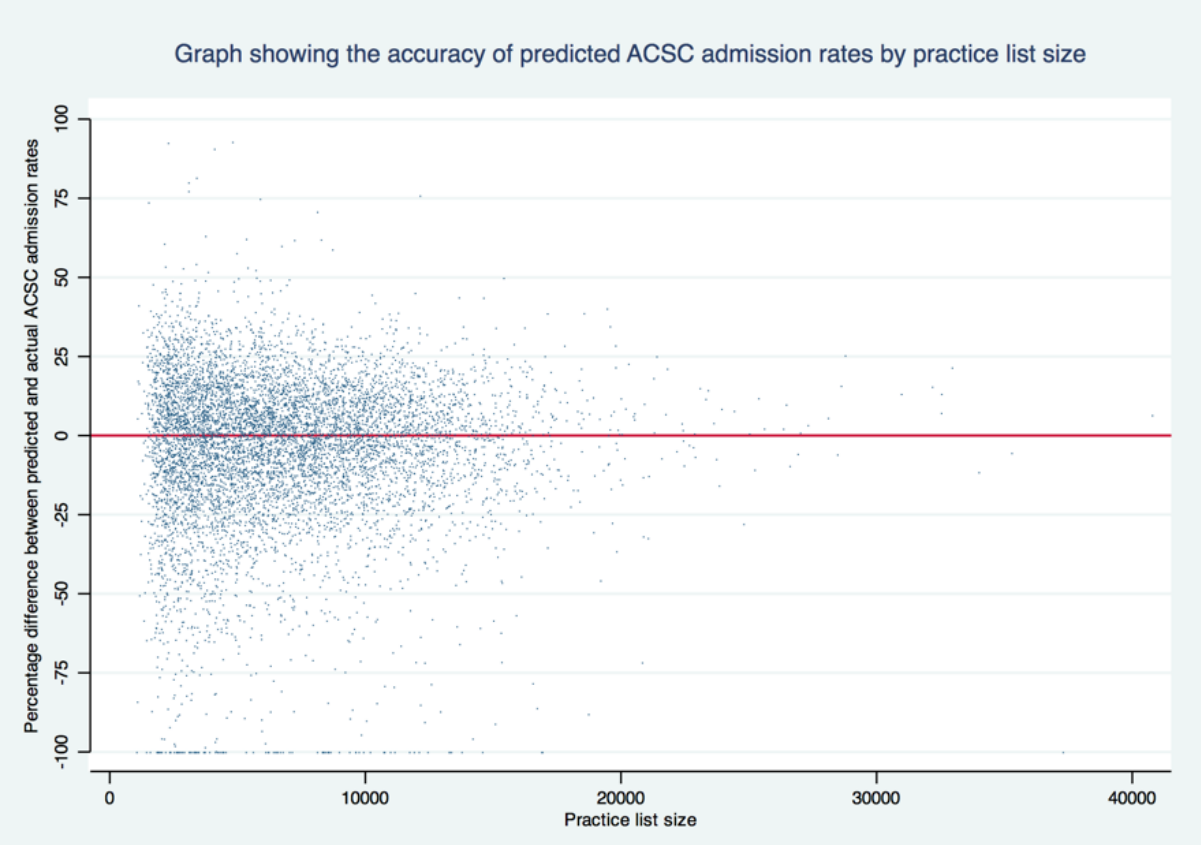


Figure 7.1 – Graph showing the accuracy of predicted ACSC admission rates by practice list size[6]

There is large variation, even for the larger practices, in the accuracy of the predicted admission rates. Aggregating the rates for several practices should lead to more accurate predictions. In particular given that CCGs are formed from groups of practices it makes sense to examine the extent to which aggregating reduces the randomness in the system and how large the population would need to be to have an ACSC admission rate that reflects the quality of the practice and not the random error.

[6] 161 data points that had a percentage difference greater than 100% have been omitted from the graph for the sake of clarity.

The difference between predicted and actual rates has a standard deviation s = 25.25 for all practices. For a sample of n practices the deviation from the predicted rate will be normally distributed with mean zero and standard error $s/\sqrt{n}$. That is, as the number of practices increases from 1 to n, so the accuracy of the predicted rates – as measured by the standard error – decreases by a factor of $1/\sqrt{n}$. This result allows for the construction of Figure 7.2 which shows how the 95% confidence interval varies as the number of practices aggregated together increases.

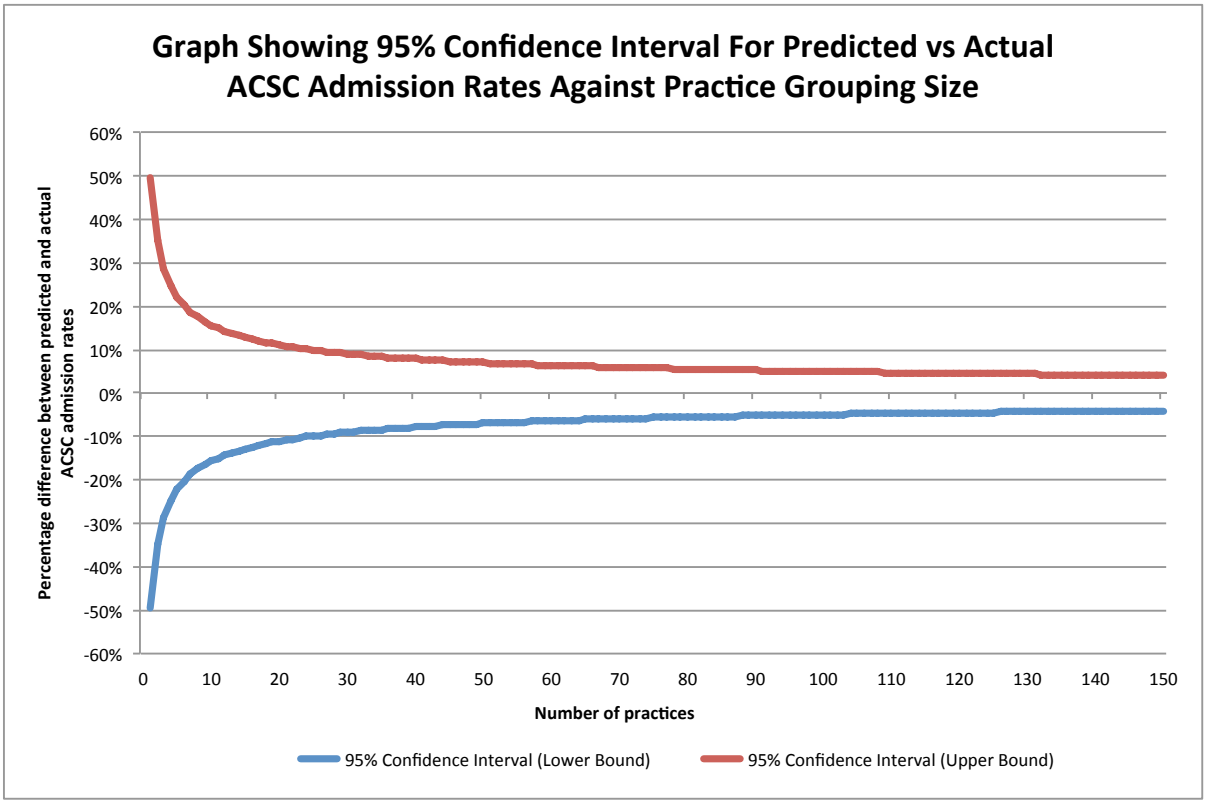


Figure 7.2 – 95% confidence interval for predicted rates against the number of practices aggregated

The average practice list size is 6,867 people. The average CCG cares for 226,000 people (Naylor, 2012) or approximately 33 practices. 95% of 33-practice-groups would be expected to have predicted rates within ±8.6% of the actual rates. This figure reduces to ±4.3% for 130-practice-groups (the size of the largest CCG).

If such a performance metric were created – over an appropriate population size – it would be important to understand how much of an improvement in ACSC admission rates were possible. Efficiency estimates seek to understand the potential for improvement; they do not suggest directly how these efficiency improvements can be made. However, they are still a useful way to demonstrate whether improvements in the system are possible, based on the activities that some

players in the system are already undertaking. Importantly, the estimates take account of factors outside the control of GP practices, such as the prevalence of a condition within the population. Therefore, where inefficiencies are identified, they demonstrate that some GP practices are delivering better care for their patients than others, and they therefore provide an estimate for the degree to which admission rates could be reduced if the 'less efficient' GP practices were to adopt the activities/practices of those that are delivering this better care.

An estimate of the amount of inefficiency in the system – that is, the extent to which ACSC admission rates could be reduced by improving practices to a 'best-practice' level, given a set of factors outside their control (e.g. population characteristics) – will be created first using Corrected Ordinary Least Squares (COLS) and then Stochastic Frontier Analysis (SFA). Both are based on regression, but they take different approaches on how they deal with the resulting residuals.

COLS creates a frontier for the data that will go through the minimum data point, by adjusting the minimum residual, on the assumption that this is the 'best practice' and highest efficiency possible within the system. However, this is likely to be overly optimistic and therefore presented below are also the (in)efficiency estimates gained by choosing to adjust the boundary to the 1%, 5% and 10% lowest residuals. The efficiency estimates given in Table 7.1 are calculated by dividing the COLS residual by the rate of admissions for all ACSCs (i.e. the dependent variable in the OLS regression) to give a figure, with maximum 1, that represents the percentage improvement achieved by moving the practice onto the COLS boundary.

Table 7.1 – Results of Corrected Ordinary Least Squares (COLS) analysis of efficiency

	Mean	Std. Dev.	Min	Max
COLS Efficiency Estimate (Minimum Boundary)	0.915	0.129	0.000	1
COLS Efficiency Estimate (1% Boundary)	0.503	0.226	-5.660	1
COLS Efficiency Estimate (5% Boundary)	0.327	0.238	-7.310	1
COLS Efficiency Estimate (10% Boundary)	0.235	0.247	-8.136	1

As shown in Table 7.1, the potential overall efficiency improvement from moving all practices onto the COLS boundary is 91.5% for the 'minimum' boundary, 50.3% for the '1%' boundary, 32.7% for the '5%' boundary and 23.5% for the '10%' boundary.

The ‘minimum’ boundary represents the best rate of admissions that any practice is achieving, given the factors deemed to be beyond their control (that is the independent variables listed in the Methods section above) such as the socio-economic deprivation of their population or the prevalence of long-term conditions, such as diabetes. Therefore, the efficiency improvement of 91.5% is the amount by which admission rates could be lowered were all practices to be operating on this ‘minimum’ boundary i.e. at the best rate currently being achieved by any GP practice for a population that is similar to their own. Without knowing what the activities of these best performing GP practices are, it is difficult to know if they are truly achievable by the other practices. Other boundaries are therefore presented that try to allow for this. Specifically the 1% boundary gives the rate of the top 1% of GP practices and the efficiency estimate is based on the improvement that would be realised from moving ‘similar’ practices (i.e. those with comparable independent variables) to the same rate. This gives an efficiency of 50.3%, which is substantially different from the estimate given by the ‘minimum’ boundary. This suggests there may be some outliers skewing the ‘minimum’ boundary result. The 5% and 10% boundaries are calculated in a similar way and their interpretation, as the top 5% and 10% of practices (allowing for population characteristics) is similarly consistent with the interpretation of the 1% boundary.

The inefficiency within the system varies considerably depending on which boundary is picked. Since we have no way of judging a given boundary to be better or worse than another, this leaves us with a fairly unsatisfactory situation. A potential solution is to use an alternative approach, SFA, which seeks to identify how much of the total possible (that given by the ‘minimum’ boundary of COLS) is due to efficiency, and how much is due to random variation.

In the terminology used at the beginning of this chapter, COLS assumes that the random variation (i.e. component (4)) is negligible. The complete residual therefore is due to component (3), practice quality (the efficiency, or inefficiency, of practices), whereas SFA splits the residual between these two components.

The results of the Stochastic Frontier Analysis are shown in Table 7.2.

Table 7.2 – Results of Stochastic Frontier Analysis (Half-Normal)[7]

Number of obs	7853
Wald Chi-Square	17417.83
Prob > Chi-Squar	0
Log Likelihood	-23290

	Coef.	Std. Err.	t	P>t	95% Confidence Interval	
Expected ACSC Rate (by age-sex of pop)	0.3029619	0.03782	8.01	0.000	0.22884	0.37708
Ethnicity Asian (proportion of list)	0.0409987	0.00891	4.6	0.000	0.02354	0.05846
IMD Deprivation Score	0.2958793	0.01033	28.64	0.000	0.27563	0.31612
Proportion of list in a nursing home	0.0536255	0.01347	3.98	0.000	0.02722	0.08003
Coronary Heart Disease Prevalence (QOF Registry)	114.9938	10.76598	10.68	0.000	93.89288	136.09480
COPD Prevalence (QOF Registry)	83.03802	10.86774	7.64	0.000	61.73763	104.33840
Mental Health Prevalence (QOF Registry)	130.4649	17.00752	7.67	0.000	97.13073	163.79900
Asthma Prevalence (QOF Registry)	35.19511	4.88571	7.2	0.000	25.61929	44.77092
Dementia Prevalence (QOF Registry)	96.23132	24.28549	3.96	0.000	48.63264	143.83000
Std. Deviation of Component (3)	5.52553	0.14215	38.87	0.000	5.25383	5.81128
Std. Deviation of Component (4)	3.38934	0.07268	46.63	0.000	3.24983	3.53483
Std. Dev. of Component (3) / Std. Dev. of Component (4)	1.63027	0.20290	8.03	0.000	1.23259	2.02795

The overarching regression model results are presented in Table 7.2. Of interest in this particular instance are the standard deviations of the inefficiency and random variation, and that the ratio of the first over the second is greater than 1, meaning that the inefficiency element makes up the greater part of the error term.

For each practice we know the actual rate of admissions for ACSCs. The stochastic frontier analysis gives two further results: the amount of random variation and the predicted efficiency. As discussed previously, the difference between the actual rate and the rate predicted by the regression line will be composed of these two elements. By dividing the predicted efficiency for a given practice (given by SFA) by the actual rate for that same practice we obtain the percentage improvement possible for that practice. By taking the average of this percentage across all the 7853 practices we are able to calculate the average efficiency among GP practices.

The boundary given by the regression line represents 'best practice', allowing for the characteristics included as variable within the model, in the same way as the minimum boundary line for the COLS calculation above. The difference here is that some of the difference between the minimum boundary line created by COLS and actual performance will have been due to random variation, and

[7] Note that the information for the PCT and Cluster dummies has been omitted from the results presented for clarity

is therefore an overestimate. SFA calculates how much of the difference is due to random variation and how much true efficiency. It should therefore present a more accurate figure.

Calculating the average as described suggests that there is 20.4% average inefficiency in the rates of admissions for ACSCs among GP practices. That is, practices could, on average, reduce their rates of ACSC admissions by 20.4% by improving their efficiency to the level of the best performing practices, allowing for factors that are out of the practice's control (described in the model above) such as population characteristics and random variation. This translates to 242,143 'inefficient' ACSC admissions per year.

