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Efficiency, effectiveness and public trust in policing in the era of austerity: a study of police forces in England and Wales, 2011 – 2017.

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Efficiency, effectiveness and public trust in policing in the era of austerity: a study of police forces in England and Wales, 2011 – 2017.

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Abstract

This research measures police efficiency, effectiveness and public trust for territorial police forces in England and Wales from 2011/12 to 2017/18, under the background of a spending reduction among the police forces from 2011/12 to 2014/15.

Research goals: to quantify the efficiency, effectiveness and public trust at the level of police force area during the period of austerity; to compare and analyse whether any police forces performed better than others and in what areas; to analyse factors contributing to improving police performance from the perspective of resource allocation; to investigate any association between efficiency, effectiveness and public trust.

Primary research methods: data envelopment analysis to measure police efficiency, panel linear regression to analyse the relationship between performance and resources, and social text mining as a supplement method to measure public trust.

Main dataset: Crime Survey for England and Wales (with low-level geographic data), Police Workforce in England and Wales, Tweets extracted from Twitter.

Innovations: Although this method is still used in other nations with crime data in recent publications, data envelopment analysis has never been employed to analyse police efficiency in the UK after 2006. This research once again applies the data envelopment analysis method to measure police efficiency. It employs survey data to measure effectiveness outcomes to include hidden crimes that were not reported to the police. To measure public trust, a supplement text mining method, sentiment analysis with Tweets, is proposed to assess attitudes toward the police.

Keywords: police performance, efficiency, public trust in policing, austerity, data envelopment analysis, Crime survey for England and Wales, social media mining

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Introduction

The introduction chapter engages with the policy context for this research by discussing the approach of new public management under various governments in the UK and their attitude and approach toward measuring police performance. The chapter also puts forward debates on these approaches, followed by how this research will contribute by filling the existing gaps in the field. Subsequently, it ends with research goals and numbered objectives.

(1) Context for research

Public service reform started in the 1980s as a result of the perception that many public institutions were seen as outdated and inefficient, and had limited accountability due to their bureaucratic nature (Hughes, 2003). It is claimed that the traditional model of administration lacked adequate performance management and that any measurements that were in place were ad hoc and inconsistent.

This need for reform led to the subsequent trend towards managerialism and the emergence of New Public Management (NPM) (Hood, 1998; Pollitt & Bouckaert, 2000). Public demand for enhanced accountability, combined with a political desire to make the public sector more "business-like", resulted in the introduction of the concept of citizens as "customers", and an increased focus on competition and performance outputs (McLaughlin et al., 2001). By establishing a quasi-market, supporters of New Public Management (NPM) sought to solve the absence of market mechanisms in public sector monopolies.

However, this effort was fraught with challenges. For example, it can be difficult to measure public service outputs since they differ from those of the private sector (Caers et al., 2006). Additionally, the NPM approach overlooks the widely-held belief that public sector objectives are multifaceted, intricate, and often in conflict with each other (Jackson, 2011). Furthermore, Pollitt (1999) contends that assessing many public service activities is difficult since they are frequently customised to meet individual needs. Hughes (2003) emphasises fundamentally distinct features of the public and private sectors, highlighting the complexity and distinct values of the former such as political independence, professionalism, and impartiality, which contrast with the latter's focus on profitability.

In the context of policing specifically, Moore and Braga (2004) criticised the quasi-market approach that policing differs from private sector management because it is unclear who the police forces' customers are – all citizens who should be protected, people who call for assistance, as well as criminals who have been arrested. Since goals for many people or sectors may conflict, it is difficult to define, assess, and balance the outcomes of policing. NPM introduced performance indicators and numerical targets as a measure of effectiveness to encourage competition and performance management in public sectors such as primary education and healthcare. Target-driven performance management significantly increased during the 1990s, notably following the New Labour period of government. For example, the 1998 Comprehensive Spending Review resulted in the introduction of 366 Public Service Agreements covering various public services, which included over 600 performance targets (James, 2004). This management system was dubbed "targets and terror".

Under New Labour, the principles of Best Value were introduced by the 1999 Local Government Act (Great Britain, 1999) to enhance the performance of police forces. Local authorities, police, and fire and rescue services were required to continuously improve their service delivery by setting enhanced performance targets to attain economic benefits, efficiency and effectiveness (Butterfield et al., 2004). The Police Reform Act 2002 (Great Britain, 2002) brought about several changes to the performance management system for the police: (a) The role of HM Inspectorate of Constabulary (HMIC) was reinforced, allowing for the inspection of police performance; (b) The Home Secretary was granted new powers to directly intervene in cases of underperformance within a police force, (c) Approximately 50% of Best Value Performance Indicators (BVPIs) were removed, and the remaining indicators were renamed Key Performance Indicators (KPIs). These were then arranged in a manner that would make them more easily understandable to the public and more operable to the police.

Under the Coalition Government of 2010-2015, the underlying approach of NPM was to reduce public spending, increase efficiency through marketisation and outsourcing, and emphasise the need for localism and greater autonomy for public sector organisations. This was reflected in policies such as the Localism Act 2011, which granted more devolved power to local authorities (Layard, 2012). The government implemented a range of policies aimed at introducing greater competition into the public sector, such as payment-by-results models (Hedderman, 2013). NPM also continued the use of performance management and target-setting to measure and improve the performance of public sector organisations. However, the Coalition government came close to eliminating the KPIs that New Labour had implemented. In performance measurement, the emphasis is shifting from centralised targets to outcomes (Perkins, 2013).

For example, specific to policing (HM Treasury, 2010), significant reforms to the police performance measurement were made since 2010: (a) real-term funding was cut by 20% in total in the 2010-2014 period; (b) a single top-down target for public confidence level was replaced by another target–crime reduction, and all KPIs were removed; (c) Police Authorities were replaced by the elected Police and Crime Commissioners (PCCs); (d) The task of inspecting, rating, and assessing the police in terms of costs and policing outcomes was given to HMIC.

The succeeding Conservative Government, which came to power in 2015 continued to support NPM as a means of improving the performance of public services. New initiatives such as the "100% business rates retention" policy for local authorities (DGLG, 2016; Mor & Sandford, 2017), allow the retention of 100% of taxes raised locally and are intended to provide financial incentives for local authorities to promote economic growth and development. Meanwhile, the tight budget had started to ease, so value for money was no longer an essential element of performance measurement (Home Office, 2018). Additionally, the government had also sought to reduce bureaucracy and increase transparency in public service delivery, while promoting digitalisation and innovation in service provision (Andrews, 2019).

Under the Conservatives, PCCs have been given increased authority to local policing priorities and to hold the police force responsible for its performance. The use of targets and performance indicators has been reduced, and the emphasis has shifted from inputs and outputs to outcomes and effectiveness. The government has also introduced a new inspection framework, *Police Effectiveness, Efficiency, Legitimacy (PEEL) Assessments* managed by HMIC, which focuses on the effectiveness of police forces in reducing crime and improving public safety, rather than on ensuring that they comply with predetermined goals or standards.

There have been numerous discussions about the potential effects of targets on the effectiveness of public services and overall police work, as well as the risk of effort distortion towards the metrics assessed.

“Targets and terror” refers to a performance measuring system that includes a set of targets and the associated fear that the organisations will suffer consequences if the targets are not met. This philosophy shares ideological similarities with the Soviet government (Bevan & Hood, 2006).

Bevan and Hood (2006) discussed the impact of imposing numerical targets in the National Health Service and concluded that under management by numbers, the organisations would demonstrate perverse incentives and behaviours that were perceived as “synecdoche” and “gaming”. Synecdoche is the practice of using the performance of a single component as a way to estimate the overall performance of the entire system, and gaming is the practice of organisations actively lowering performance in areas that are not being measured to direct resources to those that are to meet targets without actually improving performance or outcomes.

Propper (2008) evaluated the effect of “target and terror” on waiting times for hospital care based on data collected after 2001 in England and Scotland and concluded that this policy reduced the proportion of people in waiting and therefore resulted in a positive outcome. Coulson (2009) also pointed out that while the effort to manage performance through centrally set targets will indeed have a positive impact on behaviour, it will ultimately be hindered by managers who engage in unsuitable practices to meet specific targets or performance indicators, because their employment depends on achieving favourable scores.

The effort distortion could lead to unethical behaviour, gaming or manipulating performance metrics, neglecting important but less visible aspects of work, and unhealthy competition between individuals or departments, all of which could harm overall performance and service delivery. In the case of policing, numerous cases have arisen where officers have made "easy" arrests to meet targets, as well as situations of misclassifying or falsely reporting crime, and even instances of unethical conduct to achieve detection targets (Tendler, 2007; Seddon, 2008; Loveday, 2008). Cases like these have occurred due to not only the simplistic setting of targets but the easily manipulated measurement by metrics (Heinrich & Marschke, 2010).

Gaming and effort distortion also occurs when influenced by politics. Guilfoyle (2012) highlighted gaming between policing targets and PCCs. Since PCCs have the power to hire and fire Chief Constables and control police budgets, it could lead to an unexpected mix of people leading the police force, and political parties may put forward candidates. PCCs have motions to simplify the targets (e.g., a single target like crime reduction), encourage the officers to work for relatively simple targets and neglect the less visible aspects of policing. Another issue is that to demonstrate police effectiveness, PCCs will likely concentrate on a single crime reduction target, which could have unexpected consequences. If one particular issue or crime type is given disproportionate emphasis, operational activity may become unbalanced, while less visible aspects of policing, such as counterterrorism or covert operations, may be neglected. Officers may be encouraged to aim for simple targets in politically sensitive priority areas, resulting in gaming. While Chief Constables wish to avoid punishment for failure, PCCs would demonstrate successful intervention, which is likely to cause distortions in output reporting and unhealthy competition between departments.

A systematic and holistic performance measurement system is required. In order to increase efficiency and protect any unseen public service, it is expected to consider the police service as a whole and take into account how measurement functions and other factors interact.

(2) Contribution to the research gap

Since 2006, there has not been a quantitative evaluation of police effectiveness using British data, and changes in efficiency relating to changes in resources during the period of austerity from 2010 to 2014 have not been analysed in detail. The present research addresses a significant research gap by providing a comprehensive evaluation of police efficiency at a local police force level in England and Wales. The results of this research could have a significant impact on policy and practice related to policing.

(3) Research goals and objectives

The overall aims of this research are to: provide a systematic measurement of police performance in terms of efficiency, effectiveness and public trust; analyse the performance of territorial forces in England and Wales during the period of austerity; identify whether any police forces performed better than others and in which areas; examine any connections between performance and contributing resources and association among efficiency, effectiveness and public trust; provide policy advice on the future implementation of policing, particularly about resource allocation and performance management.

Research objectives are listed as follows:

a) Select appropriate datasets, representative indicators and scientific quantitative methods to construct a quantitative measurement of police efficiency that considers environmental factors that are beyond the control of the police;
b) Compare the efficiency of police forces and identify any forces that have performed better during the period of austerity, and provide suggestions for improvement to forces that have experienced a decrease in efficiency in this period;
c) Select representative indicators to reflect changes in police forces' effectiveness during the period of austerity;
d) Investigate any associations between resources and efficiency/effectiveness, and propose any factors that contribute to improving police performance;
e) Conduct a quantitative measurement of public trust using survey data and search for any types of new data that can reflect public trust;
f) Analyse the characteristics of public trust and its changes during the period of austerity；
g) Investigate any associations among effectiveness, efficiency and public trust;
h) Put forward advice on police performance management, resource allocation, policy and future policing.

This thesis will be structured as follows:

Chapter 1 introduces the police in England and Wales and the challenges faced during the period of austerity. It then reviews the concepts of efficiency, effectiveness and public trust. Chapter 2 introduces the background and application of data envelopment analysis. Chapter 3 reviews previous studies and how they measured police efficiency. Chapter 4 implements the measurement of efficiency under austerity, and then recognises police forces with better levels of efficiency. Chapter 5 discusses effectiveness outcomes and their relationship with efficiency and resources. Chapter 6 measures public trust in policing through survey data and social media data, and discusses any reflection on efficiency and effectiveness. Chapter 7 presents the conclusion and discussion.

1. Crimes, police resources and performance

This chapter provides the background information relevant to crime changes, the UK's austerity period in the 2010s, and the measurement of police performance. Section 1.1 introduces recent changes in crime and police resources, followed by an overview of police organisational structures and duties in section 1.2. Section 1.3 begins with the theory of performance management and definitions of effectiveness and efficiency before critically reviewing several measures of police performance and defining police effectiveness and efficiency (as the terms are used for present purposes). Section 1.4 reviews the reduction of public spending implemented between 2010 to 2015 as part of the government's austerity drive, the actions police forces took to overcome funding shortfalls, and the extent to which such actions were properly implemented. Section 1.5 introduces crime trends in England and Wales in recent years, with literature on crime and performance covered in section 1.6. Finally, section 1.7 introduces another perspective of measure, public trust, and section 1.8 concludes this chapter.

1.1. Introduction

Public debates on social policy and public services typically centre on issues such as healthcare, education, employment and the pension system. Notably, security, crime, and safety are perennial themes of public discourse as they impact all levels of society. Police forces in England and Wales have been working to reduce crime, ensure the public is safe, and crucially, ensure the public feel safe. Crime has fallen markedly since the mid-1990s: the Crime Survey England and Wales' (CSEW) estimates of the number of offences in England and Wales fell considerably from 1995 onwards, increasing slightly from 2005 to 2007, and 2008 to 2009, before plateauing from 2010 to 2012. From 2016 inwards, fraud and computer misuse were included as new types of crime considered in CSEW estimates. Therefore, in Figure 1.1 below, there is a large gap between the two measures (including and excluding fraud and computer misuse) from 2016 to 2017.

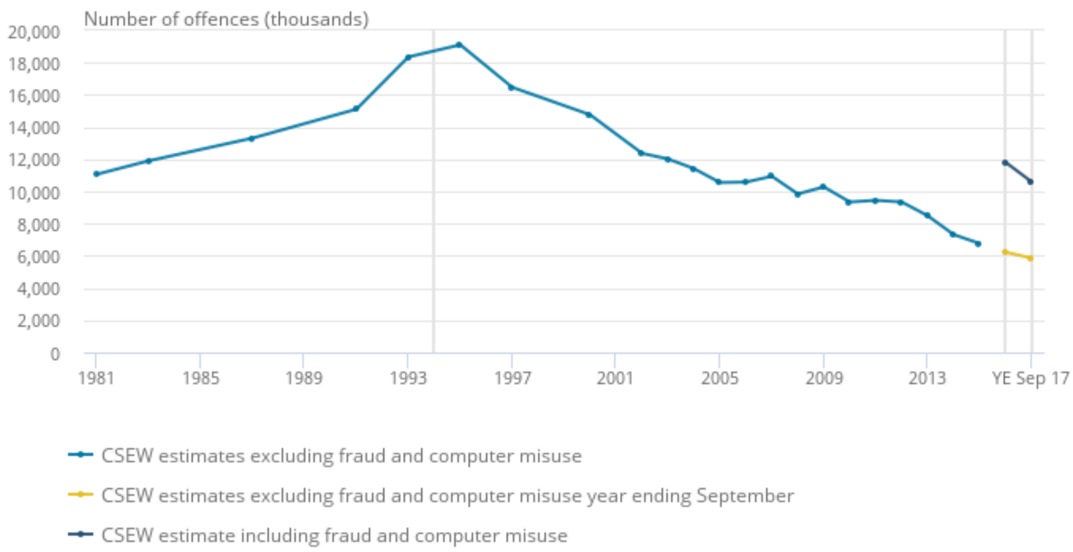

Figure 1.1. Crime estimates taken from the Crime Survey for England and Wales, year ending December 1981 to year ending September 2017.[1]

It is readily apparent that new policing challenges have taken root during the period covered by the data set. On the one hand, new types of crime appeared, such as cybercrime, anti-social behaviour and modern slavery, all of which have become new policing priorities (National Police Chief's Council, 2017, p.8). At the same time, the rates of traditional crimes (i.e., burglary, robbery and sexual offences) have also been changing in recent years due to the shifting fabric of society, which is influenced by economic development, cultural transformation and technology revolution. Population mobility frustrates crime prevention and investigation efforts; as such, police forces are required to take all necessary steps to deal with crimes and routine tasks to control order and ensure public safety.

Most notably for present purposes, policing budgets have been slashed since 2010. Funding for police forces and Police and Crime Commissioners (PCCs) largely comes from central government grants, with other sources of funding including council tax precepts and other grants. Central government funding for police was reduced during

[1] Figure reproduced from: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/crimeinenglandandwales/yearendingseptember2017 .

the austerity period from 2010/11 to 2015/16, directly leading to reductions in both policing budgets and the police workforce. Table 1.1 shows how police spending changed from 2000/01 to 2014/15, whilst Figure 1.2 shows how the police workforce changed from 1996 to 2016.