7.4 Discussion

The analysis above indicates that any metric based on an ACSC admission rate would need to be over a sizeable population to be confident that it were giving some indication of quality and not merely the randomness that exists within the healthcare system. At the level of an individual practice the random element is large, however as practices are grouped together, the metric is more likely to reflect quality (or lack thereof) within the system. The average CCG size is approximately 33 practices and gives a reasonable metric (predicted rates within ±8.6% of the actual rates). And for the largest CCGs consisting of 130 practices, this figure reduces to ±4.3%. However, for the smallest 10% of CCGs, which have a maximum of 17 practices within them, the predicted rates are within ±12.0% of the actual rates. Any metric would, therefore, need to be over a relatively large population and have some degree of leniency built in.

The advantages of a metric that is taken as a measure over a larger population need to be weighed against the disadvantages created by using a larger population. Over a larger population size there is less variation between predicted and actual rates for the population being considered and therefore differences are more likely to reflect the actual quality of services being delivered, rather than random variation. However, there will still remain large variation within the metric-population cohort and any management system (such as a CCG) would need to understand this variation; indeed, comparison with practices that are not within their cohort may make more sense from a management perspective than comparison between practices within the cohort.

Ultimately the purpose of creating a metric based on admission rates for ACSCs would be to try and reduce them. It may, therefore, make most sense to base the metric on a population size at which interventions that are aimed at reducing ACSC admissions are able to act effectively. This may be at the practice level, CCG or the whole local health economy. Further work is required to find and

evaluate such interventions. The work in the next chapter suggests a method for doing this and examines the effectiveness of some existing interventions.

Different estimates are given by the different techniques (COLS and SFA) and where COLS is used it produces different estimates based on where the frontier is drawn. 'Correct' specification of the model used for both COLS and SFA will depend on whose objectives are afforded primacy. Society, regulators, commissioners and providers may not share the same goals, in which case they will have different definitions of what constitutes efficient behaviour. Strategies that reduce ACSC admission rates by dramatically increasing primary health care costs (over and above the saving from reduced admissions) is an example of an 'efficiency' that the model would deem reasonable, but which may not be tolerable for commissioners.

Also, because the output being measured is ACSC admission rates, other desirable outputs are being ignored. It is possible that improvement in these other outputs leads to an increase in ACSC admissions. Indeed this is likely to be the case in a world with finite budgets, as money spent on one thing leads to less money being spent on another. If that were the case the extent to which the inefficiency truly existed would be less.

Efficiency, as measured in this chapter, describes the difference between the rate of admissions for ACSCs at practices that are better performing, compared to those who have the same inputs (population age, sex, condition prevalence etc.) but who are performing worse. The different methods create different versions of what the 'best performance' is, and therefore different estimates of the (in)efficiency that exists within the system.

SFA would appear to create the most reasonable estimate but this is open to discussion. What is clear is that no estimate can be completely accurate and should only be used as a guide.

Improving the efficiency of practices to best-practice levels (accounting for their population types) would mean 242,143 fewer admissions per year or an annual saving of £411m. This financial estimate assumes that any 'savings' in fewer admissions is spread evenly across the different ACSCs. It also assumes that reducing the inefficiency in the system is cost-neutral.

Further work could look at combining condition-specific models within a single stochastic frontier analysis model to allow the possibility of correlation among composite errors across SFA regressions, analogous to classical generalisation of seemingly unrelated regressions (as performed in 6.3.5). Lai and Huang (2013) demonstrate a method for achieving this, known as the copula-based maximum likelihood approach.

7.4.1 Strengths and Weaknesses

7.4.1.1 Data

Data is the same as used in previous chapters (5 and 6). However, due to the nature of the analysis (looking at frontiers) the effect of outliers is likely to be greater and therefore inaccuracies in the reporting of data of greater impact.

7.4.1.2 Techniques and Approach

The method used to show the model becomes more accurate as groups of practices are clustered together assumes that this is done at random. In reality this would not be the case if CCGs were chosen, as these groupings are typically determined by geography, and certainly not at random. Further work may be required to determine if this alters the result.

Efficiency estimates are based on two techniques (i.e. corrected ordinary least squares (COLS) and stochastic frontier analysis (SFA)) both of which require a regression model to be created as their first step. These are largely based on those developed in chapter 5. Any error in the creation of that earlier model could have implications for this analysis. However the testing performed when developing those models gives some assurance that the model being used is accurate.

The COLS method is easier to explain in laymen's terms and therefore its estimate is easier to understand. This may make it a more powerful estimate in the eyes of policy-makers. However, because four estimates are given a decision needs to be made on which frontier to use before an estimate can be made. This may discourage some from using these estimates. In contrast, the SFA method uses a statistical technique to determine the frontier. This removes the issue of having to choose which frontier to use, but adds to the complexity of the explanation and may, therefore, cause some policy-makers not to use it (even though it should provide the more accurate estimation).

Both COLS and SFA are well used in the literature. A common complaint, particularly when they are used in a healthcare setting, is that the model does not (or cannot) sufficiently account for the huge complexity of healthcare systems, and therefore the estimates are less meaningful. This is a legitimate criticism, however, without a better option available, this estimate is better than nothing.

7.4.1.3 Design

Estimates of how accuracy varies with population size use the standard deviation of the sample – in this case all practices in England. The standard deviation is very sensitive to the exclusion of outliers. Should outliers be found in the data that would be excluded from a metric – for instance because

they did not qualify due to some criteria which was also related to them being an outlier – this could significantly change the population size required to gain a given level of accuracy.

There is an ongoing debate in academia as to whether variables should be removed after performing a t-test (as is done in a regression) when performing efficiency analyses, as discussed earlier in the chapter. The method used in this analysis has been set out clearly, so that it can be replicated. It could also be recreated with a less parsimonious model and this may lead to different results.

The model used to create the regression model is based on chapter 5's all-ACSC admission rate model. It may be more accurate to use a model that combines individual condition-specific models (as shown in chapter 6), however. Due to no complete model being available, this was not done in this case.

Estimates of efficiency assume that all inefficiency in the system is undesirable. However this may not be the case, in particular, because the outcome being measured (ACSC admission rates) is just one of the outputs from primary care and other outputs, such as those related to non-ACSC conditions, may take higher priority. The efficiency estimates also assume that the activities required to enable a reduction in inefficiency are replicable across GP practices, which may not be the case.

8 The impact of interventions

8.1 Introduction

For commissioners of healthcare, an important question is which of the interventions, which they can commission, lower rates of emergency admissions for ACSCs. The NHS Choices website collects, among other things, information on NHS services available in England. Geographic information for each service allows a mapping to be made between GP practices and interventions that are within some distance of the practice. In this section propensity score matching will be used to estimate the effect of the interventions by accounting for covariates. The aim is to identify interventions that are taking place in the health service that reduce ACSC admissions and to evaluate the extent of their impact. The hypothesis is that activities that are 'external' to practices can still have an impact on ACSC admissions.

The gold standard for evaluation of an intervention or treatment is a randomised clinical trial, whereby the intervention would be assigned on a random basis to a selection of practices and the outcomes monitored over a period of time. These would be compared to a control group, picked to have similar attributes to the treatment group, but that would not be given the intervention and would be similarly monitored over the same period of time. The difference in the change in outcomes (e.g. the rate of ACSC admissions) could then be attributed to the intervention. This is clearly not possible unless the rollout of a given intervention is done with this design in mind. The author was not able to find any evidence that any such evaluation had been carried out on any of the interventions that are considered in this chapter.

It is well recognised that the estimate of a causal effect obtained by comparing a treatment group with a non-experimental comparison group could be biased because of problems such as self-selection or some systematic judgment by the researcher in selecting units to be assigned to the treatment (Dehejia and Wahba, 2002). Matching can be used to correct for sample selection bias due to observable differences between the treatment and comparison groups. Matching involves the pairing of treatment and comparison units that are similar in terms of their observable characteristics. When the relevant differences between any two units are captured in the observable covariates, matching methods can yield an unbiased estimate of the treatment impact.

The first generation of matching methods paired observations based on either a single variable or weighting several variables. However, when there are many variables, it is difficult to determine along which dimensions to match units, or which weighting scheme to adopt. Propensity score-

matching methods are especially useful under such circumstances because they provide a natural weighting scheme that yields unbiased estimates of the treatment impact (Dehejia and Wahba, 2002).

Propensity score matching mimics an experiment by constructing a suitable comparison group by carefully matching 'treated' and 'non-treated' groups. Note that in this chapter the treated group is the set of GP practices that are within a 5km radius of the given intervention. By matching propensity scores, the method aims to create a comparison group that is as similar as possible to the treatment group in terms of their observable characteristics. The method assumes that all relevant differences between the treated and non-treated are captured in their observable attributes. It also requires that the observable characteristics are not affected by treatment, both of which seem plausible assumptions for the condition-specific models developed in the previous chapter.

Estimation methods using the propensity score (i.e. the probability of an observation receiving a particular treatment conditional on covariates) are widely used in economics and other disciplines in evaluating programs and interventions (Millimet and Tchernis, 2009).

Data from the NHS Choices website has recently been made available to researchers. The website's main aim is to help patients to navigate the healthcare system and find the services that they need, typically within their local area. The website further allows patients to rate the services they have used and feedback on their experiences. The data the website holds is therefore a rich repository for researchers in the healthcare field and, as such, the chance to use the data for the research in this thesis was a great opportunity.

25 services were identified from the data the website held as being services provided outside of primary and secondary care (i.e. services that could potentially be classed as 'interventions', that this research was interested in assessing). Services were excluded from the research if there was no rationale for why they might lead to fewer ACSC admissions. Therefore, of the 25 services, 10 were excluded as they were for alcohol or drug misuse, eight excluded as they were related to stroke, kidney disease, dementia or depression (which are not ACSCs), two were excluded as they were specifically aimed at young people (and most ACSCs effect older people), and one was a telephone helpline (so did not have the location information needed to perform an analysis). The remaining four were deemed to be related to ACSCs and that they could potentially have an impact on ACSC admission rates.

The four interventions that were chosen and that will be tested using the matching method are: Patient advice and liaison service (PALS); Weight loss support groups; Information and support for diabetes; and Information and support for mental health.

The Patient Advice and Liaison Service (PALS) offers confidential advice, support and information on health-related matters to NHS patients. It provides a point of contact for patients, their families and their carers and seeks to help with health-related questions and to help resolve patients' concerns or problems while they are using the NHS. It also helps to direct patients towards the services they need. It is reasonable to expect that information provided by services like PALS could bring down ACSC admission rates by providing information to patients about how to manage their condition, as well as direct them to other services that could further help them manage their condition.

Weight loss support groups includes groups like those run by WeightWatchers (2014) that hold meetings and offer information and support for those trying to lose weight. Previous studies examining the impact of weight loss programmes have found them to be effective at reducing the weight of those that participate (Jolly et al., 2011). Being overweight or obese is a risk factor for many ACSCs and, therefore, programmes aimed at reducing this risk factor ought to lead to a reduction in acute episodes for those conditions and, therefore, fewer ACSC admissions.

Information and support for diabetes includes groups like those run by Diabetes UK (2014), with a stated aim to keep local people with diabetes informed through newsletters, websites and regular meetings about how best to look after themselves. As with the PALS service, the Information and support services for diabetes would be expected to help patients with the condition to better manage their diabetes by providing them with information (for example on the need to eat better and exercise more) and directing them towards relevant services or experts on the condition. For instance, there are techniques that can be taught, such as carbohydrate counting, that allow more accurate monitoring and adjustment of blood sugar levels. Support groups that helped a patient to obtain such skills could reasonably be expected to reduce hospital admissions.

Information and support for mental health includes groups like those run by Mind (2014) and help provide support to access opportunities in the wider community, group peer support, courses to develop skills and guided self help and talking therapies. The prevalence of mental health issues in an area was found in earlier chapters to be associated with higher rates of admissions for ACSCs. It is therefore reasonable to assume that services aimed at helping those with mental health issues could help reduce ACSC admission rates.

Each intervention will be tested against one or more of the condition-specific models developed in Chapter 6, depending on whether the intervention could reasonably be expected to impact on the particular condition (asthma, COPD, diabetes or hypertension) admission rate. PALS will be tested against rates of admission for all four conditions, as advice and support could have an impact on each. Weight loss support groups will be tested against COPD, diabetes and hypertension admission rates, as obesity is a risk factor for each condition. Information and support for diabetes will be tested against diabetes admission rates. Information and support for mental health will be tested against diabetes admission rates, as mental health prevalence was found to be associated with diabetes admission rates in the model in chapter 6.

8.2 Methods

Interventions data was provided by NHS Choices in January 2013 as an extract from their 'generic services directories'. A full list of the services or interventions they provided is below (Table 8.1).

Table 8.1 – NHS Choices Interventions List

#	Intervention
1	Alcohol addiction - support for family and friends
2	Alcohol services for offenders
3	Alcohol services for homeless people
4	Alcohol services for minority ethnic groups
5	Alcohol services for young people
6	Communication and support services for stroke
7	Counselling for drug addiction
8	Information and support for dementia
9	Information and support for diabetes
10	Information and support for kidney disease
11	Information and support for mental health
12	Information and support services for stroke
13	Mental health helplines
14	Mental health services for alcohol addiction
15	Mental health services for drug misuse
16	Mental health support for young people
17	Patient advice and liaison services (PALS)
18	Prevention services for stroke
19	Re-enablement services for stroke
20	Renal units
21	Self-help groups for depression
22	Stroke support for younger people
23	Support services for alcohol addiction
24	Treatment services for alcohol addiction
25	Weight loss support groups

Of these, four were deemed to potentially affect the rates of admissions for the four conditions being examined (Asthma, COPD, Diabetes and Hypertension). They were: Patient advice and Liaison Services (PALS); Weight loss support groups; Information and support for diabetes; and Information and support for mental health.

Many of these services are not housed within GP practices themselves, nor are particular services associated with particular practices or patients. It was therefore necessary to create a mapping between services and practices. It was decided that a practice would be deemed to be 'treated' if at least one of the interventions (e.g. PALS) was within 5km of the practice and 'non-treated' if not. This mapping was performed for each intervention type.

The distance between each intervention and each practice was calculated by converting the postcodes contained within the NHC Choices dataset and the GP practice dataset into longitudes and latitudes. The distance in kilometres (as the crow flies) from one coordinate to another is calculated as:

*ACOS(COS(RADIANS(90-LATP))*COS(RADIANS(90-LATI))+SIN(RADIANS(90-LATP))*SIN(RADIANS(90-LATI))*COS(RADIANS(LONGP-LONGI)))*6371*

where *LATP* and *LONGP* are the latitude and longitude of the practice and *LATI* and *LONGI* are the latitude and longitude of the intervention respectively.

The map below (Figure 8.1) illustrates the calculation. The red pins are GP practices within 5km of the intervention (the blue pin) and they are, therefore, deemed to be 'treated' by the intervention.