Policymakers are keenly interested in how police performance changed during the austerity period, how austerity impacted different police forces, and whether any forces performed better than others. To investigate these questions, police performance needs to be measured. This can be achieved through a variety of means, including measuring effectiveness, efficiency, and public confidence. Specifically, police effectiveness pertains to how well the police achieve outcomes regardless of expenditure, whereas police efficiency is how well the police achieve given outcomes working within a predefined budget (Murphy, 1985). Additionally, public trust reflects how well the police are doing in terms of public perception.

Table 1.1. Changes in police spending (2000/01 to 2014/15).

		Police Spending (£000)				Average annual percentage change		
		2000-01	2005-06	2010-11	2014-15	2000-01 to 2005-06	2005-06 to 2010-11	2010–11 to 2014–15
Total (£ million)	Spending	10,409	12,710	13,617	11,702	4.1%	1.4%	−3.7%
	Grant	8,673	9,648	10,182	8,168	2.2%	1.1%	−5.4%
	Precept	1,736	3,062	3,435	3,534	12.0%	2.3%	0.7%
Per person (£)	Spending	196	238	249	205	3.9%	0.9%	−4.6%
	Grant	164	181	186	143	2.0%	0.6%	−6.3%
	Precept	33	57	63	62	11.9%	1.8%	−0.3%
Proportion of spending	Grant	83%	76%	75%	70%			
	Precept	17%	24%	25%	30%			
Total (£ million)	Spending	10,409	12,583	13,147	11,138	3.9%	0.9%	−4.1%
Excluding Counter-Terrorism Grant	Grant	8,673	9,521	9,711	7,604	1.9%	0.4%	−5.9%

Source: Crawford, Disney and Innes, 2015.

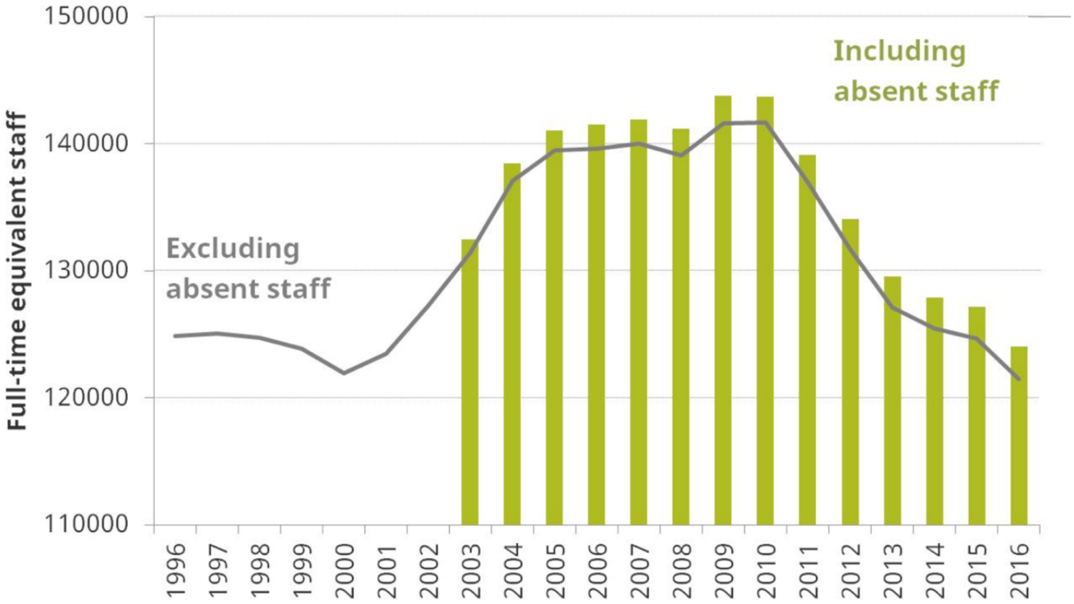

Figure 1.2. Numbers of police officers in England and Wales (full-time equivalent), 1996-2016. Source: Home Office, Police workforce England and Wales statistics, March 2016, Tables H3 and S1. The grey line is the workforce excluding absent staff and the green bars are the workforce including absent staff.

1.2. Police organisational structure, workforce and duties

There are 48 police forces in the UK: 45 territorial police forces responsible for regional areas and three national special police forces (the British Transport Police, Civil Nuclear Constabulary, and Ministry of Defence Police). Among the 45 territorial police forces, 39 forces cover regional areas in England, four in Wales, and two in Scotland and Northern Ireland, respectively. Regarding the English and Welsh forces, most are divided into Basic Command Units or equivalent units (in the Metropolitan Police Service they are boroughs), which serve sub-districts within the force area. Basic Command Units are then typically subdivided into smaller policing teams that are responsible for different functions. Police forces are now accountable to elected Police and Crime Commissioners who are expected to "secure the maintenance of the police force for that area and secure that the police force is efficient and effective" (Police Reform and Social Responsibility Act, 2011, Chapter 1 (6)).

Broadly, police forces consist of three key roles: police officers, police staff, and police community support officers. The police officers and staff generally undertake tasks relating to policing and administration, respectively, whilst police community support officers work as part of a neighbourhood policing team to patrol communities and handle anti-social behaviour and minor offences within communities. Notably, some police forces have designated officers to deal with child-related crimes. Furthermore, most police forces employ a significant number of special constables, who generally work part-time.

Association of Chief Police Officers (1990, p.9) define the purpose of police work as "to uphold the law fairly and firmly; to prevent crime; to pursue and bring to justice those who break the law; and to keep the Queen's Peace; to protect, help and reassure the community; and to be seen to do all this with integrity, common sense and sound judgement". This statement has been widely used in a range of contexts, including in a book on policing reviews (Newburn, 2008) and in a 2008 report released by the Home Affairs Select Committee (Parliament, 2008).

As noted above, the three special police forces are responsible for their particular roles for the entire country, while territorial police forces are tasked with keeping local areas safe and ensuring residents feel safe. To do so, they engage in activities to prevent crime and maintain community order. Wright (2002, p.4) listed many tasks the police perform, including but not limited to patrolling, controlling traffic, coping with emergencies, and dealing with crimes (see Table 1.2).

As with other public sector bodies, police forces in England and Wales provide public services for residents that are funded by central and local government taxation. On this basis, taxpayers can hold the police forces to account by electing Police and Crime Commissioners, giving them a role in ensuring that police perform their duties effectively and utilise resources efficiently.

Table 1.2. Policing tasks listed by Wright (2002).

Tasks related to crime	Other tasks
Crime investigation Criminal intelligence Surveillance Crime prevention Supervising arrest, questioning and detention	Foot patrols, motor patrols and specialised traffic patrols Responding to incidents and emergencies Dealing with public disorder Local problem-solving Community policing Dealing with motoring offences and traffic accidents

Source: Reproduced from Wright (2002, p.4).

In the next section, performance management and the measurement of police effectiveness and efficiency are discussed.

1.3. Police effectiveness and efficiency

In the 1980s and 1990s, New Public Management (NPM) was widely used as a direct response to the perceived inefficiencies and bureaucratic structures of traditional public administration. To be precise, this approach seeks to apply private sector management techniques to the public sector in an effort to improve efficiency and effectiveness (Hood, 1995). NPM involves the following aspects: Decentralising decision-making authority; Emphasising the use of performance measures and targets to assess the effectiveness of public services and identify areas for improvement; Creating competition and choice in public services using mechanisms such as contracting out and privatisation; Making public services more responsive to the needs and preferences of customers; and Emphasising specific outcomes, rather than simply complying with rules and regulations (Ferli, 2005).

Performance management is a key NPM tool used to achieve efficiency and effectiveness. It involves setting targets and objectives, monitoring progress, evaluating outcomes, and taking action to improve performance (Van Dooren et al., 2015). When implementing NPM, performance management involves measuring actual performance against targets with a view to improving accountability and transparency, whilst also promoting competition and innovation among public service providers. Focusing on hitting targets could also lead to numeric problems. Effort distortion could lead to unethical behaviour, gaming or manipulating performance metrics, neglecting important but less visible aspects of work, and unhealthy competition between individuals or departments, all of which could harm overall performance and service delivery (Bevan & Hood, 2006; Guilfoyle, 2012).

Section 2.1 will introduce the performance management system (PMS), which typically uses performance indicators to assess progress towards predetermined goals and objectives. However, PMS also encounters some difficulties in application, as the measurement is largely affected by the accuracy of data use and the prioritised orientation performance selection (i.e. which performance indicators are prioritised) (Keong Choong, 2013)

Regarding policing performance management, Murphy (1985) defines police effectiveness as achieving outcomes regardless of expenditure, whilst police efficiency is achieving given outcomes within a set budget. In the mid-1990s, HMIC (1995) articulated Value for Money as an assessment technique for police efficiency, evaluating the value of police work through the lens of expenditure. In doing so, the police were treated as a private entity that could be assessed by objectives to prevent crime and maintain the order of communities with business techniques. Later in 1998, HM Inspectorate of Constabulary reemphasised the importance of promoting efficiency and ensuring value for money in policing (HMIC, 1998). Later, in a subsequent report, the Home Office (1999, p.5) highlighted the “growing need for the police to make resource allocation decisions transparent, to evaluate outputs and outcomes, and to demonstrate that resources are being used to generate the best returns”. This report introduced the concept of economic evaluation, which assesses the costs of inputs and values of outputs/outcomes. Specifically, it adopted police proactivity as an example to establish the feasibility of economic evaluation methods among approaches such as performance indicators, cost-effectiveness, and cost-benefit analysis.

Although value for money is integral when public sector funding is limited, blindly focusing on value for money may lead to the neglect of important, albeit expensive local policing services. For example, it is often more resource-intensive assisting children and the disabled than assisting healthy adults.

HMIC publishes its *Police Effectiveness, Efficiency, Legitimacy (PEEL) Assessments* annually, which assess police forces in England and Wales in terms of their effectiveness, efficiency, and legitimacy. For each aspect, all police forces are classified as one of four levels: inadequate, requires improvements, good and outstanding. In PEEL 2016, for example, four core measures were included to assess police effectiveness: performance in preventing crimes, investigating, protecting and tackling serious crimes; while for judging police efficiency there were three measures: understanding demand, using resources, planning for future demand (see Table 1.5 (adapted from PEEL 2016)).

It can be seen that in HMIC’s definition, police efficiency is no longer solely determined by reference to value for money; instead, it takes a more searching view of how effectiveness is achieved. Its measures of effectiveness not only include the targets of preventive policing and proactive policing, but also reflect the protection of the vulnerable and the consideration of serious and organised crime, which are also policing priorities. It should be emphasised here that there is still ignorance of some important aspects of policing, such as community engagement and trust building.

Table 1.5. PEEL judgements for police forces. (Ignores the legitimacy aspect.)

(1) Measures to evaluate the effectiveness
How effective is the force at preventing crime, tackling anti-social behaviour and keeping people safe?
How effective is the force at investigating crime and reducing re-offending?
How effective is the force at protecting those who are vulnerable from harm, and supporting victims?
How effective is the force at tackling serious and organised crime?
(2) Measures to evaluate the efficiency
How well does the force understand the current and likely future demand?
How well does the force use its resources to manage current demand?
How well is the force planning for demand in the future?

Source: Her Majesty's Inspectorate of Constabulary.(2016).State of policing: An annual assessment of policing in England and Wales.

HMIC employs a range of comprehensive indicators to measure police performance. However, the process of ranking simply aggregates outcomes whilst drawing on little evidence from systematic supporting data. Besides these qualitative and descriptive quantitative methods to evaluate police performance, sophisticated methods developed to measure organisational efficiency in both the public and private sectors, such as in education (Bessent & Bessent, 1980), banking (Ferrier & Lovell, 1990), and health care service (Zuckerman et al., 1994). Quantitative methods were widely applied to assess police performance by Thanassoulis (1995), specifically in relation to police efficiency in England and Wales. These will be discussed in detail in chapter 2.

As the present study aims to investigate the impact of austerity and limited policing budget, the present research adopts Murphy's (1985) definition of **police effectiveness** as the degree to which the police undertake their duties and achieve goals in policing; and **police efficiency** as the ability that the police demonstrate to undertake their duties and achieve goals in policing with the minimum amount of resources. All further analysis will proceed under this framework of police performance management.

1.4. Reduction of public spending in policing

This section discusses the background of the UK government's austerity programme, reviews how the police forces planned to work around the budget cuts, and comments on how austerity influenced policing in England and Wales.

(1) The austerity programme

In the wake of the 2008 financial crisis, the worldwide recession and economic shock continued to rock the UK economy. In October 2010, the Coalition Government announced that the public spending budget would reduce from 2011/12 to 2014/15 to tackle the UK's most challenging fiscal problem environment in its peacetime history (HM Treasury, 2010a). The national deficit had become a most significant barrier (11% of GDP in 2010) (HM Treasury, 2010b) to economic growth, with the government spending as much on education as it did servicing its debt (£43bn). To reduce the budget deficit, the government paid attention to economising the welfare state and cutting wasteful spending, whilst schools, health and long-term related investments remained priorities in spending. As part of the saving plans, every department, excluding health and overseas aid, was expected to cut 19% from its budget on average during the four years of that parliament.

In such a situation, the police budget would be progressively cut over this period, in line with other public services. Ferry and Eckersley (2011) analysed the saving plans and predicted that delivering expected savings in policing would be more difficult because it is illegal to fire a police officer. Although there are several ways to maintain both sustainable services and effective organisational size, it was inevitable that frontline services would be affected by the reductions.

Given the difficulties with making officers redundant, forces had to look at other ways to make savings, such as cutting back their activities and slowing recruitment. The problem with the latter option is that this creates a future situation in which there would be a shortage of capable replacements. Some forces considered using the Police Pension Scheme A19, which sets out a rule that those who have worked for more than 30 years can be compulsorily retired to maintain the efficiency of the organisation.

It should be noted that reducing the amount forces spend on wages would also lead to a decrease in their pensions, which is an income term of a police force, paid by taxpayers. So, any potential savings from reducing salaries would be offset by a reduction in pensions, making it difficult to achieve a significant impact on the overall budget. Increasing the number of special constables—part-time volunteer police officers—is another approach for police forces to reduce labour costs. The austerity plans for the police forces will be discussed in more detail.

Figure 1.3 provides an example of the income of the Police & Crime Commissioner for Avon & Somerset in 2016/17. It shows that the main income of a police force is provided by a central government grant (see Police-revenue grant and Ex-DCLG[2] formula funding), whilst supplementary income comes from council tax (see Council tax freeze grant, Local council tax support grant, and Council tax-local authorities). In addition to contributions from the state, police forces also raise some of their income by charging for special police services.

Police - revenue grant			-105,022
Ex-DCLG formula funding			-56,491
Capital grant and contributions			-1,939
Council tax freeze grant			-3,331
Local council tax support grant			-11,378
Police pension top-up grant (note 19)	50,340	-50,340	0
Council tax - local authorities (note 10)			-97,362
Taxation and non-specific grant income			**-275,523**

Figure 1.3. Income of Police & Crime Commissioner for Avon & Somerset in 2015/16, £000. Source: Group Comprehensive Income and Expenditure Statement for the year ending 31 March 2017 in the Statement of Accounts, 2016/17. In this statement, negative numbers indicate a positive income.

According to National Audit Office (NAO, 2015), from 2010/11 to 2015/16, the central government grant to police and crime commissioners and council tax grants decreased by £2.2 billion in real terms. This represents a 22% real terms reduction, which was in line with the Coalition Government announcement, presented by Spending Review 2010 (HM Treasury, 2010a), that there would be a £1.9 billion (20% in total) reduction

[2] Ex-DCLG: "DCLG" stands for the Department for Communities and Local Government, which was a UK government department responsible for supporting local government, housing, and community issues. It was replaced by the Ministry of Housing, Communities and Local Government (MHCLG) in 2018. "Ex-DCLG" in the Group Comprehensive Income and Expenditure Statement refers to the income and expenditure that is no longer associated with this department because it has been restructured or merged with other departments.

central funding provided to the police services in the four years between 2011/12 and 2014/2015.

Given the challenges of budget cuts, police forces were expected to raise their income from local council tax bills. To cover their normal policing costs, they were able to raise real-term funding from local taxation, though the amount of funding raised in this manner widely varies between individual forces. As a result, the whole incomes of different police forces faced different levels of reduction (12-23%) in the four years. Figure 1.4 shows the real-term reduction in police funding of forces in England. Reductions varied between forces as they relied on Central Government Funding at different levels. Northumbria, Merseyside, Greater Manchester, and West Midlands were the most impacted forces, with real-term reductions in funding in excess of 20%.