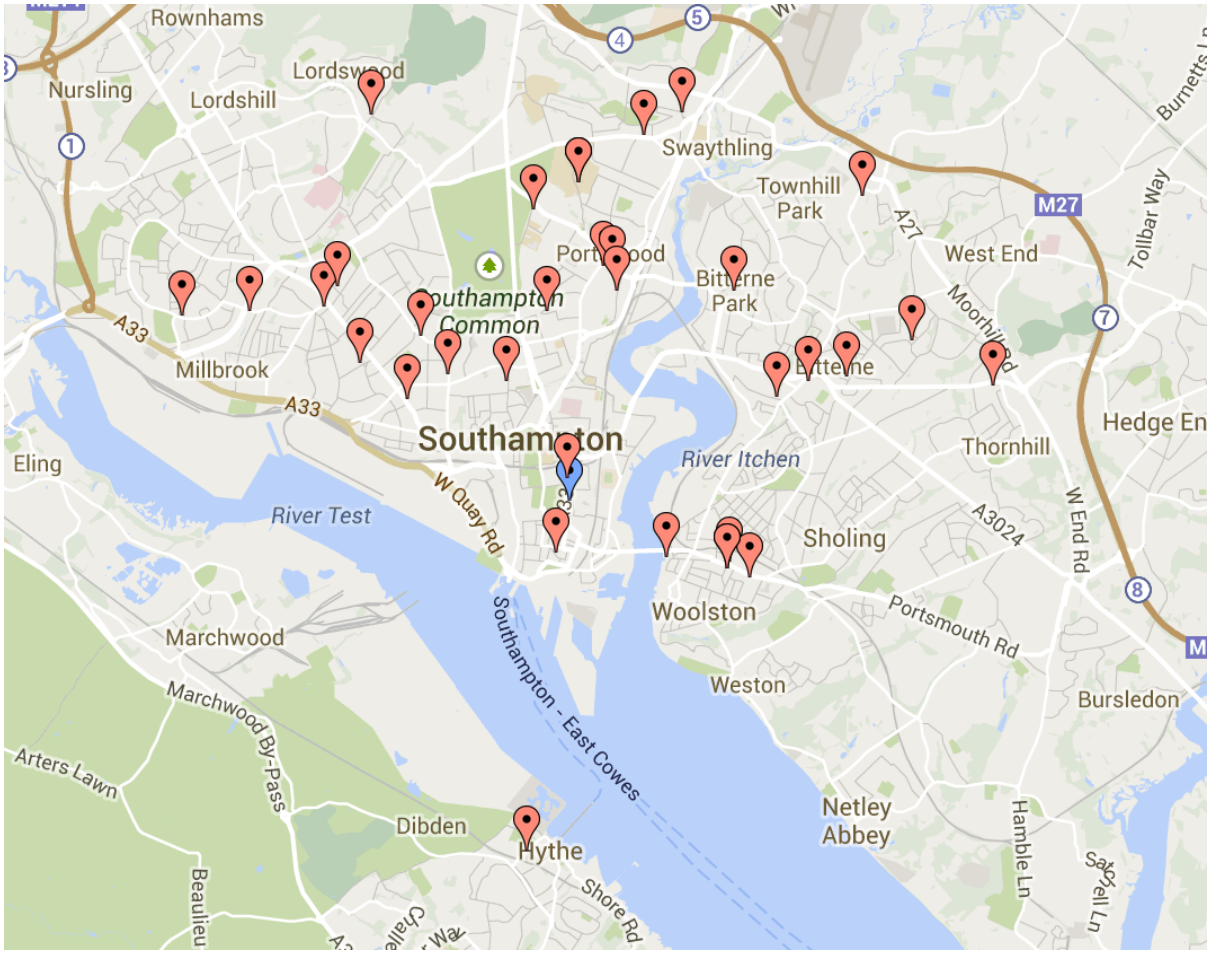


Figure 8.1 – Illustrative example of the process for determining 'treated' practices

For the four services being considered Table 8.2 below gives the number of services registered in the dataset and the number of practices within 5km of those services (i.e. the number of 'treated' practices).

Table 8.2 – NHS Choices services and mapping statistics

Service/Intervention name	Number Registered	Number of GP practices within 5km of service
Information and support for diabetes	73	1618
Information and support for mental health	164	3322
Patient advice and liaison services (PALS)	772	6024
Weight loss support groups	9680	7767

To perform the propensity score matching, the Stata module (psmatch2) developed by Leuven and Sianesi (2003) was used. Two choices have to be made when estimating a propensity score. The first concerns the model to be used for the estimation, and the second one the variables to be included in this model. Caliendo and Kopeinig (2008) discuss the options and suggest logit or probit models are generally better than linear probability models, but that the choice between logit and probit is not too critical. A decision was made to use a probit model to estimate the propensity score.

The matching strategy requires that the outcome variable must be independent of treatment conditional on the propensity score. Hence, implementing matching requires choosing a set of variables that satisfy this condition. Further, omitting important variables can seriously increase bias in the resulting estimates (Dehejia and Wahba, 1999). Therefore only variables that influence simultaneously the participation decision and the outcome variable should be included. Bryson et al. (2002) note that over-parameterised models should also be avoided, as inclusion of non-significant variables in the propensity score specification can increase the estimation variance. The condition-specific models developed in chapter 6 were used on the basis that they met each of these conditions. The dependent variable was the binary treated/not-treated flag for the given intervention and the outcome was the condition-specific rate of admission.

Heckman and Smith (1999) note that data for participants and nonparticipants should stem from the same sources, which is true for the data used (see section 3.8 for further details on the data sources used).

Millimet and Tchernis (2009) found little penalty for over-fitting propensity scores, and that in numerous cases over-specifying the model proved beneficial. They recommend that researchers report a number of estimates corresponding to different levels of polynomials used to estimate propensity scores. As well, therefore, as running the models created in chapter 6 as the independent variables, the second and third order polynomials of those variables were also included.

There was a concern that including the PCT dummy variable might 'dampen' the result because some of the impact of the intervention might be assigned to the PCT dummy variable, for instance where the intervention 'treated' all practices within a PCT area. This is plausible, in particular because a PCT might have chosen to commission the intervention for their whole population. To

counter this concern, and following the advice of Millimet and Tchernis (2009), estimates are reported that include the PCT dummy as well as those that do not.

This combination of PCT dummy and polynomials means that there are six results reported for each condition-intervention PSM.

The configuration for each matching was determined individually to ensure that the mean bias (determined using the function pstest) was less than five percent, the level which Caliendo and Kopeinig (2008) suggest is sufficient for most empirical studies.

The matching was first performed for each estimate using a caliper size of 0.01 and without replacement after matching. For 26 out of the 54 estimates this gave a mean bias less than the five percent required. For those with a mean bias greater than five percent, an adjustment was made to their caliper size (bringing a further 21 under five percent mean bias). The remaining (7) estimates were brought under five percent by imposing common support and dropping a percentage of the treatment observations at which the propensity score density of the control observations was the lowest.

8.3 Results

Interventions were chosen for each condition for which a model was developed in chapter 6. The Patient advice and liaison services (PALS) were tested for Asthma, COPD, Diabetes and Hypertension as the information provided by such a service could helpfully impact on patients with all four conditions. Weight loss support groups were tested for COPD, Diabetes and Hypertension as being overweight is a risk factor for all three conditions. Information and support for diabetes and Information and support for mental health were both tested for Diabetes. Mental health was included as mental health prevalence was found to be statistically significant in the diabetes-condition model developed in section 6.3.3.

Millimet and Tchernis (2009) find there to be little penalty for over-fitting propensity scores and that numerous cases in which over-specifying the model proved beneficial. They recommend that researchers report a number of estimates corresponding to different levels of polynomials used to estimate propensity scores. The results reported in this section will therefore follow this advice and report first-, second- and third-order polynomials of the independent variables suggested by the models developed in chapter 6. They will further report the model both with the PCT dummy included, and without the PCT dummy included. This is because, if the intervention is paid for, or

provided by the PCT, the PCT dummy is likely to include some of the impact that should be attributed to the intervention.

Tables 8.3 and 8.4 give the results of the propensity score matching for each intervention, on the given condition's rate of admission. Two results are given: The average treatment effect on the treated (ATT); and the average treatment effect on the untreated (ATU). The expected value of ATT is defined as the difference between expected outcome values with and without treatment for those who actually participated in treatment. In the sense that this parameter focuses directly on actual treatment participants, it determines the realized gross gain from the programme and can be compared with its costs, helping to decide whether the programme is successful or not (Heckman and Smith, 1999). The ATU is the predicted effect of 'treating' the practices (e.g. installing the intervention within 5km of the practice) that are currently classed as un-treated.

Table 8.3 – Results from propensity score matching – part 1

			Num. of practices in matching	Mean bias (after matching)	ATT							ATU				
					Treated	Controls	Difference	Standard er.	T-Stat	Diff > standard er.	Difference %	Treated	Controls	Difference	Diff > standard er.	Difference %
Asthma	Patient advice and liaison services (PALS)	1st Ord Poly	With PCT	2287	2.8	0.96695	0.94478	0.02218	0.02931	0.76	No	2%	0.92143	0.97134	0.04992	Yes	5%
		2nd Ord Poly	With PCT	2292	2.9	0.97716	0.95071	0.02644	0.02911	0.91	No	3%	0.93822	0.96901	0.03079	Yes	3%
		3rd Ord Poly	With PCT	2287	2.6	0.96064	0.94735	0.01329	0.02979	0.45	No	1%	0.95551	0.98516	0.02965	No	3%
		1st Ord Poly	Without PCT	2321	4.6	0.92628	0.93211	-0.00583	0.02962	-0.2	No	-1%	0.94541	0.91402	-0.03139	Yes	-3%
		2nd Ord Poly	Without PCT	1519	4.1	0.96471	0.99724	-0.03253	0.03818	-0.85	No	-3%	0.99298	0.99077	-0.00221	No	0%
		3rd Ord Poly	Without PCT	2595	4.1	0.92649	0.93466	-0.00817	0.02713	-0.3	No	-1%	0.92147	0.94471	0.02323	No	3%
COPD	Patient advice and liaison services (PALS)	1st Ord Poly	With PCT	2261	2.8	2.08356	2.10202	-0.01846	0.05833	-0.32	No	-1%	2.10711	2.06802	-0.03909	No	-2%
		2nd Ord Poly	With PCT	2296	3.0	2.13568	2.10204	0.03364	0.06098	0.55	No	2%	2.10322	2.10953	0.00630	No	0%
		3rd Ord Poly	With PCT	2303	2.9	2.04678	2.11976	-0.07298	0.05812	-1.26	Yes	-3%	2.10825	2.09606	-0.01219	No	-1%
		1st Ord Poly	Without PCT	1548	3.2	2.13520	2.17900	-0.04380	0.07456	-0.59	No	-2%	2.13352	2.14800	0.01449	No	1%
		2nd Ord Poly	Without PCT	2219	4.0	2.08327	2.11843	-0.03517	0.06125	-0.57	No	-2%	2.12691	2.08983	-0.03707	No	-2%
		3rd Ord Poly	Without PCT	1491	2.5	2.32268	2.25420	0.06848	0.08246	0.83	No	3%	2.25292	2.25308	0.00017	No	0%
COPD	Weight loss support groups	1st Ord Poly	With PCT	310	4.5	1.63778	1.35655	0.28123	0.11752	2.39	Yes	21%	1.41611	1.36024	-0.05587	No	-4%
		2nd Ord Poly	With PCT	411	4.5	1.54586	1.40855	0.13731	0.10717	1.28	Yes	10%	1.38217	1.56735	0.18518	Yes	13%
		3rd Ord Poly	With PCT	407	4.9	1.58407	1.40779	0.17629	0.11164	1.58	Yes	13%	1.38217	1.61211	0.22994	Yes	17%
		1st Ord Poly	Without PCT	358	3.8	1.61654	1.38278	0.23376	0.11419	2.05	Yes	17%	1.41042	1.55744	0.14702	Yes	10%
		2nd Ord Poly	Without PCT	345	2.5	1.58463	1.38045	0.20418	0.10322	1.98	Yes	15%	1.41609	1.59227	0.17618	Yes	12%
		3rd Ord Poly	Without PCT	215	4.4	1.79797	1.47442	0.32354	0.15532	2.08	Yes	22%	1.39781	1.68135	0.28355	Yes	20%
Diabetes	Information and support for diabetes	1st Ord Poly	With PCT	1180	4.7	0.39768	0.42819	-0.03051	0.02111	-1.45	Yes	-7%	0.38215	0.40303	0.02088	No	5%
		2nd Ord Poly	With PCT	1255	5.0	0.39764	0.43090	-0.03325	0.02200	-1.51	Yes	-8%	0.42549	0.39802	-0.02747	Yes	-6%
		3rd Ord Poly	With PCT	2388	4.2	0.40491	0.42677	-0.02185	0.01753	-1.25	Yes	-5%	0.39329	0.41294	0.01965	Yes	5%
		1st Ord Poly	Without PCT	795	4.8	0.43263	0.45467	-0.02204	0.03433	-0.64	No	-5%	0.46817	0.43081	-0.03736	Yes	-8%
		2nd Ord Poly	Without PCT	579	4.6	0.44733	0.41050	0.03683	0.03456	1.07	Yes	9%	0.40468	0.44554	0.04086	Yes	10%
		3rd Ord Poly	Without PCT	690	4.0	0.40573	0.44560	-0.03987	0.03463	-1.15	Yes	-9%	0.44864	0.40549	-0.04314	Yes	-10%
Diabetes	Information and support for mental health	1st Ord Poly	With PCT	2616	3.7	0.42532	0.41003	0.01529	0.01663	0.92	No	4%	0.40681	0.40584	-0.00097	No	0%
		2nd Ord Poly	With PCT	2562	3.9	0.41265	0.40993	0.00272	0.01625	0.17	No	1%	0.40336	0.40406	0.00070	No	0%
		3rd Ord Poly	With PCT	2553	3.9	0.41314	0.40636	0.00678	0.01638	0.41	No	2%	0.40751	0.40886	0.00135	No	0%
		1st Ord Poly	Without PCT	3130	4.6	0.41947	0.42069	-0.00122	0.01430	-0.09	No	0%	0.41072	0.41704	0.00632	No	2%
		2nd Ord Poly	Without PCT	3087	4.9	0.42439	0.41269	0.01171	0.01443	0.81	No	3%	0.40989	0.42006	0.01017	No	2%
		3rd Ord Poly	Without PCT	3000	4.2	0.42361	0.42562	-0.00201	0.01477	-0.14	No	0%	0.42757	0.42766	0.00009	No	0%