This research then examines how these police forces budgeted and operated during the austerity period.

(1) Plans at the beginning of the austerity period

Her Majesty's Inspectorate of Constabulary (HMIC) published a series of reports to assess how police forces met the challenge of austerity and show how they performed in terms of value for money. Each police force was expected to design and implement a comprehensive saving plan. HMIC (2011a) published a report containing its inspection of the preparedness of police forces and authorities in England and Wales to perform even better within a limited budget over the next four years. The report noted that police forces had several approaches to tackling the financial problem, primarily by means of reducing human resource costs.

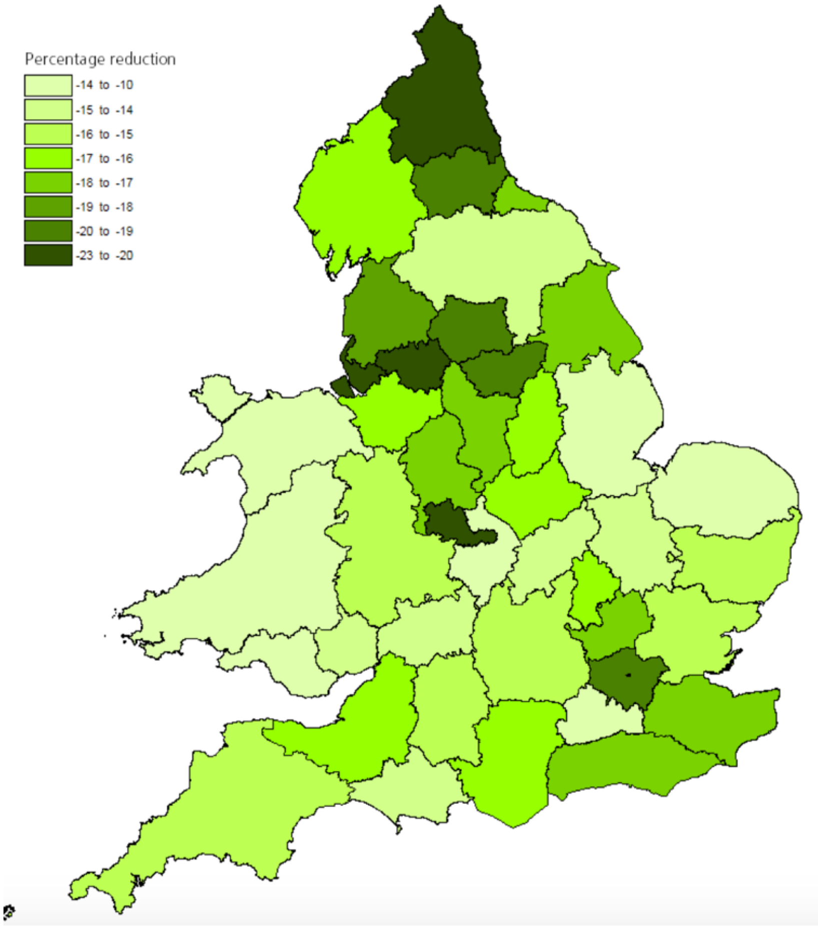

Figure 1.4. Real-term reduction in police funding – central government grants and council tax precepts, 2010/11 to 2015/16. Source: House of Commons Library 100040654(2015).

In order to save human resource costs, it was estimated that the total police workforce would shrink by 34,000 (14%) by the year ending March 2015. It should be noted that one-third of these staff were already cut in 2010/11, with the remaining 23000 to be cut between 2011 and 2015. Human resource costs accounted for a large part of police expenditure in the preceding years, so it was inevitable that a workforce reduction would save significant money for forces, clawing back £1.6 billion in savings. As some forces had already reduced non-frontline numbers before 2011 as required, some forces faced massive staff cuts whilst others did not.

Front-line officers are defined as “those who are in everyday contact with the public and who directly intervene to keep people safe and enforce the law” in *Demanding Times* (HMIC, 2011b, p.18). Due to the workforce reduction plan and the differences in the respective responsibilities of frontline and non-frontline staff, front-line staff numbers were affected to differing degrees: front-line numbers fell 2% compared to an 11% reduction in non-frontline staff in the year ending March 2012. All forces showed a greater preparedness to protect front-line positions in their plans (e.g., ring-fencing more of the budget for front-line officers) and activities (e.g., electing to reduce more non-frontline than frontline roles) than non-frontline positions.

As noted above, police forces can only reduce the number of police officers they employ by curtailing or halting recruitment, or using the Police Pension Scheme A19, under which those with over 30 years of service could be compulsorily retired. Meanwhile, most forces planned to enlarge their special constable team, which consists of part-time voluntary police officers. According to HMIC (2011a), from 2010 to 2011, the number of special constables rose by 25%; by 2015, there were 22600 special constables nationally, compared to 19300 in 2011.

The Special Constabulary consists of part-time and volunteer special constables who undertake similar frontline policing duties as their paid, uniformed counterparts Dickson (2020) stressed the significance of understanding the motives of volunteer police in his study on the role, identity, and experiences of special constables. The experiences of special constables are influenced by their desires, motivations, and the characteristics of the policing environment. Dickson also argued for the need to establish a more robust framework to enhance the volunteering experience and reap greater rewards from a more energised group of volunteers who regard their work as a genuine and meaningful contribution to the police force.

The fact that the police are not quite equipped to put together a police force with such a huge number of volunteers in a period of austerity may pose a challenge. Britton (2022) conducted research on the experiences of volunteer Special Constables and the difficulties they encounter at the beginning of their careers, including issues with integration, cultural fit, and process and organisational issues. The author recommended enhancing the assistance given to new volunteer recruits, prioritising their well-being, and creating an environment that allows them to form a positive and robust professional identity as police officers. This helps volunteers to integrate well into the team, develop relationships, and feel valued.

This subsection examines the saving plans for non-staff costs.

As described above, the government mandated a £1.9 billion funding reduction, £1.6 billion of which could be saved by cutting the workforce. As a result, there was still a shortfall of £0.3 billion. Based on data from the Chartered Institute of Public Finance and Accountancy (CIPFA) 2010-11 national total expenditure spend estimates (HMIC, 2011a), on average, across all 43 forces, 89% of total policing expenditure went on staff payments, with the remaining 11% going towards transport, supply and service, premises, capital financial costs and others.

Expenditure on costs excluding staff payments is defined as non-pay costs. After cutting staff numbers, £0.3 billion in cuts needed to found in non-pay costs during the four years. In the 2010/11 term, non-pay costs were estimated to be £2.6 billion; hence, a gradual reduction totalling 11.5% was expected during the 4-year austerity period. However, only 21 forces had concrete plans to cut non-pay costs in 2011/12, saving a total of just under £0.1 billion. It should not be understated that cutting non-pay costs was a challenge for all forces.

The corollary of austerity and cost-cutting is the potential impact on police performance. Against this backdrop, the forces planned to reduce crime rates and anti-social behaviours (ASB). All forces set up targets to reduce overall crime or particular types of crime, with 17 forces proposing explicit numerical targets. For ASB, 34 forces expressed their ambitions to reduce ASB, whilst 12 set out quantifiable targets. Bradford (2011) studied the relationship between police officer numbers and crime rates, finding a direct causal link between police numbers and crime levels, especially in relation to property crimes. To improve police efficiency while cutting costs, the police forces and authorities planned to realise policing improvements in three key areas: workforce efficiency, process efficiency, and scale efficiency. Table 1.3 summarises these methods.

Table 1.3. Methods to improve police efficiency while cutting budgets.

	Methods	How many of the 43 forces planned to do
Workforce efficiency	Optimising mix of police officers and staff Matching resources to priorities	Most planned All planned
Process efficiency	Reducing bureaucracy Changing operational processes	All required Half planned
Scale efficiency	Reducing basic command units Collaborating with other forces Unifying information system Outsourcing procurement	Most planned Nearly all planned Most done, other planned Half planned

Source: Her Majesty' s Inspectorate of Constabulary. (2011)a. Adapting to austerity: A review of police force and authority preparedness for the 2011/12–14/15 CSR period.

(2) Practice in the first year

One year later, in 2012, HMIC (2012a) published a report assessing how the 43 forces met their financial challenges while providing police services of good quality to the public, and whether they achieved the goals initially set for them. The inspection results showed that most forces succeeded in balancing their income and expenditure by controlling workforce costs, thereby allowing them to protect front-line roles and maximise the range of services they delivered to the public. However, there were still concerns about how long this would last.

As mentioned above, in the 2010/11 term, a funding reduction of £1.9 billion was required before the year ending March 2015. However, this amount was increased to £2.1 billion in the 2011/12 term due to the rising costs of salaries, commodities and inflation more generally. Later, in the 2012 statistical estimates, the amount required to cut was increased again to £2.4 billion. Forces were expected to update their saving plans in accordance with price inflation and had to make new reports based on the previous year's spending. What's worse, Spending Review 2010 stipulated that those forces that received grants from local council tax were unable to apply to increase their grant in year 2 (2011/12), though they could in year 3 (2012/13). This change further frustrated attempts to achieve financial balance for those forces more reliant on local funding, as opposed to funding from the national government.

In the first year, all forces succeeded in balancing their books by implementing their saving plans. These plans may have used dissimilar methods, but they all worked towards the same aim. However, increasingly few forces had the capacity to plan and maintain their performance in the second, third, and fourth years. Whilst four forces reported they had met their saving targets in 2014/15, 12 forces did not.

According to HMIC (2012a) all forces hold a large amount of cash for several purposes, one of which is for future pension payments. Crucially, this cash is ring-fenced and cannot be used for other purposes. During this period, six forces planned to use reserves to balance around 33% of their savings in the fourth year, which is a significantly high level of reliance on reserves. It should be noticed that if police forces were to spend out of their reserves to balance their books, this would open them up to more potential risks when unforeseen events occur, including rising inflation.

Some forces more heavily relied on workforce reduction as a means to cut costs than others, with the proportions of officer reductions in forces varying despite facing a similar level of budget cuts. There are several reasons for these differences: salary costs and redundancy costs are different between the police officer and police staff; forces made different choices in terms of non-pay cost savings; some forces adopted the prudent policy of pushing for a radical workforce reduction. Not all forces planned to recruit new members: for example, in 2011/12, 27 forces planned to recruit 2160 police officers and 1570 police staff in total. Later, in 2014/15, 30 forces collectively recruited only 1810 officers and 840 staff.

It can be seen by reviewing the front-line workforce that in the 2010/11 term, most forces only had front-line reduction plans (reduce front-line staff by 2%) for 2011/12. In 2011/12, 41 forces started to set out their plans to reduce front-line staff over the full four-year period: on average, the front-line workforce decreased by 6% on average, with the non-frontline workforce decreasing by 33%. As a result, compared to non-frontline positions, the proportion of front-line positions in the total workforce increased in 2014/15.

Further chapters of this research will examine whether changes in the proportion of frontline positions have had a positive effect on police performance.

A new local policing model called neighbourhood policing was rolled out across England and Wales in 2011/12. Essentially, this entailed widening the responsibilities of neighbourhood teams. Notably, 2000 staff members were reallocated to this role, which runs counter to the reduction trend. This required forces to better allocate resources and estimate local demand. Foot patrols, in which police community support officers (PCSOs) physically walk through the neighbourhood, are the foundation of neighbourhood policing. This serves to provide a sense of security to the public and enhance the relationship between the police and the local community. However, it is not very effective in preventing crime if used alone (Longstaff, 2015). Key policing styles in the neighbourhood policing model include intensive enforcement, hotspots policing, predictive policing, problem-oriented policing and collective efficacy. It encompasses preventive policing and proactive policing, as well as a focus on fostering relationships with the community. An increase in resources being allocated to neighbourhood policing this year indicates that the police forces believed community engagement and neighbourhood policing could facilitate outcomes under budget constraints. However, the growing neighbourhood policing workforce did not last the entirety of the austerity period. Instead, during the last two years of austerity, community workers' hours were also reduced to accommodate budget cuts.

Another change in the first year was that most forces shifted resources from visible frontline positions (such as uniformed patrols) to unseen frontline positions (like investigation and managing criminals). This reflects a trend among police forces to arrange more reactive tasks rather than preventive tasks, something that will be discussed in the following subsections.

Additionally, the forces sought out areas for collaboration to achieve scale efficiency (see HMIC, 2012b), both with each other and also with public and private sector bodies. On a national level, it was estimated £169 million could be saved by planned collaboration projects, though 62% of such projects were still in the planning stage, with just 38% already in effect as of 2011/12. Models of collaboration among forces consisted of experience sharing, front-line service sharing, and operational mutual aid. Meanwhile, collaboration models between forces and public sector bodies, such as local government, NHS, and universities, mostly benefited from sharing facilities to reduce fees and increase public accessibility. For example, police stations could be located in the same building as a local council office, thereby allowing the public to access both services in one location. Such changes can also help to build better relationships and foster collaboration between different areas of the public sector. Moreover, collaboration models involving both police forces and the private sector often occurred when data sharing was required, or when functions could be outsourced, such as information technology, financing, custody, and intelligence.

Overall, in response to budget constraints, police forces have used reserves to balance their books, changed workforce allocation for frontline posts and sought collaborations in the first year.

(3) Practice in the second year

In the second year, any model of collaboration, workforce restructuring, and reconfiguration of resources became the centre of a progressive space to maintain performance on a limited budget.

In 2012/13, HMIC (2013) tracked how the 43 forces responded to financial problems and anticipated future risks. The key findings indicated that, overall, they worked hard to make savings and meet the goals they set, though some forces were marked out for not positively engaging in neighbourhood policing and collaboration. The main reason for this was they were unable to find opportunities for collaboration.

Workforce savings proceeded at a normal pace as planned. Forces completed 95% of their workforce reductions before 2014, successfully realising significant workforce reductions. The methods used to reduce workforce numbers were similar to those used in 2011/12: halting recruitment and leaving vacancies open and making police staff redundant, and applying Regulation A19. In contrast with the previous year's plan, fewer police staff were made redundant, though more expensive senior roles were cut instead. From 2010/11 to 2012/13, the police workforce was reduced by 30600. As a response to the sharp decrease in human resources, the police forces and authorities were required to reshape and reconfigure the workforce, pushing police officers to take on more responsibilities and learn new skills.

Reshaping the workforce involved managing responses to demand, increasing cooperation with partners, and reducing internal demand. For example, Cheshire Constabulary trained one-third of their staff to be multi-skilled operatives, capable of handling both call services and crime detail recording. Reconfiguring resources involved allocating more resources to policing priorities in an effort to deliver better services to the public. It is interesting to note that policing associated with advanced technologies (e.g., crime and intelligence systems, vehicle tracking and hot spot prediction) were mentioned in the plans though rarely translated into action. In the process of reshaping the workforce, concerns were raised that some forces were widening the remit of neighbourhood teams, as their traditional responsibilities, chief amongst them preventing crime, would be negatively impacted by new tasks, such as answering demands and carrying out investigations.

Compared to the pay savings, non-pay savings were expanded in this year. Some forces renegotiated with their suppliers to secure better prices, whilst others clubbed together for collective procurement from the same suppliers for standardized purchasing at reduced costs. Most forces implemented more rigorous controls on approved purchasing, especially in relation to self-used goods. Besides, most forces considered reconfiguring their estates to release reserves to balance their books.

Most forces grasped available opportunities to collaborate with peer forces, the public, and the private sector, though not all forces looked upon collaboration positively. Situations varied, with 18 forces achieving more than 10% of their total savings through collaboration. Among those forces, West Mercia realised 94% of its savings through collaboration, whilst Warwickshire achieved 75%. Conversely, 8 forces attained only no more than 2% of their total savings through collaboration. Around this time, HMIC (2013) pointed out the significant potential for future collaboration.

(4) Practice in the following years

For the year 2013/14, HMIC (2014) inspected the scale of the financial problems forces faced and how police forces and authorities addressed such problems to maintain their performance. The total saving gap in this term grew to £2.53 billion due to inflation, creating further financial pressure. Forces planned to complete 96% of expected savings during the austerity period, with similar workforce reduction methods used as in the previous experiences, though new changes were also implemented. Besides increasing the number of voluntary constables, the number of police community support officers (PCSOs) was reduced more than planned, which raised concerns that neighbourhood policing would be eroded through workforce restructuring. For instance, most forces arranged neighbourhood teams to carry out reactive tasks and prioritise them over preventive work.

O'Neill(2014a) conducted a study on the benefits and challenges of PCSOs in neighbourhood policing. The study found that PCSOs can perform well in their role provided they are treated equally and well-integrated into the team. Social capital, or the personal relationships and knowledge that PCSOs develop within their beat is essential to their effectiveness in the position. Compared to police officers, PCSOs typically spend more time in the community, allowing them to build personal connections and learn about the community's history of crime and anti-social behaviour. However, the organisation often values PCSOs more for their intelligence gathering on suspected criminals rather than their community engagement work, leading to a conflict in their role. According to the study, institutional mechanisms should be created to recognise outstanding efforts in community interaction as opposed to just intelligence gathering.