Table 8.4 – Results from propensity score matching – part 2

					ATT							ATU				
			Num. of practices in matching	Mean bias (after matching)	Treated	Controls	Difference	Standard er.	T-Stat	Diff > standard er.	Difference %	Treated	Controls	Difference	Diff > standard er.	Difference %
Diabetes	Patient advice and liaison services (PALS)	1st Ord Poly	With PCT	2324	2.7	0.36737	0.39153	-0.02416	0.01643	-1.47	Yes	-6%	0.39976	0.35980	-0.03996	Yes	-10%
		2nd Ord Poly	With PCT	2331	2.8	0.37610	0.39169	-0.01559	0.01529	-1.02	Yes	-4%	0.40012	0.37316	-0.02695	Yes	-7%
		3rd Ord Poly	With PCT	2320	2.6	0.37113	0.39446	-0.02333	0.01519	-1.54	Yes	-6%	0.39210	0.36458	-0.02752	Yes	-7%
		1st Ord Poly	Without PCT	1614	3.5	0.38024	0.41993	-0.03969	0.01940	-2.05	Yes	-9%	0.41428	0.37663	-0.03765	Yes	-9%
		2nd Ord Poly	Without PCT	2268	4.9	0.38483	0.40205	-0.01722	0.01644	-1.05	Yes	-4%	0.40041	0.36903	-0.03139	Yes	-8%
		3rd Ord Poly	Without PCT	2582	3.9	0.37861	0.40100	-0.02239	0.01548	-1.45	Yes	-6%	0.39726	0.37936	-0.01790	Yes	-5%
Diabetes	Weight loss support groups	1st Ord Poly	With PCT	302	4.7	0.29944	0.33684	-0.03740	0.04397	-0.85	No	-11%	0.33579	0.31948	-0.01630	No	-5%
		2nd Ord Poly	With PCT	322	4.6	0.33092	0.33032	0.00061	0.04129	0.01	No	0%	0.34569	0.33738	-0.00831	No	-2%
		3rd Ord Poly	With PCT	339	4.9	0.34566	0.33387	0.01179	0.04396	0.27	No	4%	0.34035	0.37145	0.03110	No	9%
		1st Ord Poly	Without PCT	382	4.0	0.34076	0.33069	0.01006	0.03784	0.27	No	3%	0.29999	0.31921	0.01922	No	6%
		2nd Ord Poly	Without PCT	369	3.3	0.30870	0.32159	-0.01289	0.04154	-0.31	No	-4%	0.32389	0.32058	-0.00331	No	-1%
		3rd Ord Poly	Without PCT	361	3.8	0.32853	0.31926	0.00927	0.03944	0.23	No	3%	0.32084	0.29848	-0.02237	No	-7%
Hypertension	Patient advice and liaison services (PALS)	1st Ord Poly	With PCT	2345	2.7	0.10525	0.10913	-0.00388	0.00632	-0.61	No	-4%	0.11246	0.10247	-0.00999	Yes	-9%
		2nd Ord Poly	With PCT	2334	2.8	0.10707	0.11252	-0.00545	0.00645	-0.85	No	-5%	0.10785	0.10054	-0.00730	Yes	-7%
		3rd Ord Poly	With PCT	2349	2.9	0.10391	0.10884	-0.00493	0.00626	-0.79	No	-5%	0.10891	0.10079	-0.00812	Yes	-7%
		1st Ord Poly	Without PCT	1719	3.1	0.09808	0.11236	-0.01428	0.00763	-1.87	Yes	-13%	0.11298	0.09787	-0.01512	Yes	-13%
		2nd Ord Poly	Without PCT	1659	2.2	0.10711	0.10887	-0.00176	0.00756	-0.23	No	-2%	0.10861	0.11352	0.00490	No	5%
		3rd Ord Poly	Without PCT	1706	1.9	0.09594	0.10876	-0.01281	0.00746	-1.72	Yes	-12%	0.10819	0.09754	-0.01065	Yes	-10%
Hypertension	Weight loss support groups	1st Ord Poly	With PCT	410	5.0	0.08658	0.07274	0.01384	0.01488	0.93	No	19%	0.07274	0.08472	0.01198	No	16%
		2nd Ord Poly	With PCT	312	4.9	0.09419	0.07684	0.01735	0.01751	0.99	No	23%	0.07858	0.08321	0.00463	No	6%
		3rd Ord Poly	With PCT	323	5.0	0.08714	0.07638	0.01077	0.01597	0.67	No	14%	0.07230	0.08713	0.01483	No	21%
		1st Ord Poly	Without PCT	341	4.3	0.07528	0.06883	0.00644	0.01371	0.47	No	9%	0.06221	0.08571	0.02351	Yes	38%
		2nd Ord Poly	Without PCT	343	4.5	0.07115	0.06718	0.00397	0.01572	0.25	No	6%	0.07599	0.07827	0.00228	No	3%
		3rd Ord Poly	Without PCT	252	2.8	0.05344	0.07331	-0.01987	0.01571	-1.26	Yes	-27%	0.07129	0.05840	-0.01289	No	-18%

The Patient advice and liaison service does not show a significant difference (a difference greater than the standard error) for ACS asthma admission rates. Only one of the six models for the ACS COPD rate was significant, with 3% fewer admissions. All six models for the ACS diabetes rate were significant with an average treatment effect of a reduction of 5.9% (ranging from -4% to -9.5%) for those that were treated (ATT). The average expected effect of the intervention on those who have not been treated (ATU) is a reduction of 7.5% (ranging from -4.5% to 10%). Two of the six models for ACS hypertension (both of which exclude the PCT dummy) were significant with the difference across all six models average effect a 6.5% reduction (ranging from -3.6% to -12.7%) in admissions for those treated (ATT). The average expected effect of the intervention on those who have not been treated (ATU) is a reduction of 7% (ranging from 4.5% to -13.4%) with five out of the six models being significant.

The Weight loss support groups showed a significant positive difference for ACS COPD rates averaging 16.1% (ranging from 9.7% to 21.9%). For ACS diabetes the differences were insignificant. For ACS hypertension only one out of the six models was significant, with 27.1% fewer admissions in the treatment group.

Information and support for diabetes showed a significant difference in five of six of the models, with an average treatment effect of 4.1% fewer admissions (ranging from 9% to -8.9%) for the treated (ATT). The average expected effect of the intervention on those who have not been treated (ATU) is a reduction of 0.6% (ranging from 10.1% to -9.6%).

Information and support for mental health was not found to have a significant effect on ACS diabetes rates.

The average number of practices in the propensity score matching for the Patient advice and liaison service (PALS) was 2124, for the Weight loss support groups it was 339, for Information and support for diabetes it was 1148, and for Information and support for mental health it was 2824.

8.4 Discussion

The Patient advice and liaison service (PALS) appears to be effective for reducing the rate of admissions for diabetes and hypertension. The PSM suggests that admission rates have been reduced by an average of 5.9% and 6.5% for diabetes and hypertension respectively in the 75% of practices that are within 5km of a PALS. It further suggests that there may be an even greater reduction of 7.5% and 7% respectively for those remaining 25% of practices not currently within 5km of a PALS if the intervention were introduced in those areas.

The PALS service provides information to patients about their condition, as well as directing them towards other services in the health system they may need. Diabetes is a complicated condition and much of the management of the condition will be carried out by the patient. It is therefore reasonable to expect that information provided by services like PALS would bring down admissions for diabetes by providing information to patients on how to manage their condition, as well as directing them to other services, such as dieticians, that could further help them with the management of their condition. The result as it relates to diabetes therefore seems reasonable. Hypertension is typically managed with drugs. Though there are lifestyle factors that the PALS service can provide information on, it would seem more likely that the main reason hypertension admissions are reduced by PALS would be the 'signposting' provided by the service to other parts of the health service, helping the patient to get the antihypertensive drugs they require. If this is the case, it is not entirely clear why the PALS service would not be similarly effective for asthma and COPD, though possible reasons include: that these conditions are harder to provide good information for; that information relevant to these conditions alone is not enough; or that there are fewer services for these conditions towards which patients can be directed.

The Information and support service for diabetes also appears to have led to a reduction in diabetes admission rates (4.1%). The expected effect on the rest of the 80% of practices is much smaller (0.6%). However, it is likely that a targeted approach – rather than introducing the intervention in all areas – would yield a greater percentage reduction in admission rates in those selected areas.

As with the PALS service, the Information and support services for diabetes would be expected to help patients with the condition to better manage their diabetes by providing them with information (for example on the need to eat better and exercise more) and directing them towards relevant services or experts on the condition. For instance, there are techniques that can be taught, such as carbohydrate counting, that allow more accurate monitoring and adjustment of blood sugar levels. Support groups that helped a patient to obtain such skills could reasonably be expected to reduce hospital admissions.

The result for the Weight loss support groups is surprising, as it appears to show that the intervention leads to more ACS COPD admissions (and no significant difference for ACS diabetes and ACS hypertension admissions). Previous studies examining the impact of such programmes has found them to be effective at reducing the weight of those that participate (Jolly et al., 2011). The matching relied on relatively few matches compared to the other interventions (339 versus 2124 for PALS). This was due to the large number of groups that are in place across England, meaning that

there are relatively few 'un-treated' practices. This is a potential source of distortion. It is also possible that the intervention is endogenous with respect to COPD admission rates. That is, that the interventions were more likely to have been introduced in areas that had higher rates of COPD admissions (in an effort by commissioners to tackle existing, high COPD prevalence).

Indeed, it is possible that all the interventions are endogenous with respect to the admission rates being compared. Commissioners of care within an area (PCTs at the time of this analysis) are likely to target interventions on areas that require them the most and where, therefore, they would have most impact. If this were the case then, even after adjusting for other factors such as the age and prevalence of disease within a population, the intervention population would have a higher rate of ACSC admissions. It is not possible to measure the degree to which this is happening but, if it is, the estimates of intervention effect produced in this chapter are likely to be underestimates.

Going forward, data should be collected so that a longitudinal study can be performed using a difference in difference approach; this should help alleviate the issue, likely seen in the examination of the weight loss support groups, that areas with higher rates of obesity (not well captured by the model) are more likely to have the intervention in place.

Interventions can be found that reduce ACSC admissions and commissioners should consider expanding them. ACSC-impact assessments should be carried out before commissioning such interventions. Future work should look for other interventions that reduce admissions for ACSCs. This work suggests that information sharing about interventions, and in particular those that help a patient to understand and self-manage their condition, might be effective at reducing admissions. Similar programmes that focus on different conditions should be examined more closely. 'Sign-posting' services that help patients to find their way around the health service and access the care they need should also be examined. Such assessments should be careful to monitor the use of all care services, not just hospital admissions, as decreases in secondary care could (and are likely to be) due to care being provided in another setting. In that case a judgement would need to be made on the value of the care being provided by each service (i.e. the quality of the outcomes achieved in relation to the cost) as this will influence which service patients should be directed towards.

8.4.1 Strengths and Weaknesses

8.4.1.1 Data

Data on interventions was pulled from a database kept by the NHS Choices website[8]. The data could be incomplete or inaccurate. The dataset has only recently been made available to researchers and, as such, its use in the literature is limited, though there are examples, for instance (Greaves et al., 2012). Missing data on interventions, though a concern, is likely to lead to an underestimate of the impact of the intervention (as the impact would incorrectly be assigned to the control group, lessening the difference).

To determine which practices were 'treated' with the given intervention, a proxy was used of the practice being within a certain distance of the intervention. This proxy was used because no data exists on whether patients from given practices actually use (or have available to them) the interventions. Were this data to be available it would likely lead to a more accurate result. In its absence however the proxy was deemed sufficient.

NHS Choices location data may be inaccurate and, therefore, the designation of practices in the treatment group versus the control may also be inaccurate. For instance, the postcode given could be for the head-office rather than where there the intervention actually takes place. Of a sample checked this was not an issue, but it was not possible to verify all the records and should be considered in interpretation of the results.

8.4.1.2 Techniques and Approach

The mapping distance calculated is 'as the crow flies' rather than the journey the patient is likely to actually take. This may be less accurate than if actual travel time/distance were calculated but due to the very large number of comparisons required (approximately 84 million) this was not possible.

Propensity score matching will never be as accurate as a randomised clinical trial (the gold standard for evaluation of an intervention or treatment). However, given the limitations of trying to assess an intervention that is already in place, it was felt that propensity score matching provided the best opportunity for determining their impact. Propensity score matching is widely used in economics and other disciplines in evaluating programs and interventions (Millimet and Tchernis, 2009) but, as

[8] The NHS Choices website (http://www.nhs.uk) contains information on services, allowing site users to search for services that are nearby, and providing basic details about the service.

discussed by Peikes et al. (2008), caution should be taken when interpreting results as they can never replace an experimental design, such as a randomised clinical trial.

Propensity score matching mimics an experiment by constructing a suitable comparison group by carefully matching 'treated' and 'non-treated' groups. In this process it may exclude practices that do not fit into either group. This means that the results are only applicable for a subset of the overall practice population and so care needs to be taken to not imply that the results apply to practices outside the common support.

The basic idea of propensity score matching is to find a group of non-participants who are similar to the participants (those treated) in all relevant pre-treatment characteristics. That being done, differences in the outcomes can be attributed to the treatment programme. For this to be true unconfoundedness needs to hold (Caliendo and Kopeinig, 2008). That is, there exists a set of observed characteristics Z such that outcomes are independent of program participation conditional on Z. This ought to hold for the PSM performed in this chapter, but it is not possible to prove this is the case.

8.4.1.3 Design

Condition-specific models were chosen from the four modelled in chapter 5, based on which condition admissions the interventions could potentially have an impact on. A more complete list of condition-specific models might enable better comparison. In particular if an intervention such as weight-loss were thought to impact on many conditions' admissions, but not all ACSC admissions, those specific conditions could be combined within a single model and then used to test the intervention.

The 5km cut-off distance used for determining whether a practice was 'treated' or not is fairly arbitrary and a different distance could be argued for and used. This may impact the results. Further, the method used (i.e. mapping distance to intervention to determine the treatment group) would not allow the testing of non-location based interventions, such as a telephone helpline or other virtual intervention. Testing such an intervention would require a different approach.

The propensity score matching of the weight loss intervention used relatively few practices as there were not very many practices in the non-treatment group to use as a control. Counteracting this issue is difficult and it could cause some of the anomalies noted in the results and discussion sections.

A potentially more accurate econometric method, difference-in-differences, was not possible as data was unavailable that monitored the introduction of the interventions. However, going forward, as new interventions are introduced, the method, which measures the difference in the outcome after and before treatment, could be used and may counteract some of the issues identified with propensity score matching.

9 Conclusion

9.1 Main Findings

Three GP patient survey results were associated with a lower admission rate for all ACSCs. They were: the percentage of patients who report being able to see their preferred GP; the percentage who would recommend the practice; and the percentage satisfied with the phone access. These results were also found to be associated with lower admission rates within some of the condition-specific models.

A practice's total QOF score was not found to be associated with a lower admission rate for all ACSCs. However, when condition-specific models were created, some individual QOF scores were found to be associated with lower rates of admission for the given condition. A higher score on the QOF indicator Asthma06 (i.e. the percentage of patients with asthma who have had an asthma review in the previous 15 months) was associated with lower admission rates for asthma. A higher score on the QOF indicator DM25 (i.e. the percentage of patients with diabetes in whom the last HbA1c is 9 or less (or equivalent test/reference range depending on local laboratory) in the previous 15 months) was associated with lower admission rates for diabetes.