Hail et al. (2018) pointed out that appropriate visible policing tactics (e.g., foot patrols instead of motor patrols) and positive interactions between the public and police are important in building public confidence in the police. This demonstrates how PCSOs in neighbourhood policing teams uphold their values because they excel at both community outreach and patrolling. Therefore, if police forces arranged neighbourhood teams to carry out more reactive tasks rather than preventive tasks, PCSOs would lose their advantages in community engagement, which could damage public confidence.

With regard to collaboration, 22 forces achieved more than 10% of their total savings through collaboration in 2013/14, up from 18 forces in 2012/13. The collaboration here involved a wider range of partners, such as the Police Innovation Fund and the fire service. Another improvement was that regional collaboration was implemented to deal with serious and organised crime. Despite its success, it could have been more systematically managed at the regional and national levels, suggested by HMIC (2014).

(5) Further debates and strategies

In March 2015, there was an open national debate attended by representatives from police forces, criminal justice partners, local government, and other related organisations, to discuss questions about how the police should be organised and resourced in the future. Following the debate, the National Debate Advisory Group (2015) published a discussion paper based on the topics raised by the participants. The key idea was to ensure that police services meet the demands of the public whilst working within their budget using methods such as early prevention, victim support, frontline service maintenance, achieving value for money, and cooperation. It proposed a new possible framework for policing in which (1) frontline services and neighbourhood policing are of the most importance; (2) technical and special capabilities are shared and managed by a cross-force level or national level; and (3) collaboration opportunities with other partners like local forces or private sectors are seized to optimise economies of scale.

Though it approved of the Advisory Group's vision of future policing, the Police Foundation (2015) responded with two concerns: (1) The vision needed to be more explicit in how the project would be assessed to determine whether it had met the financial challenges; (2) Emphasising the neighbourhood policing (small size) and cross-force policing (large size) would place the police forces (middle size) in a difficult position. The Police Foundation answered the latter concern by referring to function as "connectivity" between neighbourhood policing units and cross-force services. However, this would then create new accountability issues at the force level.

After the austerity period, police funding gradually increased from 2015/16 to 2018/19. The Home Office (2018) published data on police funding, revealing an increase in total funding, though there was a continual, albeit slight, decrease in central government grants. Compared to the £7400 million central government grant in 2014/15, the grant fell to £7101 million in 2015/16. However, due to the growth of other resource funding, the total national budget for 2015/16 was more than the preceding year. Figure 1.5 illustrates the trend in funding changes.

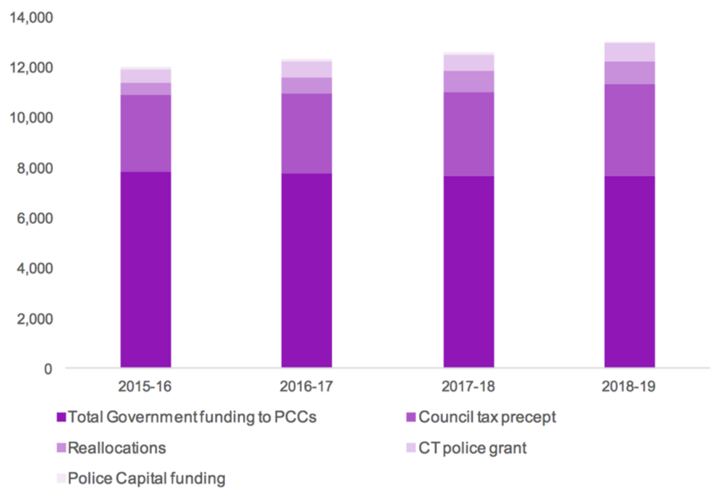

Figure 1.5. Police funding 2015/16 to 2018/19 (£m). Source: Home Office (2018). Police Funding for England & Wales 2015-2019. Statistical Bulletin 13/18.

The National Audit Office (NAO, 2018) reported on the financial sustainability of police forces in England and Wales for 2018, pointing out the problems forces were grappling with and proposing suggestions to achieve financial sustainability. Earlier, in 2015, NAO (2015) reported that police forces in the UK lacked a universal system for measuring forms of demand. Though there were some individual quantified measures in use, such as crime rates and response resources, no concrete measures for complex crime or non-crime incidents were available. This problem led to difficulties in clearly articulating demands and making progress. However, in 2018 (NAO, 2018), the same problem remained.

The government will support policing services as stated in Policing Vision 2025 (NPCC, 2016) through three main programmes:

a) The Police Transformation Fund (PTF): providing financial support to incentivise police forces in transforming services into future priorities, although approving bids has been delayed due to several issues with the process;

b) Law Enforcement Programme: including a wide range of support from advanced technologies, such as ICT, biometrics, and data services; and

c) Encouraging forces to consider opportunities for collaboration between forces and with parts of the public or private sectors to improve policing effectiveness.

The Police Foundation (2022) subsequently published a report to analyse three aspects of future police challenges (capacity, capability and organisational challenge) and proposed several recommendations for better police service delivery. It was noted that the existing funding system, in particular, has issues with reflecting little of the needs of individual forces, making it difficult for police forces to make their long-term budget plans based on their varying demands and circumstances. As a result, it proposed suggestions that the funding formula should consider both individual and national priorities as well as a grant for cross-regional crime prevention.

The austerity period has been widely analysed from different perspectives both by the governmental advisory board and also academic researchers. To address the financial problems forces face, Newlove (2011) proposed a potential policing framework named “big society” to encourage communities to take part in preventing and dealing with crimes, instead of acting as witnesses to wait for the authorities, especially in relation to anti-social behaviours. Two main types of methods encompassing 12 recommendations were proposed: financial rewards and offering resources. Newlove suggested the government rewards those who help to prevent, report and investigate crimes and advised the police to offer online resources, such as crime maps, to assist members of the community to avoid crimes. This series of proposals reallocated responsibilities between the police and communities in the hopes of easing the police’s work, and by extension alleviating financial pressure. Several police forces indicated their approval of these recommendations. For example, in line with the “big society”, the Ministry of Justice emphasized the right of householders to tackle burglars

(Townsend, 2010). Moreover, the Metropolitan Police Commissioner encouraged the public to be more interventionist in their approach to crime (McClatchey, 2010).

However, Considine (2011a) pointed out two shortcomings in Newlove's "big society". Firstly, the idea of financial rewards was controversial: given the significant degree of social inequality in different communities, those who were keen to protect themselves from crimes might not be able to do so in without adequate funding. What's worse, financial rewards are poor incentives for those who are already financially comfortable. As a result, such a system of rewards would increase inequality. Secondly, the proposals transferred compulsory police responsibilities to communities, which could lead to the blaming of witnesses. Moreover, the proposal is unrealistic as many people would not want to be involved. Considine (2011b) critically discussed whether it would be appropriate to redefine the police's responsibilities to promote the public to act as the police. The conclusion was that any such steps would need to be taken cautiously.

The notion of a "Culture of Control" has been used to identify and explain the rising expectations of the public's role in crime prevention (Garland, 2001; 2004). The term "responsibilisation" refers to the process by which individuals and communities are increasingly expected to take responsibility for preventing crime and maintaining social order. This shift in responsibility is seen as a result of the decline in the effectiveness and legitimacy of traditional criminal justice institutions, such as the police and the courts, as well as the rise of neoliberalism and the marketization of public services. In a culture of control, people are urged to be more vigilant, report suspicious activity, and take steps to protect themselves and their property. To prevent crime, communities are also expected to organize themselves and cooperate with the police. This strategy aims to establish a sense of shared accountability for upholding public safety by putting more emphasis on prevention than punishment. However, some critics (Wacquant, 2009; Vaughan, 2005; Simon, 2007) have argued that responsibilisation can lead to victim-blaming and inequality because those who can better defend themselves are given preference over those who are less able to do so.

Several researchers have focused on the impact of austerity on the police workforce. During the austerity period, the financial tightening motivated police forces to make PCSOs redundant as they were not warranted officers. From 2011 to 2013, 12.5% of all PCSOs were made redundant (Dahni, 2013). In their qualitative research based on observations and interviews with the staff of two police forces, O'Neill (2014) found that PCSOs play a vital role in neighbourhood policing by providing a close point of contact and personal services to the public. These findings contradict the popular view amongst police forces that PCSOs are marginal members of the police force. O'Neill's research appealed for retaining PCSO positions and furnishing them with adequate support.

Sindall and Sturgis (2013) studied the relationship between frontline officers, absolute officers, and public confidence in policing. Notably, they observed a significant direct positive relationship between the number of frontline officers and public confidence, and an indirect positive relationship between the absolute number of officers and public confidence. It can be implied from this that although police forces made an effort to maintain police visibility during the austerity period, public confidence may have decreased if the number of absolute officers fell.

Boag-Munroe et al. (2017) investigated the relationship between officers' perceived promotion prospects and their intention to leave the force, following the HMIC's (2014) description of "extremely limited promotion prospects" in the police force during the austerity period. The conclusion was that those who were less likely to be promoted were more likely to leave, as revealed by two measures of social exchange and psychological well-being. This study implied that police organisations should improve the promotion process and consider psychological factors when implementing workforce reforms.

These studies serve to highlight how the police services deal with a lack of resources during times of austerity and how police services can be improved from different aspects. The next section will introduce crime trends in recent years.

1.5. Crime trends

This section starts with general crime trends in recent years and then presents data in England and Wales.

According to police-recorded crime data and victim-based surveys, crime has significantly and consistently decreased in North America, Canada, Australia, and several European countries since the early to mid-1990s (Zimring 2007; van Dijk & Tseloni 2012; Farrell et al. 2013). The literature on the changes in nationwide crime levels shows that property crimes, such as vehicle theft and burglary, have seen the biggest and most sustained decline, according to Rosenfield and Messner (2009) and Farrell et al. (2011). While there has been a large decrease in violent crime, including homicide and assault, the decreases have been less consistent (Blumstein & Wallman (2006); Tseloni et al. 2010).

Some scholars have called the decline in crime across different countries a "near-universal drop" as there is enough similarity in the extent and timing of this decline. Nevertheless, several academics have cast doubt on this assumption due to notable variations among countries, particularly regarding the time frame of crime reduction as well as the nature and consistency of changes in property and violent crimes. Aebi and Linde (2010) examined the decline in crime in Western Europe and concluded that in the United States, there has been no general drop in all types of crimes as violent and drug-related offenses have risen. Property offenses may have decreased as a result of socioeconomic changes in Europe, as well as the increasing adoption of security measures by households and private security reinforcement. The increase in violent offenses can be attributed to several factors, including changes in youth's leisure activities due to the growth of the Internet, shifting demographics, and the emergence of heavy drinking and street gangs on occasion.

The difference in crime types at a macro level is significant because it raises the question of whether crime reduction has been equally distributed among the population. This is due to the widespread perception that different groups of people face varying sorts of crime. McVie (2020) studied the inequality in crime due to the crime drop and found that there has been a rise in the disparity between individuals who are at a high risk and low risk of being victimised by crime, particularly violent crime.

This section then charts how crime rates changed in England and Wales from 2007/08 to 2016/17 from the perspectives of crime volume and crime category of crime. Referring to police-recorded data, the number of offences exhibited a declining trend prior to 2015, after which point the crime numbers started to increase (see Figure 1.6). In particular, vehicle offenses and burglaries have largely declined over the decades and have started to increase after 2015, while robbery declined slightly before 2015 and increased slightly since 2015 (Figure 1.7).

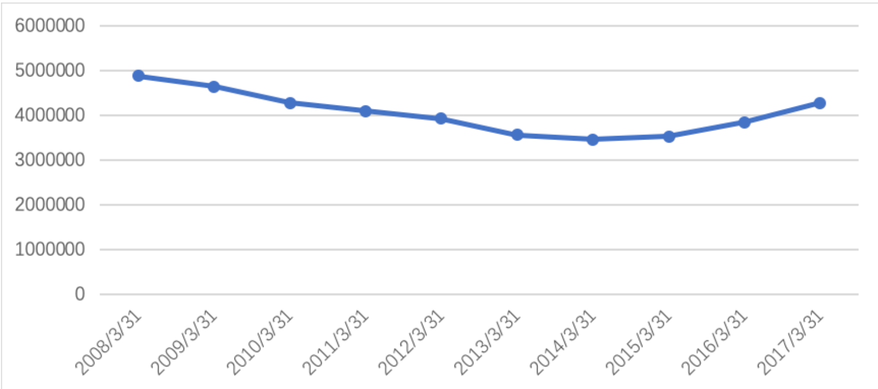

Figure 1.6. Number of offences recorded by the police in England and Wales in the years 2007/08 to 2016/17. Source: National Statistics bulletin Crime in England and Wales, year ending June 2018.

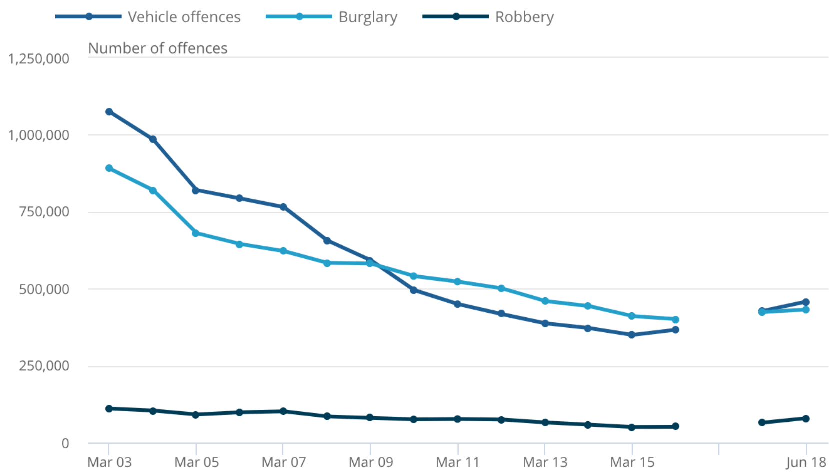

Figure 1.7. Number of vehicle offenses, burglary and robberies recorded by the police in England and Wales in the years 2003/04 to 2016/17. Source: National Statistics Bulletin Crime in England and Wales, year ending June 2018. Lines are discontinuous due to the missing data.

Crimes recorded by the police are categorised into several groups, including but not limited to bicycle theft, domestic burglary, and fraud offences. The full list of crime groups recorded by the police is set out in Table 1.4. Among these groups, four types of crime are considered crimes against society, whilst the remaining offences are classed as victim-based crimes.

Table 1.4. Full list of crime groups recorded by the police

victim-based crimes	Violence against the person	Homicide Violence with injury Violence without injury Stalking and harassment Death or serious injury - unlawful driving
	Sexual offences	
	Robbery	
	Theft offences	Burglary Residential burglary Residential burglary (households) Non-residential burglary Vehicle offences Theft from the person Bicycle theft Shoplifting All other theft offences
	Criminal damage and arson	
crimes against society	Drug offences Possession of weapons offences Public order offences Miscellaneous crimes against society	

Source: National Statistics bulletin Crime in England and Wales, year ending June 2018.

Anti-Social Behaviours (ASB) have been a pressing concern for both the police and the public in recent years. The ASB trend for the study period is shown in Figure 1.8. The sharp decline shows that the concerned ASB were successfully controlled over the decade sampled. Another group of crimes drew the police's attention: online and financial-related fraud. Action Fraud, a service dealing with online and financial crimes, found that financial fraud exhibited an accelerated increasing trend from 2010/11 onwards (see Figure 1.9).

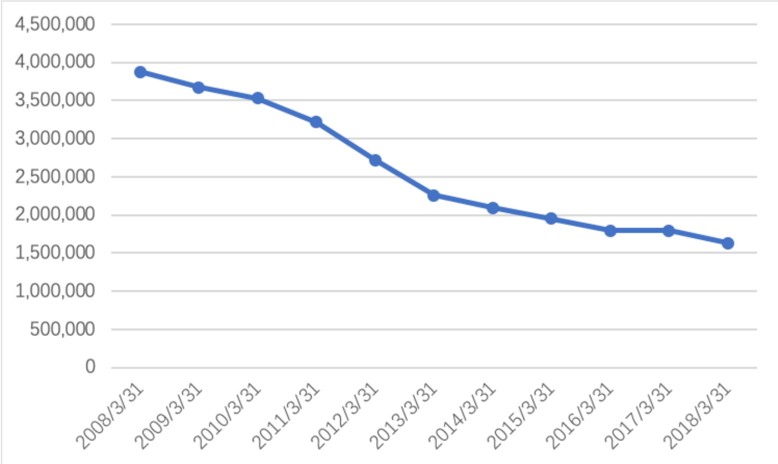

Figure.1.8. Anti-Social Behaviours recorded by the police in England and Wales, from 2007/08 to 2017/18. Source: National Statistics bulletin Crime in England and Wales, year ending June 2018.