Though higher mental health prevalence within the population was found to be associated with a higher admission rate for all ACSCSs, of the four conditions modelled separately, higher mental health prevalence was only associated with higher rates for diabetes.

Any metric based on an ACSC admission rate, would need to be over a sizeable population to be confident that it were giving some indication of quality and not merely the randomness that exists within the healthcare system. At the level of an individual practice the random element is large. However as practices are grouped together, the metric is more likely to reflect quality (or lack thereof) within the system. The average CCG size (approximately 33 practices) gives a reasonable metric (predicted rates within ±8.6% of the actual rates). And for the largest CCGs (130 practices) this figure reduces to ±4.3%. However, for the smallest 10% of CCGs (which have a maximum of 17 practices within them) the predicted rates are within ±12.0% of the actual rates.

Stochastic Frontier Analysis suggests that there is 20.4% average inefficiency in the rates of admissions for ACSCs among GP practices. That is practices could, on average, reduce their rates of ACSC admissions by 20.4% by improving their efficiency to the level of the best performing practices, allowing for factors that are out of the practice's control such as population characteristics. This translates to 242,143 'inefficient' ACSC admissions per year or an annual saving of £411m. This

financial estimate assumes that any 'savings' in fewer admissions are spread evenly across the different ACSCs. It also assumes that reducing the inefficiency in the system is cost-neutral.

The Patient advice and liaison service (PALS) appear to be effective for reducing the rate of admissions for diabetes and hypertension. Propensity score matching suggests that admission rates have been reduced by an average of 5.9% and 6.5% for diabetes and hypertension respectively in the 75% of practices that are within 5km of a PALS. It further suggests that there may be an even greater reduction of 7.5% and 7% respectively for those remaining 25% of practices not currently within 5km of a PALS.

The Information and support services for diabetes also appear to have led to a reduction in diabetes admission rates (4.1%). The expected effect on the rest of the 80% of practices is much smaller (0.6%).

9.2 Findings in relation to other studies

This thesis builds on the existing literature and, in particular, on the works identified in the literature review carried out in the introductory chapter.

As expected from previous research, population characteristics, such as deprivation, age and sex, were found to be associated with varying rates of admissions in each of the condition models. What was new in this research though was the finding that QOF scores related to diabetes and asthma interventions were positively associated with lower rates of admission for ACSCs. Previous research on the association between QOF scores and admission rates found only weak associations for asthma admissions (Downing et al., 2007) and diabetes (Bottle et al., 2008). In Italy however, Lezzi et al. (2014) found that diabetes-care incentives were associated with lower numbers of admissions for ACS diabetes. And research by Campbell et al. (2007) over the period that QOF was introduced found a statistically significant increase in the rate of improvement in clinical quality for diabetes and asthma (though the authors did not consider ACSC admission rates). The fact that the research in this thesis shows that differences in the attainment of these QOF scores reflect different levels of ACSC admissions suggests that, either most practices improved with the introduction of QOF, raising quality across the board, or good practices improved more than poorer ones, thereby bringing up the average. Either way, this research suggests that, in the case of diabetes and asthma, the QOF result does reflect better practice quality. This finding has not been shown in this way before.

GP headcount per 1000 population on the practice's list was found to be associated with higher rates of admission for both asthma and diabetes. Calderon-Larranaga et al. (2011) and Zhan et al.

(2004) have previously shown that an increase in primary care provision leads to fewer admissions for ACSCs. However, these studies were both in countries where access to primary care is incomplete and therefore, as the authors note, fewer admissions in this context is associated with improved access to primary care. The result shown in this research is from a setting where patients do not face significant barriers to accessing care and suggests that a higher GP headcount per 1000 population within a locality is indicative of a sicker population with a larger demand for healthcare. This is an interesting result that has not been shown in previous research, made possible from conducting the research in an area where significant barriers to access do not apply.

Two of the survey results related to access, suggesting that easier access to a GP practice may lead to fewer emergency admissions for ACSCs and that patients are well placed to provide accurate judgements in relation to accessibility. Much previous research has also shown the importance of GP access to achieving lower ACSC admission rates (Starfield et al., 2005b) (Ansari, 2007) (Leibowitz et al., 2003) (Wilson and Childs, 2006). However, none of these studies were based on patients' own perceptions of access and this is therefore an important result showing that patients' judgements of practice accessibility appear accurate.

Previous research, such as that by Kontopantelis et al. (2010) has looked at the impact of different population types on the responses patients give to the GP patient survey (being younger, of Asian ethnicity or working full time were all associated with lower rates) but none have looked at the association between survey responses and ACSC admissions. This thesis shows three GP patient survey results were associated with a lower admission rate for all ACSCs. Since the factors found in (Kontopantelis et al., 2010) were factored into the model it is unlikely that the result is the effect of groups who give lower survey responses also having more ACSCs. Instead it would appear likely that patients are a good judge (in aggregate) of their practice's quality (with regard to ACSC admissions). Previous research by Menec et al. (2006) has shown an association between continuity of GP and reduced levels of admissions, but not (as the first survey result shows) that the patients' choice of GP specifically is important. An alternative explanation is that the survey results are actually reflecting a difference in the practice population, not picked up by the characteristics included in the model, such as how able the patient is to manage their condition. This attribute, sometimes described as 'patient activation', impacts on a patient's confidence in dealing with their condition, giving them a more positive experience of their care, which is then reflected in better survey results. Previous work in this area, such as by Mosen et al. (2007), has identified an association between patient activation and outcomes, but not whether one causes the other. Further work is needed to explore this relationship, and how it relates to patients' opinions of their care.

Previous research has found that those with a range of long-term conditions are more likely to experience mental health problems than the rest of the population (Naylor et al., 2012). This thesis finds a higher prevalence of mental health issues associated with higher admission rates for diabetes and for all-ACSC admission rates. Further work is required to understand whether ACSCs (and in particular diabetes) causes people to have mental health issues, or whether mental health issues make those with diabetes more likely to have an emergency admission (or a combination of both).

Martin et al. (1997) used the same technique as that shown in this thesis to show how the aggregation of small areas leads to a diminution in the percentage variability of utilisation and therefore the population size required for GP fundholding. This thesis re-applies this technique to practice-level data to show the population size required to make an ACSC-admission-rate performance metric viable. At the level of an individual practice the random element is large. However, as practices are grouped together, the metric is more likely to reflect quality (or lack thereof) within the system. The average CCG consists of approximately 33 practices and this is sufficient to give a reasonable metric (predicted rates within ±8.6% of the actual rates). For the largest CCGs consisting of 130 practices, this figure reduces to ±4.3%. However, for the smallest 10% of CCGs, which consist of at most 17 practices, the predicted rates are within ±12.0% of the actual rates. Any metric would, therefore, need to be over a relatively large population and have some degree of leniency built in. This result adds to the academic literature in this area, and will be useful for policy makers considering adopting such a metric as a performance measure.

In England the most recent research looking at efficiency in primary care is from Giuffrida and Gravelle (2001) who used data envelopment analysis (DEA) to estimate the efficiency of primary care. The unit of analysis used was the Family Health Service Authority (FHSA), which was, during the period of study, the administrative unit for primary care in England. At that time, there were 90 FHSAs, with average populations of around 560,000 people, served by around 290 GPs. The study found a technical efficiency of 98.4% and cost efficiency of 96.4%. This thesis uses a different technique, called stochastic frontier analysis, to estimate the efficiency at the level of the GP practice, for all practices in England. This is not only an important update (as efficiency is likely to vary over time) and over a more granular population unit (the GP practice), but it also focuses on ACSC admissions specifically and so it gives a helpful estimate of the degree to which ACSC admissions could be reduced through improvements in efficiency.

The NHS Choices services data is a new dataset and, as such, there is not yet any research using it. Though other datasets created by NHS choices, such as users' comments on hospitals, have been

used by Greaves et al. (2012). Propensity score matching is used extensively in the literature to assess interventions, for example (Steventon et al., 2012b) and (Millimet and Tchernis, 2009). However, it has not been used to evaluate the impact interventions have on ACSC admission rates. It is, therefore, hoped that the work in this thesis, evaluating the impact that interventions have on ACSC admission rates using data from NHS Choices, will be both interesting, in and of itself, and also encourage other researchers to evaluate other interventions using a similar method.

Previous research has found that interventions that improve doctors' and patients' understanding of the correct pathway of care for diabetes (such as the computer-assisted intervention evaluated by Glasgow et al. (2005) improved process measures. Associated improvements in outcomes were not found however. Similarly Deakin et al. (2005) found that adults with type 2 diabetes who have participated in group-based training programmes show improved diabetes control (fasting blood glucose and glycated haemoglobin) and knowledge of diabetes in the short (four to six months) and longer-term (12 to 14 months) whilst also having a reduced need for diabetes medication. They also found some evidence that group-based education programmes may reduce blood pressure and body weight, and increase self-empowerment, quality of life, self-management skills and treatment satisfaction. However, they were not able to show that such patient education programmes reduced emergency admissions into hospital. The research in this thesis therefore adds weight to the existing literature to suggest that emergency admission rates are also reduced for diabetes patients who receive information about their condition and the care they should expect to receive.

9.3 Direction of future research

This research points to many areas of interesting and potentially fruitful research that should be conducted in the future.

As people live longer, populations are aging around much of the world. An aging population means more people with more long-term conditions and a larger group of people who interact with multiple services. It will, therefore, be all the more important to monitor the rate of admission for ACSCs (which typically represents a breakdown in the provision of care for these patients) and to ensure that rates are driven down. Additionally, as more is understood about the way different parts of the healthcare system interact with one another, research in areas that build directly on the research conducted for this thesis will become even more important.

Specifically, the models developed in chapters 5 and 6 should be taken further in three key ways. First, condition-specific models should be developed for each of the ACSCs. This would allow a

complete model to be created using seemingly unrelated regression. The results of this model could then be compared to the all-ACSC rate model. This would allow the researcher to understand which associations are cross-condition and which are condition-specific.

Second, as further data becomes available, increasing the amount of information models have about the practice population and practice characteristics could enhance the models. For instance, other research has shown that the distance a patient has to travel to hospital affects admission rates. Adding information on how far away patients are from their practice and secondary care may increase model accuracy. The quality of the care provided in the secondary care setting may also have an effect on admission rates. Data on the quality of secondary care, for instance readmission rates, could also be added to the models.

Third, future work could add further rigour to the models by investigating if any of the variables being used are endogenous. The current models assume that the independent variables are exogenous. However, GP headcount per 1000 population was associated with higher rates of admission for both asthma and diabetes. The number of GPs in a practice may be higher because the population is sicker and a decision has been made to increase the number of GPs to counteract this. Indeed, it may be that sicker or more challenging patients select particular types of GP and that the models do not account for these characteristics (for instance if they are not currently measured). As more data becomes available future research might seek to address potential endogeneity problems through longer panels or valid instruments.

The modelling work in chapters 5 and 6 also indicated an interesting association, namely between the prevalence of mental health issues and the rate of admissions for all ACSCs. Of the four conditions looked at separately, only diabetes was found to have an admission rate associated with the prevalence of mental health issues. This is interesting because none of the ACSCs are mental health issues. Future work should investigate this further to understand the relationship between poor mental health and hospital admission. Further regression modelling is likely to add little, though including prescription data, in particular key mental health related pharmaceuticals, may produce interesting results. Another way to investigate the relationship might be to examine interventions that aim to improve mental wellbeing and seeing if they have an impact on admissions.

Further work looking at the interaction between different conditions would also be valuable. For instance, does someone with diabetes and asthma and dementia receive the same level of care for their diabetes as someone with only diabetes, and indeed, should the care be the same? The

models in this thesis use the prevalence of different conditions within a population, but they do not (due to a lack of available data) look at the prevalence of multi-morbidity (that is the proportion of the population with multiple conditions). As more data becomes available this will be an important area to explore.

Chapter 7 demonstrates how a metric could be constructed using the rate of admissions for all ACSCs. Future work should investigate whether creating a metric by first modelling each ACSC separately and then combining them would create a more accurate and relevant metric that could be used (accurately) over a smaller population size. This combined model could further be used to re-evaluate the inefficiency estimate obtained, using the copula-based maximum likelihood approach demonstrated by Lai and Huang (2013) to run a stochastic frontier analysis over the individual condition-specific models.

Chapter 8 finds that there are interventions taking place in the healthcare community that appear to reduce admissions for particular ACSCs. It does this using propensity score matching, the best method available given the data limitations. Once the data becomes available, a more rigorous approach will be to perform a longitudinal analysis. Difference-in-differences, which measures the difference in the outcome after and before treatment, could be used and may counteract some of the issues identified with propensity score matching.

The interventions work could be taken further, and made more useful to commissioners and policy-makers, by looking at how much the interventions cost. This would allow their 'value' with regard to ACSC-reduction to be understood as well as allow a ranking of the interventions based on how effective they were.

As well as research that builds directly on that conducted for this thesis, there are a number of areas that have come to the attention of the author as being important and likely to generate valuable outputs were they to be investigated in the future.

One interesting area for future research might be to examine whether the inequality within a population has an impact on admission rates. The work in this thesis used indicators for socioeconomic wellbeing within a population, such as the Index of Multiple Deprivation, but this provides a population average. Future work might examine whether the variation in socioeconomic wellbeing within an area impacts on admission rates. For instance, a population that included a large socioeconomic gap might have worse results than otherwise expected due to the 'sharp elbows' of the better off, that could lead to more resource being deployed on those with less need.

A key task for the future will be to understand how GPs can achieve better results. Linkage of hospital data with GP practice data at the patient-level (as opposed to the practice-level, as performed in this thesis) would seem essential to making further progress in this area. Increasingly there is a move towards electronic patient records that contain information about patients and the care they have received, and expect to receive. When used well, these records are shareable among different organisations; for instance both primary and secondary care givers are able to view and edit the information they contain. The availability of this new and detailed dataset creates interesting opportunities for future research. In particular, to further research in this area, the dataset should be used to test questions about the pathway of a patient's care, and also to test whether the electronic patient record itself helps to improve care by allowing better coordination among disparate organisations.

As more patients with multiple conditions use more than one health care service, it will become more important to be able to measure and evaluate a system's ability to coordinate the care of individual patients. An ACSC admission rate could form part of a suite of metrics that help to do this. Further research to identify the other metrics to be included in the suite of metrics, and to better understand what influences each of them, would be valuable.

In the UK, social care and health care are funded and provided as separate services. However, because some of the highest volume users of health care also require social care, it is likely that the performance of social care services has a substantial impact on the performance of health care services. Examples include step-down care that helps patients return home after a hospital stay, and the health-related outcomes of elderly patients who receive help at home to take their medicines. Further work investigating the impact that social care has on health care, and vice versa, would fill an important gap in the research literature.

The research in this thesis was conducted, for the most part, on data from 2009. Since this time, as a result of the 2012 Health and Social Care Act, there has been a change in the way the English healthcare system is organised. In particular, a change was made which put CCGs in charge of most of the secondary care budget. Research to examine if this change had an impact on ACSC admission rates would be welcome and would usefully add to the body of knowledge about the impact of system incentives.