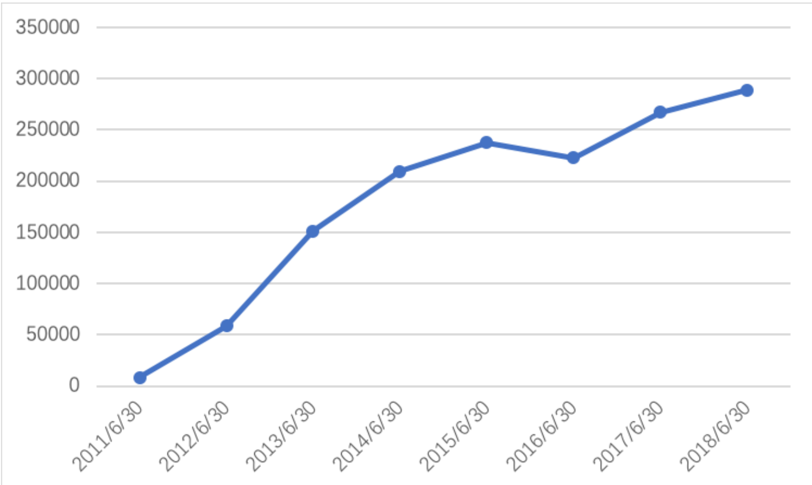

Figure. 1.9. Online and financial related fraud recorded by the Action Fraud in England and Wales, from 2010/11 to 2017/18. Source: National Statistics bulletin Crime in England and Wales, year ending June 2018.

1.6. Statistical evidence: police performance and crimes

Before moving on to discuss how to *measure* police performance in quantitative methods, it is first necessary to review what *impact* police performance has had on crime, as reported in previous quantitative studies. The majority of the existing research employed regression analysis and economic and econometric techniques to test policing and socio-demographical factors and determine their influence on the crime level, social reactions, and police performance.

(1) Crime levels, police workforce, and police workload

Two UK studies tested the relationship between crime level and police workforce (or equivalent police presence). Machin and Marie (2005) found that increased expenditure of police attendance on robberies led to a reduction in the number of reported robberies. Draca et al. (2008) analysed the relationship between police presence and "susceptible" crimes, including violence, sexual offences, theft and handling, and robbery. This research found a correlation between police presence and susceptible crimes: increased police presence significantly diminished the crime rate. These two UK studies were consistent with a landmark American study (Marvel & Moody, 1996), which investigated the relationship between the number of police officers and the levels of all types of crime, concluding that most crimes are significantly affected by the number of police officers.

Other studies conducted in America and Canada reported inconsistent conclusions when analysing police workload and crime levels. For instance, Klinger (1997) used American data to assess how police workforce size affected workload, and in turn how workload affected police responses to crime. It was concluded that a larger police workforce would reduce the workload effect, with the crime level then decreasing as a result. Levitt (2002) used an advanced regression method to test Klinger's findings, demonstrating that crime levels were significantly affected by both workforce and workload. Contrastingly, Pare et al. (2007) used Canadian data to test the relationship between police workload and crime clearance rate and failed to find a significant relationship.

(2) Recording and reporting crimes

The “Dark number” of crimes refers to crimes that are committed but not recorded in official statistics. It should also be noted that victims are less willing to contact the police when encountering certain types of crimes than others. For example, Belson (1975) showed that people were more willing to report a burglary (99%) as opposed to seeing a fight in a cafe (39%). Even if victims report crimes to the police, there is still a possibility that officers do not record delinquents. West and Farrington (1973) identified a large gap between official and self-reported delinquents. Levitt (1998) interpreted this phenomenon using a panel study: larger police forces had more officers to record and deal with crimes, which led to higher recorded crime rates at the force area level. Thus, the relationship between the police workforce and the recorded levels of crime is both complex and interdependent. In light of the potential unreliability of recorded crime data, another widely used source of crime statistics is the Crime Survey for England and Wales. Notably, this is a crime survey of victims that aims to reveal “actual” crime levels.

Meanwhile, the increase in recorded crime is linked not only to a rise in the number of persons who can record the data but also to an increase in the willingness to report crimes to the police, which means that more crimes come to the attention of the police. The public is more likely to report crimes when they have higher confidence in the police (Tarling & Morris, 2010). Therefore, this factor also has an impact on how many crimes the police can record. Trust in the police is discussed further in section 1.7 and chapter 6.

(3) Factors influencing the level of criminal activities

A number of socio-demographic factors influence criminal activities, which will disrupt assessments of police performance due to the dissimilar socio-demographic conditions in different areas. Carr-Hill et al. (1979) highlighted seven traditional factors: immigrants, females, neighbourhoods, unemployment, working class, youth, and family background. Moreover, the Demonstration Project (Home Office, 2001) put forward a series of measures (more than 250 potential variables) that could be considered when measuring police efficiency, one group of which were environmental factors.

Socio-demographic factors and economic changes that would affect a region's crime rates are outside the police's control. Besides this, other wider factors beyond policing play effective roles in influencing crime. For example, technological changes have shifted the prevalence of several types of crime, e.g., cybercrimes. Additionally, the rising problem of drug use and the mental health of the public is linked with patterns of violent crimes (Police Foundation, 2022).

(4) Police efficiency and crime rates

The worldwide quantitative research carried out by Domínguez et al. (2015) assessed police efficiency values at the country level. Specifically, a panel of data envelopment analysis models with data from 72 sample countries was used to analyse data from the 1998-2006 period. When environmental factors like population, education and economics were controlled, the police efficiency of countries maintained a positive relationship with crime rates. In this article, the authors implied that high police efficiency is determinative of low crime rates. Such a conclusion agrees with Buscaglia and Van Dijk (2003), whose research describes a negative relationship between the level of organised crimes and police performance using data from multiple countries.

The next section will introduce another perspective of police performance measurement: public trust.

1.7. Another evidence-based perspective: public trust

In addition to effectiveness and efficiency, this section provides another metric that examines how the public views the police. It examines research on the idea of public trust and how it relates to policing and the efficiency of the police.

(1) Confidence and trust

Public trust, or public confidence, is another measure that can be deployed to assess police performance. Police effectiveness and efficiency are both measures from the perspective of service delivery; by way of contrast, public trust can be considered as a measure from another perspective, namely, public perception.

Standard survey questions are widely used in research when investigating public attitudes toward the police. For example, in the British Crime Survey (the predecessor of the Crime Survey in England and Wales), the question “taking everything into account, how good a job do you think the police in this area are doing?” probes the issue of public perception (Home Office, 2010). Bradford and Jackson (2010) defined the answer to the single measured question above as “overall” confidence. However, this then leads to consideration of what the difference is between confidence and public trust. Following a widely accepted conception (Tyler & Huo, 2002; Sunshine & Tyler, 2003), a police force is trustworthy if the public perceives it as effective, fair, and engaged with the local community. In detail, the public trusts police effectiveness when police officers are seen to be effectively carrying out their duties. Meanwhile, trust in police fairness stems from when the public respect and perceive dignity in the process, whilst trust in community engagement stems from the public believing that the police deeply understand the community’s demands and interests. Bradford and Jackson (2010) defined the sum of the three trust components above as the global image of public confidence.

Through analysing survey data from London, Bradford and Jackson (2010) concluded that the overall public confidence is not significantly diverse amongst different groups due to the complex, interrelated components. However, minority populations or those who have had special experiences in their interactions with crime and policing (e.g., being witnesses or victims) have widely varying orientations in relation to the three components of public trust. The second finding is that the more a person trusts the police, the more likely they are to cooperate with the police and authorities.

(2) Visibility, quality of contact and confidence

Several researchers have focused on the relationship between frontline performance and public confidence. Sindall and Sturgis (2013) analysed administrative data and confidence answers from the British Crime Survey, concluding that police visibility (frontline workforce) significantly affected public confidence. Total workforce size also positively affected confidence, though frontline workforce size was more significant than absolute workforce size.

Quality of police contact also plays a pivotal role in public confidence. Fitzgerald et al. (2002) found that the main reason why citizens reported disappointment in the police was the unfairness and careless attitudes they perceived in their interactions with police procedures. Instead, the "result", as an end result, would not impact confidence as much as contact. Skogan (2006) pointed out that personal contact negatively affected confidence. To phrase this another way, unsatisfactory contact was significantly associated with negative opinions of the police. Skogan (2006) introduced an "asymmetric" dilemma faced by police officers: an officer will struggle to demonstrate their effectiveness through personal contact, though they can easily convey their personal shortcomings. Reporting conclusions consistent with Skogan (2006), Bradford (2009a) analysed Met Police survey data to prove that positive contact improved public confidence through the procedural justice model (as mentioned in Tyler 2007). On this basis, he disagreed with Skogan's remarks about the asymmetric dilemma and recommended that officers should grasp opportunities to demonstrate fairness and public engagement when engaging in personal contact with the public. Bradford (2010) later expanded his analysis using Crime Victims Survey data from the Met Police, arriving at a conclusion consistent with his earlier research (Bradford (2009a)): the symmetric association supported the positive opinion that public confidence can be improved through personal contact.

Myhill and Quinton (2010) recorded an overview of policing trends in terms of confidence. When public confidence plummeted in 2001/02, it was reused as a measure of police performance, at which point it was found that confidence was associated with the perception that crime was decreasing. Myhill and Quinton (2010) summarised two main factors to influence public confidence: neighbourhood policing and police-public contact. It is notable that compared with crimes, social disorder had a greater impact on public confidence. This relationship could incentivise the police to address both problems.

(3) Effectiveness and confidence

Hohl et al. (2010) studied how communication influences the public-police relationship, by conducting a leaflet drop experiment with representative samples from London (as opposed to conducting the study through personal contact). The analysis results showed that direct communication (by newsletter, for example) improved public confidence, which in turn enhanced enthusiasm towards the police, although written communication was required to be cautious and engaged in with “transparency, truthfulness, sincerity and veracity” (Habermas, 1979).

Apart from British research, there have been several studies carried out using data from countries. A Ghanaian study (Tankebe, 2012) verified an assumption that police legitimacy was associated with police effectiveness to some degree. The empirical models using survey data from Ghana led to an insignificant result. However, a key finding was that effectiveness and police trustworthiness were correlated, and effectiveness could be strongly correlated when emphasising police legitimacy. In conclusion, requirements of trustworthiness enhanced both police effectiveness and legitimacy in this model.

A Thai study (Sahapattana & Cobkit, 2016) discussed the interrelations between several factors and public confidence. Researchers divided the studied factors into four categories, including environmental factors and effectiveness factors. Though most factors were shown to have an impact on public confidence, the attitudes toward crime suppression and prevention were the main two significant factors affecting overall confidence.

A Belgian study (Verschelde & Rogge, 2012) employed conditional data envelopment analysis to evaluate citizen satisfaction with local police effectiveness. Specifically, three categories of environmental characteristics were used in the evaluation: demographic, socioeconomic, and neighbourhood municipality characteristics. A negative relationship was observed between the proportion of young citizens and satisfaction with local police effectiveness in Belgium.

1.8. Conclusion

This chapter reviews the background information relevant to crime changes, the UK's austerity period in the 2010s, and the measurement of police performance.

This research uses the Performance Measurement System (PMS) approach to assess police performance, which is based on the assumption that measuring and evaluating police performance will result in better improvements in police efficiency and effectiveness. This approach is grounded in the broader management approach of New Public Management, which emphasises the significance of performance measurement, goal-setting, and accountability in public sector organisations. However, there have been also criticisms of PMS, such as the risk of "gaming" or distorting performance metrics, the risk of neglecting important but less visible aspects of policing, and the difficulty of assessing complex goals like community safety and trust.

Three criteria will be used in this research to assess police performance: police efficiency, police effectiveness and public trust. Figure 1.10 demonstrates how resources are categorised and feed into the three measures.

It adopts the concepts of public trust from Tyler and Huo (2002) as well as the definitions of effectiveness and efficiency from Murphy (1985):
Police Effectiveness: the degree to which police undertake their duties and achieve goals in policing; **Police Efficiency**: the ability that the police demonstrate to undertake their duties and achieve goals in policing with the least amount of resources; and **Public Trust**: the public perceives the police as trustworthy in its effectiveness, legitimacy and public engagement.

Resources are categorised by two aspects: workforce expenses and non-staff costs. Various functions of the workforce are identified in later analysis. Police resources are seen as the inputs in police efficiency measures and the quantification of effectiveness is seen as the outputs.

In the next chapter, the mathematical methodologies for measuring efficiency in public sector organisations are introduced. It should be noted that, as efficiency can more readily be quantified than effectiveness, mathematical methodologies focus on discussing "efficiency", setting aside "effectiveness". Using the theory of operation research and experience of efficiency measurement in other areas of the public sector, such as education and healthcare, the relative efficiency of police forces can be quantitatively measured.

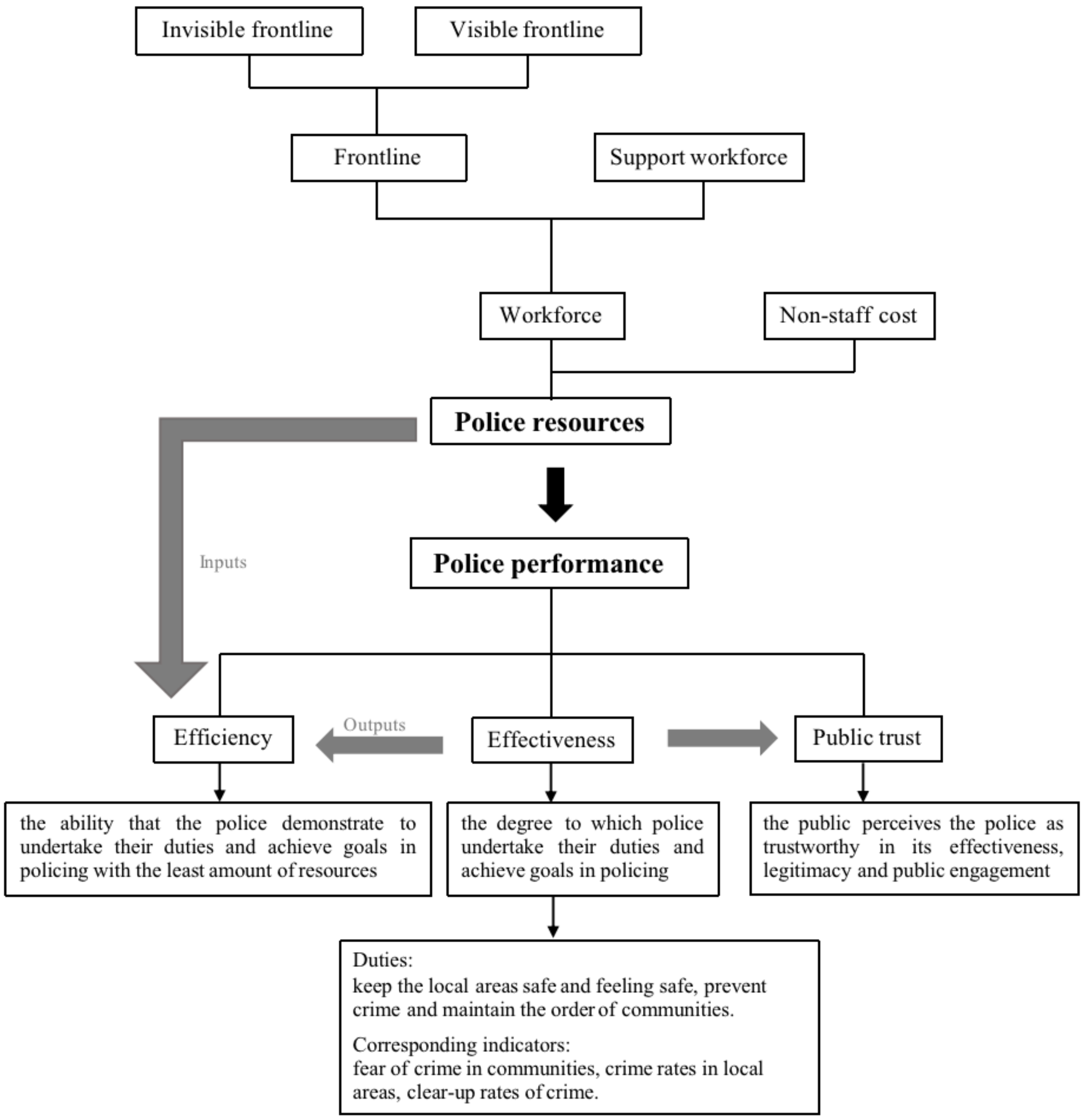

Figure 1.10. Framework of police performance measurement.