Finally, personalised medicine is care which is focused on specific targeted groups most likely to have a positive reaction to the care. The use of personalised medicine is likely to increase in the future as improved data, which allows easier identification of patients with specific characteristics,

becomes more readily available. Further research and evaluation of existing interventions, by patient characteristic, would be a valuable way of focusing interventions and strengthening the outcomes they create and, therefore, the value they deliver.

9.4 Policy implications

Rates of ACSC admissions are an important area, and are likely to attract even greater attention from policy-makers going forward due to the promise that reducing them can save money, improve the quality of care and improve the healthcare service overall. Further, the type and number of patients who typically have many of the long term conditions that cause ACSC admissions is likely to rise in the future, as the population ages, creating a further reason to place greater importance on research in this area. This research, therefore, has some important early lessons for policy-makers.

Two QOF scores were found to be associated with lower rates of ACSC admission. Both were related to an 'intervention' that is carried out within the GP practice – namely an asthma review and a test to ensure blood glucose levels for diabetics is being kept under control. This has two main implications for policy makers. Firstly, it is possible to incentivise behaviour among GP practices that is associated with lower rates of ACSC admissions. And secondly, at least in respect of the ACSC admission indicator, interventions that impact directly on patient treatment seem to be more effective than some of the more general indicators that are included in QOF. It is worth bearing in mind that for some of these more general indicators, reducing ACSC admissions would not be an intended consequence as they may be focused on some other aspect of care. This is not true for all of them however.

Mental health prevalence within the population was found to be significant only for admissions for diabetes. It was not significant for the other three conditions considered (i.e. asthma, COPD and hypertension). One potential reason might be that diabetes typically requires more and stricter self-care (e.g. monitoring blood glucose levels) than the other three conditions, and that this self-care is harder for those with mental health issues. There is growing acceptance of the importance of mental health care among policy-makers and politicians. This research further underscores the importance of mental health and its relationship to physical health. It follows from this research that policy makers should consider whether offering mental health support to specific groups of patients, such as those with diabetes, would be more effective than a less targeted approach.

Three patient survey results were found to be associated with lower rates of ACSC admissions. This suggests that patients are (in aggregate) good at judging the quality of their practice. Further work is

required to clarify this result, but if found to be accurate it could lead the way to re-designing incentive schemes so that they reward practices achieving higher patient reported satisfaction levels. This could have the advantage of lower data-collection costs, and avoid the accusation levelled at many pay-for-performance programmes, such as QOF, that all they encourage is better form filling.

This research shows that it is possible to predict admission rates for ACSCs, but not so accurately that they should be used at the average practice population level. Any metric developed would need to be at the population size of the average CCG or larger, and a degree of leniency would also be required. Further, significant adjustments for population characteristics, and other factors outside the practices' control, would also be needed before the metric could be used to judge how well a group of practices was performing. Policy makers should consider trialling such a metric. Allowing CCGs to compare themselves against one another in this way would have a number of advantages. For example, it would force CCGs to start to question why some practices (or groups of practices) are performing so much better or worse than the average. It would encourage CCGs to identify features and ways of working that result in lower ACSC admission rates; and to consider what support or incentives poorer performing practices might need in order to improve.

The analysis in this thesis indicates that there is considerable inefficiency (approximately 20%) in the performance of practices across England, which could be targeted to improve ACSC admission rates. This is an average figure and therefore suggests that many practices could make very substantial improvements. Further work should examine what practices are doing in the best performing areas that can be replicated in the worst performing areas. As mentioned above, publishing ACSC admission rates as a first step, would likely lead to more questioning as to the reasons why such large amounts of inefficiency exist in the system and who the worst offenders are.

As CCGs are increasingly held to account for the health and care of their population it will be important to be able to measure their performance. Adjusted ACSC admission rates should be added to the range of metrics used for this purpose.

Current commissioning models, whereby CCGs led by GPs commission most secondary care services, and NHS England commissions primary care and some specialist services (either high cost or very low volume), are not likely to be conducive to the sorts of changes that are required to lower ACSC admission rates. Investment in primary care and interventions, such as those identified, are likely required to lower ACSC admission rates. However, under the current model the additional costs would sit in the NHS England commissioning budget and any savings (from fewer ACSC admissions)

would land in the CCGs' commissioning budget. This mismatch will slow improvements, even though those improvements may lead to lower health system costs and better quality of care. Co-commissioning of services may help to alleviate this mismatch. Co-commissioning might involve investment in primary care services being matched by an understanding that a proportion of savings are returned to NHS England, or CCGs being given greater commissioning budget responsibility for primary care with NHS England retaining oversight to ensure that funds are not inappropriately funnelled to the practices of the GPs in charge of the CCG.

This research does not consider the impact a person having multiple conditions (e.g. diabetes, asthma and hypertension) has on the number of admissions into hospital. Little work has been done on this in the UK as, until very recently, data sets that allow the required linking of a patient's data have not been available. However, some areas (such as Somerset CCG) are now able to create person-level data sets, and these could usefully be used to test the impact of multi-morbidity on both the number of admissions into secondary care and the type of primary care required for such patients (likely to be a more complex intervention than that currently offered to the rest of the population). Promising models from the US (such as CareMore) use a case management approach where a secondary care physician (such as a geriatrician) works with a small number of multi-morbid patients to provide care outside of the hospital setting. Starfield et al. (2005a) found in the US that a high morbidity burden in the elderly leads to higher use of specialist physicians. However, it did not lead to higher use of primary care physicians, even for patients with common diagnoses not generally considered to require specialist care. This suggests that the potential for improvements in primary care is even greater for those with multiple morbidities. Further work in this area, as UK sites begin to adopt the approach seen in the US, would be valuable.

Finally, this work shows that interventions already exist that reduce ACSC admission rates. Further work needs to be done to find more interventions that also reduce ACSC admission rates. For the most part, ACSC admission rates have not been considered before, and they have not been tracked when introducing and establishing interventions. As shown in this research, interventions that are in relatively common use may have an impact on ACSC admission rates and it is important to ensure these are evaluated and their effect fully understood. Better data (such as when interventions begin and end and which patients use them) that allow longitudinal analysis to be performed should be available to researchers to enable their evaluation. Commissioners should consider such analyses when making commissioning decisions and, where possible, an assessment for impact on ACSC admission rates should be built into existing evaluation models. Many of the interventions considered were provided by third sector organisations. Further work should be done to evaluate

the impact of such interventions. Where they are found to be effective, policy makers should consider how they could encourage and promote the care providers. This research found that targeting specific groups of patients was an important part of ensuring that interventions were effective. Sharing data on patient characteristics (with appropriate anonymisation of patient details) with the organisations providing these services would be a useful first step to encouraging more targeted and effective approaches.

More broadly, commissioners of healthcare services need a greater focus on the value delivered by services. There needs to be a clear understanding of both the costs of the service and the outcomes improved by it. This research found that cost information was lacking in most instances, and that outcomes information, where available, was incomplete. For instance, the impact on secondary care usage was not well understood. Tracking ACSC admission rates should help this situation by placing a greater emphasis on the value that a service delivers. Without this, commissioning choices are not being based on the best available information.

9.5 Overall thesis conclusion

This thesis had four main aims. The first was to model the admission rate for ACSCs into secondary care at the practice level. In doing so it aimed to understand the factors related to varying rates, in particular focusing on the characteristics of the general practice to which a population was registered and the characteristics of the population itself. The second aim was to take this understanding further by exploring whether it was possible to model at the level of individual ACSCs and then, if so, how practice and patient characteristics impact on the rate of admission for the chosen ACSC. The third aim was to evaluate the potential for using (an adjusted version of) ACSC admission rate as a metric to gauge the performance of a practice, or group of practices, and further to understand by how much the practice(s) could potentially improve. Finally, the fourth aim was to identify existing interventions in the health service that reduce ACSC admissions and to evaluate the extent of their impact.

Each chapter explored one of these areas using a quantitative analysis of a large dataset that the author had built using routinely collected data sets, combined at the level of the GP practice, for all general practices in England. An array of econometric techniques were applied to further understanding in each of the areas, including multiple linear regression, corrected ordinary least squares, stochastic frontier analysis, and propensity score matching.

This thesis demonstrates that it is possible to model both the annual ACSC admission rate and a condition-specific admission rate for a given practice, if sufficient data is available, with a reasonable level of accuracy. It also produced several interesting results that had not previously been shown, notably: higher GP Patient Survey results were found to be associated with lower admission rates; mental health appears to play a role, despite not being an ACSC, in determining the risk of someone being admitted for an ACSC; and overall QOF scores were not associated with lower ACSC admission rates, but particular intervention-specific QOF scores were associated with lower rates of admission for their particular conditions.

These results potentially suggest that patients are (in aggregate) good at judging the quality of their practice and could lead to practices or groups of practices, being rewarded based on the result of such patient surveys. They also suggest that more attention should be given to mental health among policy makers and that programmes of support targeted at those who have mental health issues as well as particular physical health conditions may be more effective at reducing emergency admissions. Finally, they suggest that QOF may not be a good measure of GP quality with regard to ACSCs in general, but that some interventions that QOF measure are reducing admissions for some conditions.

This thesis explored the potential for creating an ACSC admission rate metric. In condition-specific models examined, the greater the total number of admissions being modelled the more of the variation in the admission rate that was accounted for by the model. And as the population size increased, the randomness within the system was diminished. Any metric would therefore need to encompass as many admissions (conditions) as possible and be over the largest population size possible. An all-ACSC admission rate over a population size covered by an average sized CCG (33 practices or 226,000 people) was found to give a reasonable metric for judging practice quality with regard to ACSCs. However, a degree of leniency would still be required, even at this level. This is an important result that has not been shown before. It gives policy makers both a useful guide to the design of such a metric (including the population size required) but also a warning that even a well designed metric would need to be applied with care and any associated incentive would need to allow for the random variation seen in complex systems such as healthcare.

The most recent estimate of inefficiency among general practices is more than 10 years old (Giuffrida and Gravelle, 2001). This thesis updates that estimate and for the first time applies it to the ACSC admission rate. Stochastic Frontier Analysis (SFA) suggested that there was 20.4% average inefficiency in the rates of admissions for ACSCs among GP practices. That is, practices could on

average reduce their rates of ACSC admissions by 20.4% by improving their efficiency to the level of the best performing practices, allowing for factors that are out of the practice's control such as population characteristics and random variation. This translates to 242,143 'inefficient' ACSC admissions per year. If they were avoided it would save commissioners £411m per year. Further work would be required to identify how to avoid this inefficiency but SFA could suggest which practices are among the better performers. This result adds further weight to the argument for an ACSC admission rate metric and for an incentive to be given to general practitioners to become more efficient and reduce their rates.

Finally, this thesis showed that existing interventions can be found, such as the Patient advice and liaison service (PALS) and Information and support services for diabetes, that reduce ACSC admissions. It suggests that commissioners should consider expanding such interventions. Further research is needed to find other interventions that lower ACSC admission rates and future work should investigate the cost-benefit of such services. Going forward, in order to ensure more is understood about what causes lower ACSC admission rates, and that more services that do lower rates are provided to patients, evaluations should be built into the role-out of interventions and, where possible, ACSC-impact assessments should be carried out before commissioning such services.

This thesis builds on the existing academic literature and presents some important results for policy makers in England and around the world. The author hopes that other researchers build on the research presented in this thesis and that this important area is given the attention that it deserves.

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11 Appendix I

Below is a table showing the descriptive statistics for each of the variables in the practice level dataset.

Table 11.1 – Descriptive statistics for all variables used in regression analysis

Variable Name	Variable Description	Number of Observations	Mean	Std. Dev.	Min	Max
standardis~o	Age-sex standardised ratio of ACSC admissions (actual number of ACSC admissions / expected number based on age-sex makeup of practice's list)	7984	0.9427	0.3949	0.0331	5.6701
ethni_asian	Percentage of registered patients of Asian/Asian other ethnic origin	8006	6.4087	14.6494	0.0000	97.0900
ethni_black	Percentage of registered patients of black/black other ethnic origin	8006	3.4367	7.4097	0.0000	72.3900
ethni_irish	Percentage of registered patients of Irish ethnic origin	8006	1.0108	1.6503	0.0000	21.7300
ethni_mixed	Percentage of registered patients of mixed ethnic origin	8006	5.2078	7.9220	0.0000	80.3400
ethni_other	Percentage of registered patients of ethnic origin other	8006	1.9098	3.1147	0.0000	41.1300
ethni_white	Percentage of registered patients of white ethnic origin	8006	82.0262	23.6949	0.0000	100.0000
imd_depscore	Deprivation Score (IMD)	7984	23.7462	12.1639	2.8560	68.4660
idaci_deps~e	IDACI (Income Deprivation Affecting Children) Score	7984	0.2264	0.1263	0.0110	0.6840
idaopi_dep~e	IDAOPI (Income Deprivation Affecting Older People) Score	7984	0.2259	0.1132	0.0380	0.8020
NumberinNu~e	Number of persons on GP list who are in a nursing home (per 1000 persons on list)	8224	5.5489	20.8373	0.0000	1000.0000
listsize	GP practice's list size	8245	6691.2850	4210.9490	8.0000	40766.0000
gpsheadcou~l	Number of GPs (Headcount) per 1000 population	8224	0.8147	2.3580	0.1100	135.5900
coronaryhe~e	Coronary Heart Disease Prevalence	8245	0.0339	0.0138	0.0000	0.4832
strokeortr~k	Stroke or Transient Ischaemic Attacks (TIA) Prevalence	8245	0.0167	0.0087	0.0000	0.2570
hypertensi~e	Hypertension Prevalence	8245	0.1360	0.0384	0.0000	0.6891
chronicobs~a	Chronic Obstructive Pulmonary Disease Prevalence	8245	0.0168	0.0092	0.0000	0.2899
hypothyroi~e	Hypothyroidism Prevalence	8245	0.0298	0.0104	0.0000	0.1685
cancerprev~e	Cancer Prevalence	8245	0.0153	0.0067	0.0000	0.2353
mentalheal~e	Mental Health Prevalence	8245	0.0084	0.0061	0.0000	0.2379
asthmaprev~e	Asthma Prevalence	8245	0.0589	0.0142	0.0000	0.2003
heartfailu..	Heart Failure Prevalence	8245	0.0071	0.0042	0.0000	0.2143
h~duetolvd~e	Heart Failure Due to LVD Prevalence	8245	0.0039	0.0026	0.0000	0.0588
palliative~e	Palliative Care Prevalence	8245	0.0017	0.0035	0.0000	0.2757
dementiapr~e	Dementia Prevalence	8245	0.0050	0.0117	0.0000	0.5978