2. Methods to measure efficiency

This chapter introduces the Decision-Making Unit (DMU) concept, which refers to each police force as a distinct unit that makes decisions about how it uses resources, undertakes tasks, and delivers services to the public. DMU was first proposed by Kotler (1967) in a marketing context, where it referred to any individual or organisation involved in the decision-making processes relating to the negotiation of products or services. Subsequently, the DMU concept was applied in the manufacturing industry, business organisations, and the public sector began when groups were tasked with performing their responsibilities and missions with limited resources. Accordingly, those stakeholders interested in or affected by these DMUs will pay close attention to their efficiency.

This chapter introduces and details the methods available for measuring police efficiency. Section 2.1 outlines the performance measurement system and analyses its specific use to measure police efficiency. Next, section 2.2 illustrates how efficiency is mathematically defined in the production domain, whilst section 2.3 moves on to discuss several statistical and frontier methods that are used to assess efficiency and section 2.4 introduces Ferrell's efficiency, a nonparametric measure of efficiency. In section 2.5, the basic DEA model and its extension are used to assess purely technical efficiency, scale efficiency, and overall efficiency. Finally, section 2.6 provides programming packages for implementing the DEA models and section 2.7 briefly describes how DEA can be extended to the measurement of police efficiency.

2.1. Performance measurement system

To measure police efficiency, it is first necessary to consider the police system from the perspective of Performance Measurement System (PMS). PMS is an accountable means to track and evaluate the efficiency and effectiveness of DMUs. Specifically, PMS contains five elements: data (variables), measure, metric, indicator, and method (Keong Choong, 2013).

Data can be either quantitative or qualitative, with an increasing number of researchers supporting the use of non-financial data and discussing which forms of non-financial data are optimal (e.g. Gunasekaran & Kobu, 2007). Moreover, measure, metric and indicator function to measure attributes, thus demonstrating how the measurement system links with strategic objectives to generate useful information. It should be noted that the methods used in DMU are predominately quantitative. As the accounting system is subject to inherent limitations, a range of statistical techniques is used to measure non-financial performance and test the reliability and validity of the measurement system. A well-designed PMS provides an effective measuring tool to be deployed in the decision-making process. As a result, stakeholders can determine how the DMU is performing and drive further improvement by highlighting traceable and accountable information pertaining to those parts that are under or over-performing.

However, not all PMSs are effective: Firstly, the design of a PMS is strongly influenced by the DMU's objectives. Under the influence of different objectives, the system will select different variables as priorities, introducing variation in the efficiency and effectiveness evaluation results (an example of two PMSs with different policy orientations is given in the next paragraph). The issue of which orientation should be prioritised to reflect performance is a central issue when designing the measurement system. Secondly, unless the reliability and accuracy of the data can be assured, the PMS will not be truly reliable. In the policing context, policing data does not reflect the significant proportion of crime that goes unreported, as will be discussed in later chapters.

De Toni and Tonchia (2001) compared traditional PMSs and initial PMSs. With a traditional PMS, organisations focus on cost efficiency, whilst organisations are required to perform in line with a “value-based” measurement system with an initial PMS. Another key distinction is that traditional PMSs often consider the trade-off between performance, whereas initial PMSs emphasise performance compatibility. These theories suggest a new direction for police performance measurement. To be precise, when assessing “police efficiency” in the new policy environment, the focus should not only be on reducing costs or maximising performance, but also on ensuring that the services provided to the public meet the served communities’ demands and expectations (Paulsen, 2019). For example, community-oriented policing (e.g. Neighbourhood Policing in the UK) is a typical example of value-based measurement. It focuses on providing reliable community safety, improving public engagement, and increasing public confidence in the police. Notably, it differs from previous approaches (e.g. cost-based measurement) to police effectiveness in that it no longer leads the police to control costs at the expense of community benefits.

2.2. Productivity ratio and the definition of efficiency

Derived from microeconomics, the **productivity ratio** is an index that measures the efficiency of the DMUs (Coelli, et al., 2005, p.2):

$$Productivity\ ratio = \frac{output}{input}.$$

In this measurement, a high productivity ratio indicates the DMU is efficient. The formula above involves single output and single input values. Contrastingly, the advanced approaches to be introduced later aggregate multiple inputs and outputs.

A DMU is regarded as **fully efficient** when none of its inputs and outputs can be improved and other inputs and outputs are no less than before. In practical analysis, theoretical efficiency is hard to achieve due to the limited availability of empirical data. Alternatively, a DMU is classed as **relatively efficient** if it is efficient based on the evidence of other observed DMUs (Banker et al., 1984, p.1081). Figure 2.1 provides definitions of the concepts relevant to assessing efficiency (based on Coelli, et al., 2005, pp.4-5).

A known production frontier (i.e. a known relationship between the single input *x* and the single output *y)* is plotted as the curve OF in Figure 2.1. The **production frontier** represents all ideal outputs that correspond to every given input. Points along the curve OF (A and B) represent technical efficiency; those points beneath the curve (C) are not technically efficient points. To achieve technical efficiency, the DMU should improve its output when the input resources are fixed, namely, by moving to A or trying to reduce the input when the output goal is fixed, so as to move to B.

In Figure 2.1, OD is a tangent line of the curve OF featuring the tangent point D. Compared to any other ray connecting the origin and points on OF, the slope of OD is at the maximum, which reflects the output-input ratio. Point D defines the optimal scale at which a DMU can perform most efficiently.

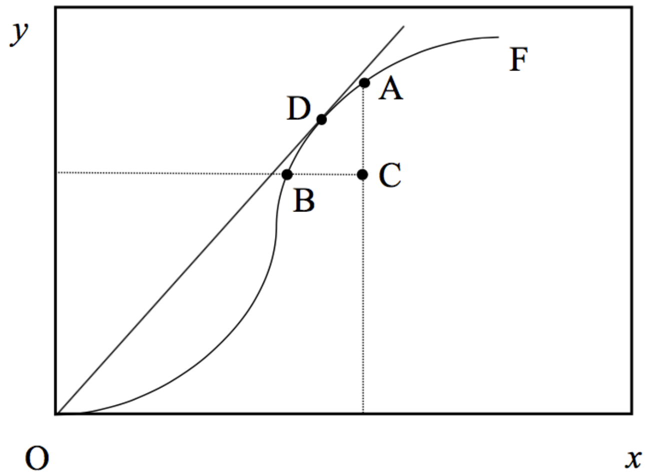

Figure 2.1. Production frontier and efficiency

2.3. Statistical and frontier methodologies

There are four main methods to measure efficiency (Coelli, et al., 2005, p.6):

(1) least-squares econometric production models;

(2) total factor productivity indices;

(3) data envelopment analysis; and

(4) stochastic frontiers analysis.

By focusing on central tendencies, efficiency can be measured using statistical methods, such as (1) and (2). The least-squares econometric production model (e.g. Antle et al., 1994) aims to estimate the statistical relationship between inputs and outputs, typically by using time series data[3] on a fixed DMU. Accordingly, relative efficiency is not available with this method and DMUs cannot be compared. The second method, total factor productivity indices (e.g. Zellner et al., 1966) aggregates different inputs (i.e. indicators of labour and capital) that are weighed through nonparametric models and used to calculate the total productivity index. This method can also be applied to time-series data on a fixed DMU, though an extended model is able to deal with relative efficiency for DMUs at the same time point.

If focusing on frontiers, frontier methodologies can be used, such as (3) and (4). To be precise, frontier methodologies measure the distance between the DMUs' actual performance and "best practice", namely, an efficient frontier, like the distance between points A and C in Figure 2.1. The data structures required by frontier methodologies can be time series or panel data[4], meaning it is possible to measure relative efficiency among a group of DMUs simultaneously or alternative chart changes in the efficiency of a fixed DMU over a period.

There are two frequently used frontier methodologies (Chen, 2015; Aigner, et al., 1977), **Stochastic Frontier Analysis (SFA)** and **Data Envelopment Analysis (DEA)**, which

[3] Time series data are data listed in time order. For example, the number of total annual crimes in England from 2001 to 2010.

[4] Panel data are data pertaining to several individuals observed over time. For example, the number of total annual crimes across all police forces from 2001 to 2010.

are parametric and nonparametric methods, respectively. In SFA, the frontier is described as a specific function (e.g. Cobb-Douglas), whereas it is described as a piece-wise linear surface in DEA.

Due to the significant discrepancy above, DEA does not require any assumed relationship between inputs and outputs of DMU, whilst SFA is premised on the assumption of the explicit frontier function. Moreover, DEA computational results are easily obtained from a series of linear programming problems. Contrastingly, the SFA results rely on an estimation of the maximum likelihood of known probability distributions, which gives rise to more complex issues.

A weakness of DEA is that a non-statistical method has no random errors, whereas SFA incorporates random noise. On this basis, DEA results may be more susceptible to sampling errors and outliers. Due to the lack of an error term, statistical tests cannot be used to examine the credibility of model results. In response, several statistical tests have been extended and developed for use in DEA (e.g. Banker, 1993; Banker, 1996).

There is no method for unambiguously measuring relative police efficiency that does not feature some drawbacks. All methods necessarily rely on simplified assumptions and approximations to reduce real-world complexity to a mathematical expression. Spottiswoode (2000) put forward various recommendations for how to assess police efficiency, including a demonstration of the SFA and DEA methods. Specifically, (1) As DEA can allow these weights to be any value, to prevent DEA attributing a high weight to a relatively low priority outcome, the weights given to each outcome measure should be constrained in DEA; (2) The raw DEA results should be reviewed and analysed to understand differences in results and any data issues or differences in service quality that may influence the results. Based on this analysis, the raw results can be adjusted as necessary.

Farrell’s Efficiency is introduced below to lay the groundwork for the later use of basic DEA models.

2.4. Farrell's Efficiency

In 1957, Farrell first modelled multiple inputs and a single output. Figure 2 (adapted from Farrell (1957, p.254)) is an example with two inputs that illustrates the efficiency definitions he mentioned. In this simplified example, returns to scale are assumed to be constant.[5]

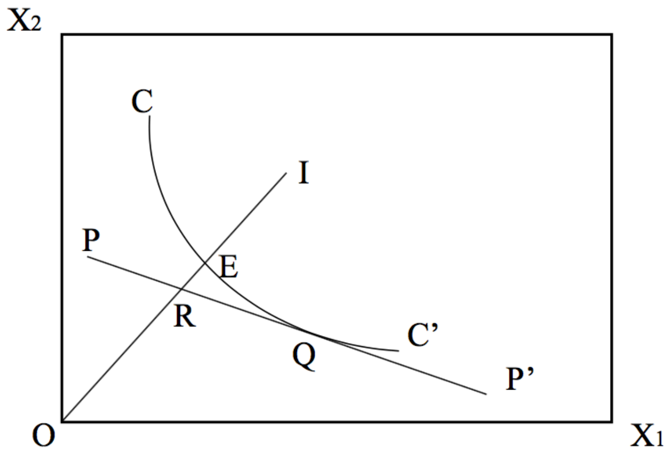

Figure 2.2. Farrell's efficiency.

In Figure 2.2, the X_1 and X_2 axes represent two inputs, respectively, meaning that the points in the coordinate are pairs of DMU inputs. Where a DMU is inefficient, point I and another efficient DMU, point E on line OI, produce the same output. It is apparent that point I and E share the same ratio of X_1/X_2 whilst differing in the values of inputs. Rather than changing the input ratio, point I can be moved to efficient status by improving "production techniques". On this basis, the efficiency OE/OI is called **technical efficiency**.

Curve CC' is an "iso-output" curve, where points C, E, Q, and C' are different combinations of inputs that produce the same level of output. Assuming there is a three-

[5] "Constant returns to scale" means outputs increase by the same proportion as all inputs change.

dimensional input-input-output space, curve CC' can be seen as a contour line of the productivity frontier.

Line PP' is a price ratio line, on which points P, R, Q, P' are different combinations of inputs that cost the same. Point Q is the tangent point of curve CC' and line PP', indicating that point Q is the optimal solution, as it produces the same output as E but costs the least.[6] Point R is where line OI and line PP' intersect, indicating that R costs the same as Q. The efficiency OR/OE is termed **price efficiency**. Furthermore, **overall efficiency** is defined as the multiple of technical efficiency and price efficiency, OR/OI. In the real world, the price efficiency concept is frequently used when resources are limited.

When conducting practical analysis, the key to the efficiency problem in Farrell's theory is the estimation of the approximate iso-output curve CC'. The approximate curve CC' is composed of several line-segments joining certain pairs of points, chosen from observed points. The pairs of points chosen for the line-segments should satisfy two conditions:

(1) The slope of each line-segment is not positive, meaning that the approximate curve is convex to the origin;
(2) There are no points observed between this line and the origin, meaning that it links the efficient input points observed.

Figure 2.3 (adapted from Farrell (1957, p.256)) plots the approximation case. Points in this figure are scatter points of observed DMU data. The line-segments approximate parts of CC'.

Below is the algebraic expression of CC' approximation:

Write any point from a two-dimensional coordinate in the form $P_i = (x_{i1}, x_{i2})$, with λ, μ forming the solutions of the equations below:

6 Assuming a series of lines with the same slope as PP', intersecting each point on curve CC' respectively, the tangent line PP' represents the least budget among them. Hence, the point Q is an optimal solution.

$$\begin{cases} \lambda x_{i1} + \mu x_{i2} = x_{k1} \\ \lambda x_{j1} + \mu x_{j2} = x_{k2} \end{cases}$$

where P_i, P_j and P_k are points in set $A^2 = (\text{all observed points}) \cup (R^+)^2$. It denotes λ_{ijk}, μ_{ijk} as solutions in the equation involving points P_i, P_j and P_k. Then the line $P_i P_j$ is part of CC' if and only if

$$\lambda_{ijk} + \mu_{ijk} \geq 1$$

for all P_k in set A.[7]

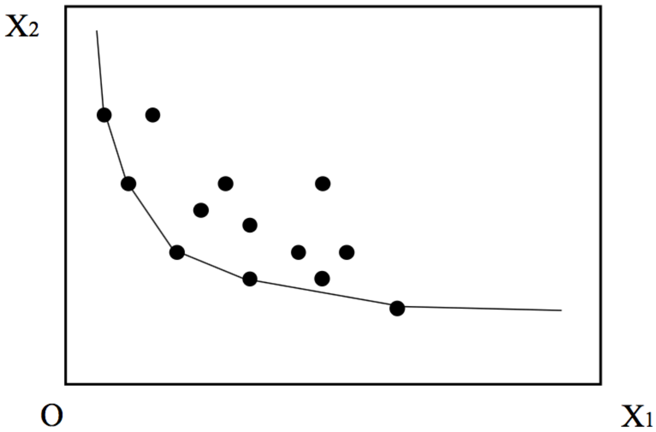

Figure 2.3. Approximation of curve CC'.

Here, the technical efficiency of P_k is the maximum of

$$\frac{1}{\lambda_{ijk} + \mu_{ijk}}$$

for all segments $P_i P_j$ of CC'.

Figure 2.4 gives an example of line-segments P_1P_2 and P_2P_3 of CC'. In this figure, line P_1P_2 is an efficient boundary line, which given that all points except P_1 and P_2 are on the right side of line P_1P_2, can be approximated as a line-segment. However, line P_1P_3 is ineligible to be seen as the line-segment, due to the left point P_2. It should be noted that line P_2P_3 is also a line-segment of CC'.

[7] If P_k is on the line $P_i P_j$, $\lambda_{ijk} + \mu_{ijk} = 1$; if P_k is on the other side of the line $P_i P_j$ opposite to the origin, $\lambda_{ijk} + \mu_{ijk} > 1$.

From the perspective of efficiency value, take P_4 as an example: Figure 2.4 makes an extension line of P_1P_2 to P_1C, denotes the intersect point of line OP_4 and P_1C as B, and the intersect point of line OP_4 and P_2P_3 as A. Meanwhile, the ratio $OB\ /\ OP_4 = 1/(\lambda_{124} + \mu_{124})$ and the ratio $OA/OP_4 = 1/(\lambda_{234} + \mu_{234})$. According to the formulae above, the technical efficiency of P_4 should be the maximum of these two values. By the same argument, OA/OP_4 is larger, such that the technical efficiency of DMU P_4 can be interpreted as the ratio OA/OP_4, which is equivalent to the ratio OE/OI in Figure 2.2.

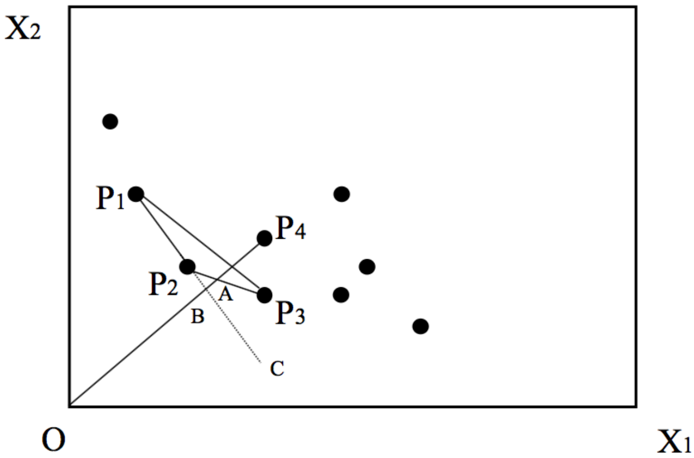

Figure 2.4. Example of line-segments of CC'.[8]

Following on from the modelling of two-inputs one-output scenario, if generalised to *n* inputs, the previous set *A* should be defined as a set $\mathrm{A}^n =$ (all observed points) $\cup$ $(\mathrm{R}^+)^\mathrm{n}$. The efficient curve CC' is now extended to a surface C in *n* dimensions. The equation above is then generalized as a matrix equation:

$$[x_i, x_{i+1}, \dots, x_{i+n-1}]\boldsymbol{\lambda} = x_k$$

where $\boldsymbol{\lambda}$ is a column vector. The facet with *n* points $P_i,\ P_{i+1}, \dots, P_{i+n-1}$ is a part of the approximated surface C if and only if

$$\boldsymbol{\lambda}'\mathbf{1} \geq 1$$

for all P_k in set A^n, where **1** is a column vector with *n* elements all equal to 1.

[8] For simplicity, some observations presented in Figure 2.3 are omitted.

Here, the technical efficiency of P_k is the maximum of $1/\boldsymbol{\lambda}'\mathbf{1}$ for all facets of surface C.

2.5. Basic DEA models and extensions

Building on Farrell's work, Charnes, Cooper, and Rhodes (CCR) (1978) expanded the measurement to multi-input-multi-output productivity from an operational perspective. The **CCR model,** known as the original DEA, is introduced below.

Assume that there are *n* DMUs. For the *j*th decision-making unit, DMU_j, $\boldsymbol{x}_j$ and $\boldsymbol{y}_j$ represent the *m*-element input vector and the *s*-element output vector, respectively:
$\boldsymbol{x}_j = (x_{1j}, \dots, x_{ij}, \dots, x_{mj})$, $\boldsymbol{y}_j = (y_{1j}, \dots, y_{rj}, \dots, y_{sj})$, for $j = 1, \dots, n;\ i = 1, \dots, m;\ r = 1, \dots, s;$
where $x_{ij} \geq 0, y_{rj} \geq 0$; and for each DMU, $\boldsymbol{x}_j, \boldsymbol{y}_j \neq \boldsymbol{0}$.

$\boldsymbol{x}_j, \boldsymbol{y}_j$ are observed data, while $\boldsymbol{u}, \boldsymbol{v}$ are vector variables, where $\boldsymbol{u} = (u_1, \dots, u_r, \dots, u_s)$ for outputs $\boldsymbol{y}_j$, and $\boldsymbol{v} = (v_1, \dots, v_i, \dots, v_m)$ for inputs $\boldsymbol{x}_j$. Elements in $\boldsymbol{u}$ and $\boldsymbol{v}$ can be seen as weights for outputs and inputs in the assessing model.

Based on the definitions of efficiency detailed above, to aggregate multiple inputs into a "virtual" input, and multiple outputs into a "virtual" output, the relative efficiency optimisation for $DMU_{()}$ to be evaluated can be written as:
$\max h_{()}(\boldsymbol{u}, \boldsymbol{v}) = \sum_r u_r\, y_{r()} \,/ \sum_i v_i\, x_{i()},$
subject to
$\sum_r u_r\, y_{rj} \,/ \sum_i v_i\, x_{ij} \leq 1$ for $j = 1, \dots, n,$
$\sum_i v_i\, x_{i()} = 1,$
and $u_r, v_i \geq 0$ for all *r* and *i*.

It should be noticed that every $DMU_{()}$ is to be related to all DMU_j for $j = 1, \dots, n$, and for every DMU, whilst the process of optimising should be repeated to solve a unique set of weighting variables (Charnes et al. (1978, p.430)).

In this model, the goal is to maximise the efficiency subject to three restrictions: 1) Efficiency is limited to no more than 1; 2) A unique solution must be guaranteed; 3) All vector variables must be positive.

To transform to a linear formula, it is written as follows:
$\max z = \sum_r u_r\, y_{r()}$
subject to

$\sum_r u_r \, y_{rj} \leq \sum_i v_i \, x_{ij}$

$\sum_i v_i \, x_{i()} = 1$, and

$u_r, v_i \geq 0$ for all r and i.

The formula above can then be written as a linear programming dual problem, which can more easily be solved:

$\theta^* = \min \theta$

subject to

$\sum_j x_{ij}\lambda_j \leq \theta x_{i()}$

$\sum_j y_{rj}\lambda_j \geq y_{r()}$, and

$\lambda_j \geq 0$ for all j.

This formula presents an approximation process of a surface C relating to the CCR model to Farrell's theory. The solution of $\theta^*(\leq 1)$ is the efficiency score of $DMU_{()}$. In this model, DMUs with $\theta^* = 1$ are boundary points, indicating they are efficient, whilst those with $\theta^* < 1$ are inefficient points. However, when solving the problem, some boundary points may have non-zero slacks[9], which are the root of the "weakly efficient" problem.

When there are positive slacks associated with some input variables, the related inputs can be reduced by the respective amounts of those positive slacks without changing any outputs or weights. Similarly, if there are positive slacks associated with some output variables, the related outputs can be increased without any alterations. As a result, as long as slack variables are non-zero, DMUs can theoretically reach a new strong efficiency.

Charnes et al. (1978) addressed the problem of non-zero slacks, which were not accounted for by Farrell (1957). The model considering non-zero slacks can be written as

[9] In an optimisation problem, an inequality constraint $a < b$ is able to be transformed into an equality $a + s = b$ by adding a non-negative slack s.

$$\max \sum_i s_i^- + \sum_r s_r^+$$

subject to

$\sum_j x_{ij}\lambda_j + \sum_i s_i^- = \theta x_{i()}$

$\sum_j y_{rj}\lambda_j - \sum_r s_r^+ = y_{r()}$, and

$\lambda_j, s_i^-, s_r^+ \geq 0$ for all *j, i,* and *r,*

where s_i^- are slacks associated with input i, and s_r^+ are slacks associated with output *r*.

In this model, a DMU is fully efficient if $\theta^* = 1$ and all slacks $s_i^-, s_r^+ = 0$. Contrastingly, a DMU is weakly efficient if $\theta^* = 1$ and $s_i^- \neq 0$ and/ or $s_r^+ \neq 0$ for some *i* and *r.*

It should be stressed that the CCR model above should be associated with the assumption of constant returns of scale (CRS). Banker, Charnes and Cooper (BCC) (1984) extended it to a model with variable returns of scale assumption by adding the following constraint:

$\sum_j \lambda_j = 1$ called the **BCC model**.

To interpret the variable returns of scale (VRS) assumption and its influence on efficiency measurement, the module returns back to one-input/one-output efficiency for simplicity.

In Figure 2.5 (adapted from Drake (2000, p.57)), for a DMU, the function of input (*x*) and output (*y*) are plotted based on two assumptions: function OC for constant returns of scale and function VV' for variable returns of scale. The DMU exhibits a decreasing output growth rate when the input increases.

A fixed output level is marked as line EE'. Point Q is the point where OC and line EE' intersect, whilst point R is the point where VV' and line EE' intersect. The productivity ratio (efficiency) on Q, y_Q/x_Q, represents the overall technical efficiency, accounting for influence from scale, while the productivity ratio R, y_R/x_R represents pure technical efficiency setting aside scale. Drake (2000) defined scale efficiency as the ratio of pure technical efficiency to overall technical efficiency, as illustrated by EQ/ ER (see Figure 2.5).

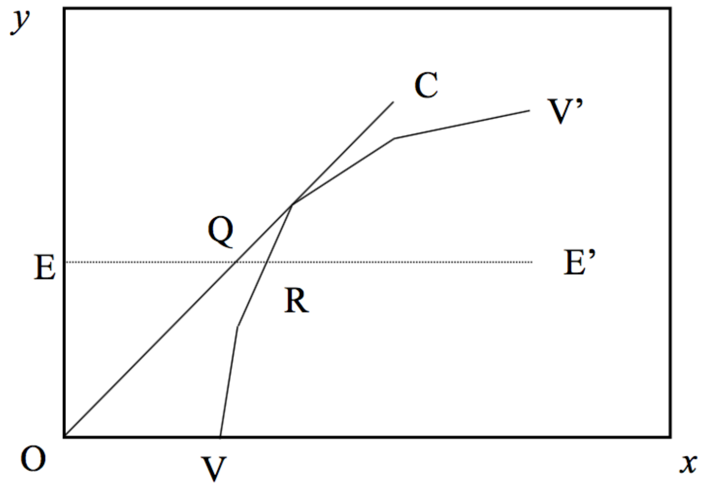

Figure 2.5. Efficiency on the assumption of variable returns of scale.

According to Farrell's definition of price efficiency, it is worthwhile calculating efficiency in terms of cost where budgets are limited and price data are available.

Another extension with cost factor (Cooper et al., 2007) is written as follows:

$\min \sum_i c_{i()} x_i$

subject to

$\sum_j x_{ij}\lambda_j \leq x_i$

$\sum_j y_{rj}\lambda_j \geq y_{r()}$, and

$\lambda_j \geq 0$ (constant returns of scale)

$or\ \sum_j \lambda_j = 1$ (variable returns of scale) for all j.

In this model, the ratio

$$0 \leq \frac{\sum_i c_{i()} x_i^*}{\sum_i c_{i()} x_{i()}} \leq 1$$

represents the overall efficiency of the $\mathrm{DMU}_{()}$ to be evaluated, where the x_i^* are the optimal value solved from the cost efficiency model.

2.6. Programming and Software

Several commercial and non-commercial pieces of software have been developed for DEA solvers (Barr (2004).

Excel DEA Solver is a basic tool for DEA modelling and solving. Zhu (2003) introduced the usage of visual basic of application (VBA) codes in Excel to automate the calculation. This novel development allows for an abundance of modelling options, including constant/variable returns of scale, input/output-oriented models, super-efficiency, and categorical variables. It should be pointed out that the Excel DEA Solver is limited by the capacity of the Excel Solver.

Another piece of software mentioned in the previous British policing DEA modelling (Thanassoulis, 1995) was the Warwick DEA Software developed by the University of Warwick. Thanassoulis (2001) later published an associated guidebook to explain how to use the software step-by-step. Though basic models and optional assumptions are available in this software, weighting constraints can only be completed for the assumption of constant returns of scale. In addition, Barr (2004) found that the running time was unsatisfactory during testing.

In recent years, R has become popular amongst statisticians for its free-of-charge, strong statistical, and graphical techniques, as well as the variety of extensions available. The R environment is "an integrated suite of software facilities for data manipulation, calculation and graphical display"[10], which is suitable for Linux, Microsoft and OS X systems. To date, there are more than 10000 extension packages available on CRAN[11] addressing a large number of statistical or geographical tasks, among which packages—*nonparaeff, rDEA,* and *benchmarking*—can implement DEA models in an R environment.

These three packages each offer their own advantages. For instance, *nonparaeff* focuses on functions for measuring efficiency of DMUs using a DEA methodology that

[10] Source available at: https://www.r-project.org/about.html .

[11] Source available at: https://cran.r-project.org/ .

incorporates a wide range of variations (Oh & Suh, 2015). Meanwhile, *rDEA* produces robust DEA scores with and without environmental variables and can accomplish returns-to-scale tests (Simm, & Besstremyannaya, 2016). Finally, *Benchmarking* can carry out both DEA and SFA calculations, which is useful when conducting comparative research of these two models (Bogetoft & Otto, 2015).

2.7. Conclusion

Section 2.1 introduced the performance measurement system and analyses how it relates to the policing environment. Sections 2.2-2.5 mathematically introduced the efficiency measure and section 2.6 outlined the available programming packages that can be used to implement it. The mathematical explanation is based on a production scenario, which will then be expanded upon in later chapters to measure policing efficiency. In this context, a police force is seen as a DMU, the human and financial costs and a number of initial situations can be seen as inputs, and the policing services they deliver to the public, how the public feels, and public confidence can be regarded as outputs. In this measurement system, quantitative measures of the policing environment and services are crucial, though they will be influenced by the goals and objectives set by the system, and also the accessibility and reliability of the data.

The next chapter reviews the previous research, the application of DEA to police efficiency measurement in England and Wales, before moving on to discuss technical controversies, data support, and specific empirical research questions.

3. DEA for police efficiency measurement

Prior to the introduction of Data Envelopment Analysis (DEA) to measure policing efficiency, it was applied to a wide range of sectors, including education (Bessent & Bessent, 1980), banking (Ferrier & Lovell, 1990), and healthcare (Zuckerman et al., 1994).

Crime data in England and Wales, such as the crime statistics recorded by the ONS[12], typically take the form of annual panel data describing general or specific criminal and policing conditions for the 43 police forces. A DEA model is well-suited to measuring policing efficiency, especially the relative efficiency of all police forces and the efficiency improvements of a police force over any period of time for which data are available.

This chapter first briefly returns to the definitions outlined in chapter 2. When applying DEA to assess policing, the relative (overall) efficiency of a police force is defined as its performance across the full range of its duties (as compared to peer forces). Meanwhile, scale efficiency refers to how a police force used its labour resources to deliver the best policing. Finally, cost efficiency pertains to how a police force made use of the available capital resources (in terms of costs).

With regard to real policing problems, in DEA models, the 43 police forces in England and Wales are denoted as decision making units (DMU). Indicator variables–inputs and outputs representing general or local capital resources, labour resources, criminal conditions and performance outcomes–must be carefully selected in response. Notably, it is challenging to represent resources or outcomes using quantified variables, since selected indicators may fail to capture relevant factors, introduce bias, or be unduly complex. For example, clearance rate is a typical outcome indicator as it shows police performance from the perspective of solving crimes. However, only using clearance rate as an outcome indicator will lead to bias, since solving crimes is only one aspect

[12] Source available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice .

of the work police forces carry out. Therefore, thought should go into selecting a comprehensive range of indicators.

This chapter begins in section 3.1, which provides an overview of the selected variables, followed by an overview of the previous DEA model research carried out to examine English and Welsh policing efficiency in section 3.2. Section 3.3 then moves on to discuss the weaknesses and solutions of DEA when applied to measure police efficiency. Section 3.4 presents several developed options for DEA and section 3.5 discusses the selection and treatment of environmental factors to explain why the present research uses a set of time-constant variables as environmental indicators. Section 3.6 also discusses the shortcomings of officially recorded crime data and the selection of other types of data, such as CSEW data. Specifically, it explains how hidden crime affects the measurement of performance from different perspectives. Finally, section 3.7 concludes and puts forward the empirical research questions to be developed in chapters 4-6.

3.1. Indicators selected in previous research

The Public Service Productivity Panel (Spottiswoode, 2000) proposed a plan to determine the efficiency rankings of police forces to determine which were most efficient. This was followed by the Demonstration Project (Home Office, 2001), which drew on a large series of potential inputs and outputs (over 250 potential variables) that could be considered when measuring police efficiency. The variables were categorised into several groups, including but not limited to the interpretation of performance measures (i.e. crime rates), environmental factors (i.e. unemployment), cost variables, and survey variables. Outputs have proven more difficult to quantify as, although the core duties remained the same, the objectives of policing have gradually changed over time. The Demonstration Project proposed three types of measures to be used when assessing policing outcomes: managerial efficiency measures, response/reactive efficiency measures, and proactive/ preventative efficiency measures. It should be noted that these novel viewpoints were highly influential on subsequent police efficiency research.

Drake and Simper (2003a) conducted a detailed analysis of the types of input and output indicators proposed in the Demonstration Project. For the input side, they emphasised that it is important that the measures are composite and not overly restrictive in their specification. For the output side, the measures should reflect the full range of services provided by the police, including response/reactive variables, proactive/preventive variables, and quality of service variables (as suggested by the Demonstration Project). In addition, it has been suggested that environmental and sociological variables should be directly incorporated into DEA models or evaluated in regression models to interpret the full extent of their impact on police effectiveness.