atrialfibr~e	Atrial Fibrillation Prevalence	8245	0.0137	0.0076	0.0000	0.2941
cardiovasc~v	Cardiovascular Disease Primary Prevention Prevalence	8245	0.0128	0.0084	0.0000	0.3750
livewithep~1	Live with EPS Release 1	8125	0.8916	0.3109	0.0000	1.0000
livewithep~2	Live with EPS Release 2	8125	0.0123	0.1103	0.0000	1.0000
livewithgp~p	LIVE With GP2GP	8125	0.5429	0.4982	0.0000	1.0000
usedgp2gp~12	Used GP2GP in JAN 12	8125	0.4217	0.4939	0.0000	1.0000
livewithscr	Live with SCR	8125	0.5408	0.4984	0.0000	1.0000
sh02	QOF Score % - Indicator SH02	8245	0.8885	0.1222	0.0000	1.0000
sh03	QOF Score % - Indicator SH03	8245	0.8919	0.1975	0.0000	1.0000
cs01	QOF Score % - Indicator CS01	8245	0.8340	0.0705	0.0000	1.0000
pe07	QOF Score % - Indicator PE07	8245	0.8178	0.1513	0.0000	1.0000
pe08	QOF Score % - Indicator PE08	8245	0.7505	0.1776	0.0000	1.0000
record23	QOF Score % - Indicator RECORD23	8245	0.8639	0.0637	0.0000	1.0000
smoke03	QOF Score % - Indicator SMOKE03	8245	0.9561	0.0285	0.0000	1.0000
smoke04	QOF Score % - Indicator SMOKE04	8245	0.9307	0.0511	0.0000	1.0000
af03	QOF Score % - Indicator AF03	8245	0.9382	0.0792	0.0000	1.0000
af04	QOF Score % - Indicator AF04	8245	0.9528	0.1211	0.0000	1.0000
ckd02	QOF Score % - Indicator CKD02	8245	0.9726	0.0697	0.0000	1.0000
ckd03	QOF Score % - Indicator CKD03	8245	0.7485	0.1041	0.0000	1.0000
ckd05	QOF Score % - Indicator CKD05	8245	0.9078	0.1796	0.0000	1.0000
ckd06	QOF Score % - Indicator CKD06	8245	0.8235	0.1305	0.0000	1.0000
dep01	QOF Score % - Indicator DEP01	8245	0.8906	0.0910	0.0000	1.0000
dep02	QOF Score % - Indicator DEP02	8245	0.9133	0.1592	0.0000	1.0000
dep03	QOF Score % - Indcator DEP03	8245	0.7526	0.2799	0.0000	1.0000
dem02	QOF Score % - Indicator DEM02	8245	0.8054	0.1622	0.0000	1.0000
asthma03	QOF Score % - Indicator ASTHMA03	8245	0.9000	0.1077	0.0000	1.0000
asthma06	QOF Score % - Indicator ASTHMA06	8245	0.7958	0.0831	0.0000	1.0000
asthma08	QOF Score % - Indicator ASTHMA08	8245	0.8789	0.0906	0.0000	1.0000
mh04	QOF Score % - Indicator MH04	8245	0.9121	0.2634	0.0000	1.0000
mh05	QOF Score % - Indicator MH05	8245	0.8519	0.2944	0.0000	1.0000
mh06	QOF Score % - Indicator MH06	8245	0.8943	0.1176	0.0000	1.0000
mh07	QOF Score % - Indicator MH07	8245	0.7567	0.4214	0.0000	1.0000
mh09	QOF Score % - Indicator MH09	8245	0.9248	0.1063	0.0000	1.0000
cancer03	QOF Score % - Indicator CANCER03	8245	0.9276	0.1577	0.0000	1.0000
thyroi02	QOF Score % - Indicator THYROI02	8245	0.9581	0.0433	0.0000	1.0000
epilep06	QOF Score % - Indicator EPILEP06	8245	0.9562	0.0740	0.0000	1.0000
epilep07	QOF Score % - Indicator EPILEP07	8245	0.9521	0.0782	0.0000	1.0000
epilep08	QOF Score % - Indicator EPILEP08	8245	0.7396	0.1527	0.0000	1.0000
copd08	QOF Score % - Indicator COPD08	8245	0.9352	0.0738	0.0000	1.0000

copd10	QOF Score % - Indicator COPD10	8245	0.8848	0.1099	0.0000	1.0000
copd12	QOF Score % - Indicator COPD12	8245	0.8883	0.1429	0.0000	1.0000
copd13	QOF Score % - Indicator COPD13	8245	0.9117	0.1077	0.0000	1.0000
stroke05	QOF Score % - Indicator STROKE05	8245	0.9683	0.0496	0.0000	1.0000
stroke06	QOF Score % - Indicator STROKE06	8245	0.8870	0.0745	0.0000	1.0000
stroke07	QOF Score % - Indicator STROKE07	8245	0.9149	0.0781	0.0000	1.0000
stroke08	QOF Score % - Indicator STROKE08	8245	0.7718	0.1002	0.0000	1.0000
stroke10	QOF Score % - Indicator STROKE10	8245	0.9009	0.0863	0.0000	1.0000
stroke12	QOF Score % - Indicator STROKE12	8245	0.9379	0.0841	0.0000	1.0000
stroke13	QOF Score % - Indicator STROKE13	8245	0.8890	0.1587	0.0000	1.0000
dm02	QOF Score % - Indicator DM02	8245	0.9487	0.0449	0.0000	1.0000
dm05	QOF Score % - Indicator DM05	8245	0.9729	0.0358	0.0000	1.0000
dm09	QOF Score % - Indicator DM09	8245	0.9161	0.0751	0.0000	1.0000
dm10	QOF Score % - Indicator DM10	8245	0.9139	0.0757	0.0000	1.0000
dm11	QOF Score % - Indicator DM11	8245	0.9836	0.0289	0.0000	1.0000
dm12	QOF Score % - Indicator DM12	8245	0.8137	0.0801	0.0000	1.0000
dm13	QOF Score % - Indicator DM13	8245	0.8880	0.0905	0.0000	1.0000
dm15	QOF Score % - Indicator DM15	8245	0.8928	0.1353	0.0000	1.0000
dm16	QOF Score % - Indicator DM16	8245	0.9607	0.0381	0.0000	1.0000
dm17	QOF Score % - Indicator DM17	8245	0.8273	0.0652	0.0000	1.0000
dm18	QOF Score % - Indicator DM18	8245	0.9119	0.0630	0.0000	1.0000
dm21	QOF Score % - Indicator DM21	8245	0.9108	0.0754	0.0000	1.0000
dm22	QOF Score % - Indicator DM22	8245	0.9695	0.0375	0.0000	1.0000
dm23	QOF Score % - Indicator DM23	8245	0.5441	0.0949	0.0000	1.0000
dm24	QOF Score % - Indicator DM24	8245	0.7776	0.0752	0.0000	1.0000
dm25	QOF Score % - Indicator DM25	8245	0.8805	0.0611	0.0000	1.0000
bp04	QOF Score % - Indicator BP04	8245	0.9184	0.0410	0.0000	1.0000
bp05	QOF Score % - Indicator BP05	8245	0.7968	0.0657	0.0000	1.0000
hf02	QOF Score % - Indicator HF02	8245	0.9546	0.1125	0.0000	1.0000
hf03	QOF Score % - Indicator HF03	8245	0.9026	0.1220	0.0000	1.0000
hf04	QOF Score % - Indicator HF04	8245	0.8315	0.1797	0.0000	1.0000
pp01	QOF Score % - Indicator PP01	8245	0.8012	0.1842	0.0000	1.0000
pp02	QOF Score % - Indicator PP02	8245	0.8261	0.1405	0.0000	1.0000
chd02	QOF Score % - Indicator CHD02	8245	0.9425	0.1046	0.0000	1.0000
chd05	QOF Score % - Indicator CHD05	8245	0.9767	0.0441	0.0000	1.0000
chd06	QOF Score % - Indicator CHD06	8245	0.9025	0.0592	0.0000	1.0000
chd07	QOF Score % - Indicator CHD07	8245	0.9357	0.0601	0.0000	1.0000
chd08	QOF Score % - Indicator CHD08	8245	0.8190	0.0764	0.0000	1.0000
chd09	QOF Score % - Indicator CHD09	8245	0.9358	0.0567	0.0000	1.0000
chd10	QOF Score % - Indicator CHD10	8245	0.7491	0.1095	0.0000	1.0000
chd11	QOF Score % - Indicator CHD11	8245	0.8930	0.1077	0.0000	1.0000

chd12	QOF Score % - Indicator CHD12	8245	0.9273	0.0678	0.0000	1.0000
sh02except~e	QOF Exception Score % - Indicator SH02 Exception Rate	8221	0.0165	0.0234	0.0000	0.3170
sh03except~e	QOF Exception Score % - Indicator SH03 Exception Rate	8158	0.0567	0.0900	0.0000	1.0000
cs01except~e	QOF Exception Score % - Indicator CS01 Exception Rate	8227	0.0727	0.0613	0.0000	0.5710
stroke05ex~e	QOF Exception Score % - Indicator STROKE05 Exception Rate	8216	0.0164	0.0298	0.0000	1.0000
stroke06ex~e	QOF Exception Score % - Indicator STROKE06 Exception Rate	8216	0.0445	0.0531	0.0000	1.0000
stroke07ex~e	QOF Exception Score % - Indicator STROKE07 Exception Rate	8216	0.0429	0.0534	0.0000	1.0000
stroke08ex~e	QOF Exception Score % - Indicator STROKE08 Exception Rate	8216	0.1163	0.0832	0.0000	1.0000
stroke10ex~e	QOF Exception Score % - Indicator STROKE10 Exception Rate	8217	0.1576	0.0883	0.0000	1.0000
stroke12ex~e	QOF Exception Score % - Indicator STROKE12 Exception Rate	8195	0.0414	0.0642	0.0000	1.0000
stroke13ex~e	QOF Exception Score % - Indicator STROKE13 Exception Rate	8138	0.0837	0.1031	0.0000	1.0000
smoke03exc~e	QOF Exception Score % - Indicator SMOKE03 Exception Rate	8228	0.0070	0.0072	0.0000	0.2000
smoke04exc~e	QOF Exception Score % - Indicator SMOKE04 Exception Rate	8227	0.0104	0.0173	0.0000	0.4620
mh04except~e	QOF Exception Score % - Indicator MH04 Exception Rate	7657	0.0244	0.0856	0.0000	1.0000
mh05except~e	QOF Exception Score % - Indicator MH05 Exception Rate	7657	0.0855	0.1545	0.0000	1.0000
mh06except~e	QOF Exception Score % - Indicator MH06 Exception Rate	8220	0.0842	0.0855	0.0000	1.0000
mh07except~e	QOF Exception Score % - Indicator MH07 Exception Rate	6753	0.0630	0.1837	0.0000	1.0000
mh09except~e	QOF Exception Score % - Indicator MH09 Exception Rate	8216	0.1237	0.1222	0.0000	1.0000
thyroid02e~e	QOF Exception Score % - Indicator THYROID02 Exception Rate	8222	0.0062	0.0199	0.0000	1.0000
bp04except~e	QOF Exception Score % - Indicator BP04 Exception Rate	8228	0.0114	0.0207	0.0000	1.0000
bp05except~e	QOF Exception Score % - Indicator BP05 Exception Rate	8228	0.0424	0.0421	0.0000	1.0000
hf02except~e	QOF Exception Score % - Indicator HF02 Exception Rate	8160	0.0612	0.0857	0.0000	1.0000
hf03except~e	QOF Exception Score % - Indicator HF03 Exception Rate	8150	0.0823	0.1079	0.0000	1.0000
hf04except~e	QOF Exception Score % - Indicator HF04 Exception Rate	8144	0.3376	0.1920	0.0000	1.0000

epilepsy06~e	QOF Exception Score % - Indicator EPILEPSY06 Exception Rate	8212	0.0379	0.0607	0.0000	1.0000
epilepsy07~e	QOF Exception Score % - Indicator EPILEPSY07 Exception Rate	8211	0.0374	0.0609	0.0000	1.0000
epilepsy08~e	QOF Exception Score % - Indicator EPILEPSY08 Exception Rate	8212	0.1636	0.1550	0.0000	1.0000
dm02except~e	QOF Exception Score % - Indicator DM02 Exception Rate	8226	0.0313	0.0336	0.0000	1.0000
dm05except~e	QOF Exception Score % - Indicator DM05 Exception Rate	8226	0.0275	0.0313	0.0000	1.0000
dm09except~e	QOF Exception Score % - Indicator DM09 Exception Rate	8226	0.0582	0.0513	0.0000	1.0000
dm10except~e	QOF Exception Score % - Indicator DM10 Exception Rate	8226	0.0589	0.0519	0.0000	1.0000
dm11except~e	QOF Exception Score % - Indicator DM11 Exception Rate	8226	0.0160	0.0243	0.0000	1.0000
dm12except~e	QOF Exception Score % - Indicator DM12 Exception Rate	8226	0.0630	0.0501	0.0000	1.0000
dm13except~e	QOF Exception Score % - Indicator DM13 Exception Rate	8226	0.0540	0.0488	0.0000	1.0000
dm15except~e	QOF Exception Score % - Indicator DM15 Exception Rate	8144	0.0713	0.1039	0.0000	1.0000
dm16except~e	QOF Exception Score % - Indicator DM16 Exception Rate	8226	0.0266	0.0315	0.0000	1.0000
dm17except~e	QOF Exception Score % - Indicator DM17 Exception Rate	8226	0.0959	0.0579	0.0000	1.0000
dm18except~e	QOF Exception Score % - Indicator DM18 Exception Rate	8226	0.1549	0.0675	0.0000	1.0000
dm21except~e	QOF Exception Score % - Indicator DM21 Exception Rate	8225	0.0752	0.0589	0.0000	1.0000
dm22except~e	QOF Exception Score % - Indicator DM22 Exception Rate	8226	0.0218	0.0285	0.0000	1.0000
dm23except~e	QOF Exception Score % - Indicator DM23 Exception Rate	8226	0.1389	0.0976	0.0000	1.0000
dm24except~e	QOF Exception Score % - Indicator DM24 Exception Rate	8226	0.1000	0.0732	0.0000	1.0000
dm25except~e	QOF Exception Score % - Indicator DM25 Exception Rate	8226	0.0768	0.0581	0.0000	1.0000
dep01excep~e	QOF Exception Score % - Indicator DEP01 Exception Rate	8226	0.0277	0.0340	0.0000	0.8000
dep02excep~e	QOF Exception Score % - Indicator DEP02 Exception Rate	8192	0.1470	0.1519	0.0000	1.0000
dep03excep~e	QOF Exception Score % - Indicator DEP03 Exception Rate	8175	0.2729	0.1736	0.0000	1.0000
dem02excep~e	QOF Exception Score % - Indicator DEM02 Exception Rate	8132	0.0767	0.0979	0.0000	1.0000
copd08exce~e	QOF Exception Score % - Indicator COPD08 Exception Rate	8209	0.1399	0.0762	0.0000	1.0000
copd10exce~e	QOF Exception Score % - Indicator COPD10 Exception Rate	8210	0.1177	0.0982	0.0000	1.0000
copd12exce~e	QOF Exception Score % - Indicator COPD12 Exception	8186	0.1412	0.1320	0.0000	1.0000

	Rate					
copd13exce~e	QOF Exception Score % - Indicator COPD13 Exception Rate	8210	0.1115	0.0910	0.0000	1.0000
pp01except~e	QOF Exception Score % - Indicator PP01 Exception Rate	8209	0.1651	0.1252	0.0000	1.0000
pp02except~e	QOF Exception Score % - Indicator PP02 Exception Rate	8222	0.1026	0.0899	0.0000	1.0000
chd02excep~e	QOF Exception Score % - Indicator CHD02 Exception Rate	8191	0.0748	0.0930	0.0000	1.0000
chd05excep~e	QOF Exception Score % - Indicator CHD05 Exception Rate	8216	0.0103	0.0186	0.0000	1.0000
chd06excep~e	QOF Exception Score % - Indicator CHD06 Exception Rate	8216	0.0297	0.0354	0.0000	1.0000
chd07excep~e	QOF Exception Score % - Indicator CHD07 Exception Rate	8217	0.0260	0.0352	0.0000	1.0000
chd08excep~e	QOF Exception Score % - Indicator CHD08 Exception Rate	8217	0.0864	0.0607	0.0000	1.0000
chd09excep~e	QOF Exception Score % - Indicator CHD09 Exception Rate	8217	0.0315	0.0405	0.0000	1.0000
chd10excep~e	QOF Exception Score % - Indicator CHD10 Exception Rate	8218	0.2228	0.1122	0.0000	1.0000
chd11excep~e	QOF Exception Score % - Indicator CHD11 Exception Rate	8166	0.0704	0.0821	0.0000	1.0000
chd12excep~e	QOF Exception Score % - Indicator CHD12 Exception Rate	8218	0.1332	0.0701	0.0000	1.0000
ckd02excep~e	QOF Exception Score % - Indicator CKD02 Exception Rate	8199	0.0071	0.0341	0.0000	1.0000
ckd03excep~e	QOF Exception Score % - Indicator CKD03 Exception Rate	8204	0.0737	0.0857	0.0000	1.0000
ckd05excep~e	QOF Exception Score % - Indicator CKD05 Exception Rate	8032	0.1145	0.1590	0.0000	1.0000
ckd06excep~e	QOF Exception Score % - Indicator CKD06 Exception Rate	8202	0.0424	0.0698	0.0000	1.0000
cancer03ex~e	QOF Exception Score % - Indicator CANCER03 Exception Rate	8134	0.0174	0.0574	0.0000	1.0000
af03except~e	QOF Exception Score % - Indicator AF03 Exception Rate	8201	0.0364	0.0536	0.0000	1.0000
af04except~e	QOF Exception Score % - Indicator AF04 Exception Rate	8165	0.0601	0.0829	0.0000	1.0000
asthma03ex~e	QOF Exception Score % - Indicator ASTHMA03 Exception Rate	8170	0.0265	0.0569	0.0000	1.0000
asthma06ex~e	QOF Exception Score % - Indicator ASTHMA06 Exception Rate	8226	0.0503	0.0706	0.0000	1.0000
asthma08ex~e	QOF Exception Score % - Indicator ASTHMA08 Exception Rate	8226	0.0635	0.0719	0.0000	1.0000
totalqofpo~s	Total QOF score (Percentage of total available)	7984	94.9323	4.2720	39.2090	100.0000
refViaAE	Percentage of ACSC admissions with method of admission = via A&E	9771	0.7346	0.2139	0.0000	1.0000

refViaGP	Percentage of ACSC admissions with method of admission = via GP	9771	0.1785	0.1829	0.0000	1.0000
refViaBedB~u	Percentage of ACSC admissions with method of admission = via Bed Bureau	9771	0.0164	0.0591	0.0000	1.0000
refViaOutp~t	Percentage of ACSC admissions with method of admission = via Outpatients	9771	0.0145	0.0386	0.0000	1.0000
refViaOther	Percentage of ACSC admissions with method of admission = via Other	9771	0.0560	0.0958	0.0000	1.0000
survey_sat~e	GP Patient Survey - % satisfied with phone access	7979	77.6568	16.1491	17.2540	100.0000
survey_see~s	GP Patient Survey - % able to see a doctor within 2 days	7975	80.2243	11.4100	24.8450	100.0000
survey_boo~d	GP Patient Survey - % able to book appointment >= 2d ahead	7935	71.5647	15.0490	0.0000	100.0000
survey_sat~s	GP Patient Survey - % satisfied with opening hours	7980	78.6291	7.1991	43.8780	100.0000
survey_abl~p	GP Patient Survey - % able to see preferred GP	7907	71.5839	15.2876	11.7650	100.0000
survey_wou~e	GP Patient Survey - % would recommend practice	7979	82.0674	10.6224	34.0210	100.0000
survey_sup~s	GP Patient Survey - In the last 6 months, have you had enough support from local services or organisations to help you to manage your long-term health condition(s)? (%)	8046	0.5377	0.0750	0.1938	0.9000
survey_tol~n	GP Patient Survey - Did the doctor or nurse ever tell you that you had something called a ‘care plan’? (%)	8009	0.1156	0.0619	0.0000	0.6000
survey_tak~s	GP Patient Survey - Did the doctor or nurse take notice of your views about how to deal with your health problem? (%)	8016	0.8949	0.0686	0.4444	1.0000

12 Appendix II

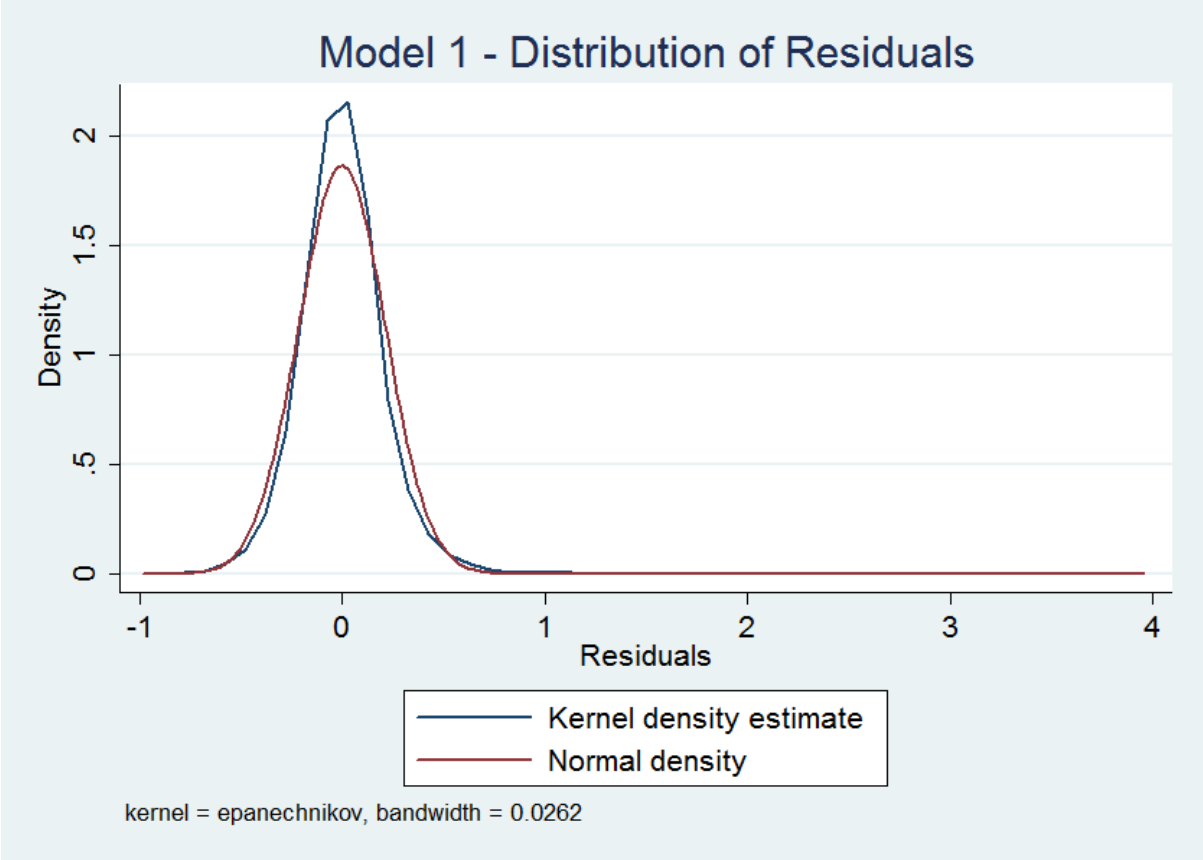


Figure 12.1 – Test for normality of the residuals from model 1

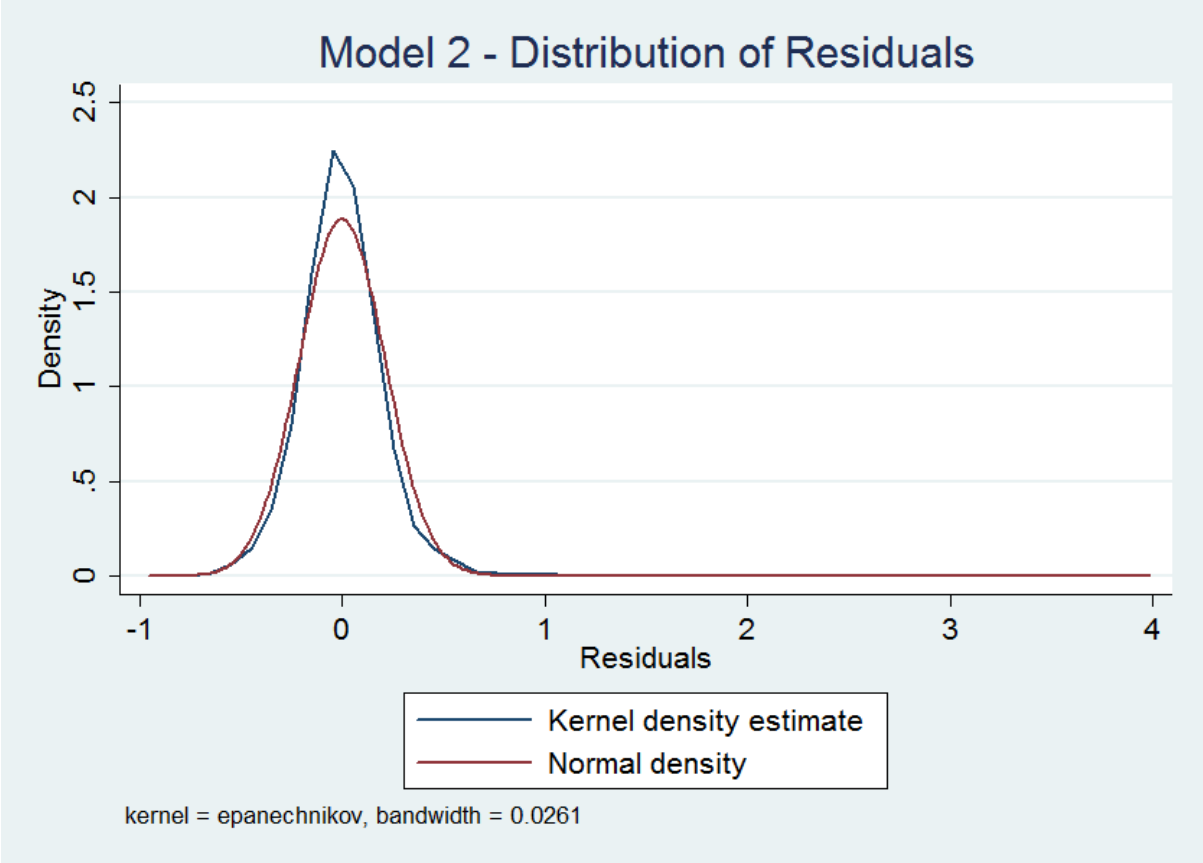


Figure 12.2 – Test for normality of the residuals from model 2

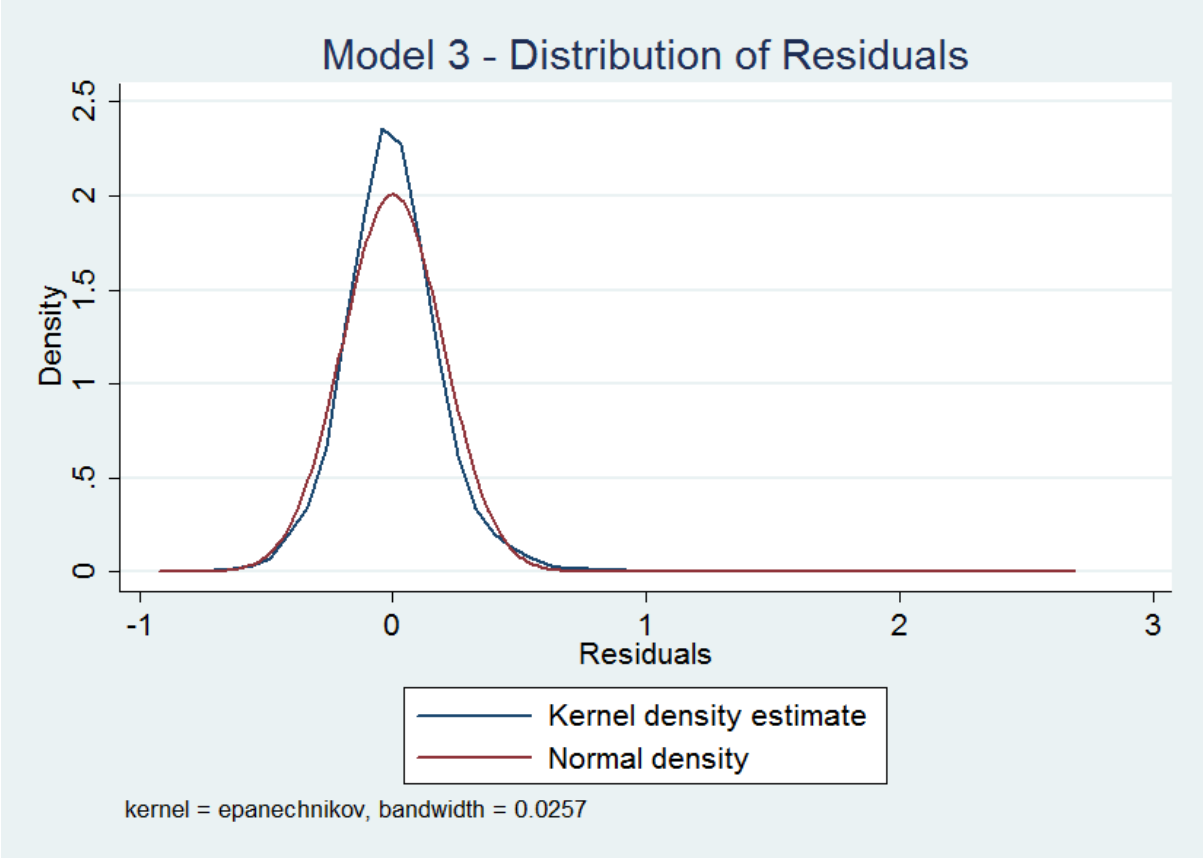


Figure 12.3 – Test for normality of the residuals from model 3