Table 3.1 summarises the input and output indicators used in previous research on English and Welsh policing efficiency. The table below suggests there are three main types of indicators: number of crimes, labour resources, and capital resources. Meanwhile, the indicators for outputs were mostly related to the number of crimes solved or the clearance rate. The remaining indicators were related to the managerial and proactive measures mentioned in the Demonstration Project (2001).

There is also value in looking at how DEA has been applied to evaluate police performance in other countries to identify further indicators not mentioned in any studies of English or Welsh policing.

For inputs:
(1) Average of police wages (Darrough & Heineke, 1979);
(2) Separate indicators for police officers and civilian employees (Sun, 2002) / for sworn police officers and other employees (García-Sánchez, 2007);
(3) Efficiency in previous years (García-Sánchez et al., 2013);
(4) Environmental factors (Aristovnik et al., 2013).

For outputs:
(1) Crime rates (or numbers) for specific crime types (Darrough & Heineke, 1979);
(2) Non-criminal activities recorded (Sun, 2002);
(3) Variables reflecting clearance through more specific procedures, such as the number of persons arrested/charged/convicted or the number of trials completed (Verma & Gavirneni, 2006);
(4) Citizen satisfaction with public security (Wu et al., 2010);
(5) Changes in socio-economic indexes (García-Sánchez et al., 2013).

As data for the indicators derived from non-British studies are also available in the UK, future research could consider utilising these new indicators to realise a more comprehensive DEA of police efficiency.

Table 3.1. Inputs and outputs of DEA models in previous studies with English and Welsh data.

Research	Inputs	Outputs
Thanassoulis, 1995 (Data in 1991)	Number of violent crimes. Number of burglaries. Number of other crimes. Number of officers.	Violent crime clear ups. Burglary clear ups. Other crime clear ups.
Drake and Simper, 2000 (Data from 1992 to 1997)	Employment costs. Premises-related costs. Transport-related costs. Capital and other costs.	Total clear up rate. Total number of traffic offenses. Total number of breathalyser tests.
Drake and Simper, 2001 (Data from 1996 to 1998)	Employment costs. Premises related costs. Total transport costs. Other capital costs.	Percentage of time officers spend patrolling. Violent clear up rate. Burglary clear up rate. Percentage success rate in answering 999 calls. Percentage of cases officers arriving within target response time.
Drake and Simper, 2002 (Data from 1992 to 1997)	Employment costs. Premises related costs. Total transport costs. Other capital costs.	Total clear up rate. Total number of traffic offenses. Total number of breathalyser tests.
Drake and Simper, 2003b (Data from 1996 to 1999)	Employment costs. Total transport costs. Other capital costs.	Total clear up crimes. Total violent clear up crimes. Total burglary clear up crimes. Total number of breathalyser tests.
Drake and Simper, 2004 (Data from 1998 to 2000)	Employment costs. Premises related costs. Total transport costs. Other capital costs.	Number of complaints per officer. Average number of days lost per officer. Number of crimes solved. Number of emergency calls answered in target time. Number of breathalyser tests.
Drake and Simper, 2005a (Data from 2001 to 2002, only England)	Number of offences.	Total offences clear up rates.
Drake and Simper, 2005b (Data from 2001 to 2002)	Number of burglaries. Number of vehicle crimes. Number of robberies. Net budget revenue.	Total offences clear up rates. Total days lost to sickness.

3.2. Review of English and Welsh empirical studies

This section discusses how previous empirical studies of policing in England and Wales have employed DEA models and how the results have been interpreted, with particular attention paid to the weaknesses of such approaches and how they can be addressed.

(1) Efficient peers, weight restrictions and environmental groups

Thanassoulis (1995) was the first to apply DEA to English and Welsh data to assess policing performance. This research used crime and manpower data from 1991 covering 41 police forces. Notably, the London Metropolitan Police Force and the City of London Police Force were excluded from the study due to their special duties. To simplify the analysis, all crimes were divided into three categories—violent crimes, burglaries and other crimes—based on their degree of harm and the difficulty experienced investigating them.

To identify efficient and inefficient forces, Thanassoulis referred to clear-up rates relative to crime conditions and manpower. In an initial DEA model, he set the number of each category of crimes and the number of officers as inputs, whilst the number of clear ups was taken as the output. The initial results provided efficient ratings for each police force, determining them to be efficient (100% for genuinely efficient or above 90% for relatively efficient) or inefficient (under 90%). During the interpretation phase, the efficient police force results were adjusted by a constraint on the marginal rates of substitution between inputs and outputs. Finally, the inefficient forces were contrasted with their respective "efficient peer"[13] to determine in which aspects they were deficient.

Thanassoulis recognised and addressed two key weaknesses in this model. First, the initial model created counter-intuitive weights for different categories of crime. To solve this problem, additional constraints—weight restrictions—were added to the formula. When adjusting the value system, the weight attributed to resolving (i.e.

[13] From Thanassoulis (1995), "the efficient peers to force j_0 are the forces which attain relative efficiency of 1 with the weights that render force j_0 relatively efficient."

clearing up) one violent crime was 10 times that of a burglary, which in turn was two times more than that of all other crimes. As a result, the revised model produced more intuitively acceptable results. Second, an inefficient force and its efficient peer might be not comparable as they are located in areas with dissimilar socio-economic conditions. In response, the 41 police forces were grouped into "police families" by the Audit Commission (1993) based on several socio-economic and settlement pattern indicators. This then allowed for each inefficient force to be compared to their efficient peers within their police family.

Finally, by building two DEA models with manpower and crime number inputs, the research offered could offer separate perspectives on manpower efficiency and clear-up efficiency, respectively. Interestingly, these changes also revealed a weak negative correlation between these two efficiencies.

(2) Scale efficiency and X-efficiency

Across two studies, Drake and Simper made significant contributions to the application of DEA to policing assessment in England and Wales.

In their first study, Drake and Simper (2000) introduced a scale efficiency formula based on the CCR (Charnes et al., 1978) and the BCC models (Banker et al., 1984). The CCR model is based on an assumption that the constant scale of returns results in overall efficiency. Meanwhile, with the BBC model, the results from the variable scale of returns assumption indicate pure technical efficiency. On this basis, the researchers defined scale efficiency as the ratio of pure technical efficiency over overall efficiency. The resulting scale efficiency score reflected the staff scale efficiency of a police force, i.e. whether the police force in question used its labour resources efficiently.

Data from all 43 police forces from 1992 to 1997 were used to carry out the modelling. However, the efficiency scoring results were presented separately in two groups: one group consisted of 27 non-metropolitan English forces and four Welsh forces, whilst the other consisted of eight metropolitan English forces. This division demonstrates that police forces can be more readily compared to those within their own group. Four input indicators—labour resources quantified by the total employment costs, capital resources measured by premises-related costs, transport-related costs, and other capital costs—were measured by costs. The output indicators were selected with reference to crimes and traffic offences: total clear up rates, total number of traffic offences, and number of breathalyser tests.

The DEA results suggested that pure technical efficiency could be more readily realised in smaller police forces, whilst scale efficiency exhibited an inverse U-shape change as staff size increased. Thus, attaining overall efficiency would be a complex problem because there was a trade-off between pure technical efficiency and scale efficiency. Moreover, for X-efficiency, defined as perfect usage of costs given any level of output, mid-sized police forces (as measured by the number of staff) were less likely to be highly technically efficient than small or large-sized police forces.

To confirm the significance of scale efficiency across forces with various workforces, Drake and Simper divided all police forces into four groups according to their number of staff. After doing so, the four groups were subjected to an analysis of variation and multiple discrimination analysis. The test results were consistent with the conclusions from the DEA models: mid-sized forces achieved the best scale efficiency, while small or large-sized forces exhibited lower scale efficiency.

In a later study, Drake and Simper (2001) focused on the scale efficiency of police forces in England and Wales. In contrast with their 2000 study, the analyzed data was from 1996 to 1998. Although four input indicators remained the same as in the earlier study, there were improvements in output indicator selection (detailed in Table 3), which included patrolling activities, response/reactive outcomes, and clear up duties.

The model results indicated a negative relationship between scale efficiency and pure technical efficiency, which was consistent with their previous findings (Drake and Simper, 2000). To confirm the significant difference, police forces were divided into three groups according to capital expenses (as opposed to labour resources as before). Hypotheses testing then verified the significance of the scale efficiency within different capital expenditure groups.

(3) Comparisons with other methodologies

In 2002, Drake and Simper (2002) utilised the same empirical DEA models as in 2000, though this time they aimed to compare DEA models using the distribution-free approach models. In this research, the same data and similar indicators for inputs and outputs were employed in both methods. The results from both models indicated similar relative efficiency rankings for all police forces, echoing the findings pertaining to the scale effects on policing with various staff sizes. The evidence in this research suggested that the DEA models were more susceptible to data quality than the distribution free approach models.

Drake and Simper (2003b) conducted a further similar comparison between DEA and distance function methodologies (free disposal hull, super-efficiency DEA (SDEA) and stochastic frontier analysis (SFA)). The results were presented using four methods for comparison to assess police force efficiency using data from 1996 to 1999. This research also suggested the combined and joint use of different distance function approaches to ensure consistency and maximise potential complementary benefits.

(4) Managerial measure and cost efficiency

Drake and Simper (2004) used the same inputs in their earlier research (Drake and Simper, 2000), though they also incorporated more managerial outputs (number of complaints per officer and average number of days lost per officer) in their assessment of police forces using data from 1998 to 2000. The study concentrated on scoring cost efficiency, which was broken down into allocative efficiency and pure technical efficiency. The results showed that scale efficiency significantly impacted cost efficiency, which suggested that police forces could identify an optimal scale to attain more relative efficiency. This study also imposed weight restrictions on minimum outputs, thereby ensuring the revised models produced more realistic results.

(5) Offense clearance, BCU level

Drake and Simper (2005a) were the first to assess basic command units' (BCU) efficiency in England. Based on the police force subdivisions, the efficiency of BCUs warranted further investigation to reveal the deficient aspects of police forces. In total, 293 BCUs from 38 forces were evaluated using data from 2001 to 2002 (note that the City of London police (two BCUs) and those covering airports were not included due to their distinct policing duties).

As this study concentrated on offence clearance, the inputs selected were the number of offence crimes and net budget revenue, whilst the output was the offence crime clear up rate. Both DEA and SFA were carried out to maintain the consistency of results, as it had been suggested that solely relying on one approach would produce bias. When modelling, BCUs were denoted as individual DMUs in the efficiency theory, while the efficiency scoring results of BCUs were represented within the scope of their respective police forces. Consequently, there were efficiency variations identified both between BCUs and within individual police forces. This study proposed concentrating on scale efficiency evaluations at the BCU level, rather than only looking at the police force level.

(6) Environmental factors, public confidence

Drake and Simper (2005b) discussed the impact of environmental factors on police force efficiency. Two models were built using data from the same period (2001 to 2002) and the same outputs (total offences cleared and total days lost to sickness), albeit with different inputs. The first model included three inputs (number of burglaries, vehicle crimes and robberies), while the second model incorporated four inputs including the additional net budget revenue input. The results from the two models exhibited significant differences in police force rankings, thus evidencing the impact of environmental factors, which are outside the control of individual police forces.

Finally, the researchers employed regression estimation to better understand the relationship between DEA efficiency scores and the surveyed public confidence in police forces (data were taken from a relevant Home Office assessment). The regression indicated the existence of a significant positive relationship between estimated efficiency and surveyed public confidence, although the researchers highlighted the potential bias of the survey data.

3.3. Discussions on DEA applications

There have been several academic debates between researchers on the application of DEA to measure the efficiency of public services. Stone (2002) criticized the DEA for its weakness and suggested the inclusion of a supplementary method, Value-Based Analysis (VBA). In response, Cooper and Ray (2008) discussed how to understand and use DEA better. In total, over 15 researchers (see Stone, 2002) both from British and international institutions also joined this debate to express their critiques.

Stone (2002) articulated six critical features characterising the use of DEA to measure public service efficiency: (1) Any results will be significantly influenced by a judgement of the values of disparate selected outcomes; (2) The omission of any output, which reflects the implicit functions of the service, will expose the issue of discrimination; (3) The assumption relating to dictating local priorities will be weak for 43 police forces; (4) Units on upper bound are difficult to rank for practical problems; (5) Any assumption of returns to scale is uncertain for units; (6) It is difficult to fully demonstrate how the covert unit-based allowance for typically undocumented environmental factors corresponds to local priorities.

At the end of Stone's paper, 15 researchers contributed their perspectives on this discourse, offering developed techniques or further considerations that compensate for some of the shortcomings mentioned in the preceding paragraph. The main reflections offered were as follows: (1) Choosing the outcomes entails determining the key important priorities in policing, such that the entire endeavour is more of a political problem than a technical one; (2) By reallocating those resources that contribute to the selected outcomes, a police unit can easily control a small selection of outcomes (though this may be detrimental to the overall quality of policing); (3) DEA can feasibly work with value judgements, though this depends on the determination of value orientation within the policy; (4) Total police hours can be used an an input, whilst the number of unemployed young men (this differs from the previous research which has proposed the *total young men*) can be incorporated as an environmental factor; (5) It is possible to maximise success subject to the given budget by using an output-oriented formulation; (6) Although establishing subsets of variables and conducting DEA within each subset may be an accessible approach to transcend the limits of dimension, it will also limit the analysis of contributions to the subset; (7) Bootstrapping techniques, statistical inference, and hypothesis testing are feasible methods assessing the efficiency.

Cooper and Ray (2008) honed in on the most serious problems highlighted by Stone and constructively discussed how to account for these problems in a DEA model applied to the 43 police forces. They started by pointing out some misunderstandings in Stone's research and underscored the benefits of DEA, such as the addressability of boundary limitations, sensitivity, and stability. They concluded that Spottiswoode's (2000) report still warrants careful consideration and that DEA is a practicable and effective measure for assessing the efficiency of police forces.

Drawing on this discussion, the present research still uses DEA as the main measure to assess police efficiency, though it will consider its weaknesses and try to avoid any misleading results.

3.4. DEA improvements

There has not been a police efficiency assessment carried out applying sophisticated quantitative methods to British data since 2002; as such, there is a pressing need for a contemporary study of police efficiency in England and Wales. It should also be pointed out that the main research problems in previous studies largely pertained to assessing which police force performed best, with less attention paid to how efficiency changes correspond to resource changes. In particular, there has yet to be any research on the relative success of different police forces in achieving efficiency with reduced central government funding during the period of austerity between 2010/11 to 2014/15. The National Audit Office (2015) reported that, after taking inflation into account, police funding fell by 18% into account from 2010/11 to 2014/15. It would be instructive if research could shed light on how police performance was influenced by such a drastic reduction in resources.

Figure 3.1 illustrates the future efficiency evaluation framework matrix which consists of four elements: improved models, comprehensive indicators, environmental factors considered, and new data.

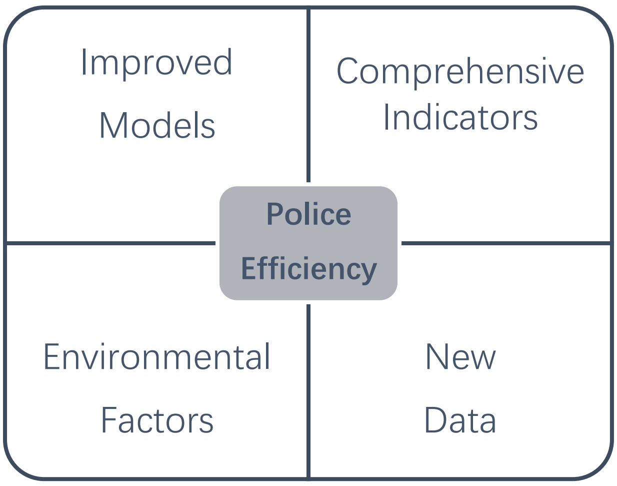

Figure 3.1. Further framework for the measurement of police efficiency

Since the DEA method was created by Charnes et al. (1978), it has been built upon and developed by many other researchers. Besides the assumption extension from constant to variable returns of scale (explained in section 2.4), several model variations and their applications to policing study are worthy of mention:

1. Cross efficiency: Sexton et al. (1986) and Doyle and Green (1994) developed the cross efficiency model, which is obtained by cross-computing target DMU with

other all DMUs. This method provides a good view of good and poor performance when distinguishing DMUs, such that it could be of use in police force efficiency scoring.

2. Network DEA: Fare and Grosskopf (1997) introduced more inner workings in the process, shifting the focus in DEA modelling from inputs to outputs. Static network DEA considers sub-activities that form a network. This could be used to measure intermediate different functions within one police force. Dynamic network DEA accounts for those activities in which one function impacts how the next function acts. When assessing both proactive outcomes (i.e. response time to target crimes) and response outcomes (i.e. clear up rate), the dynamic network DEA may be an optional method.
3. Non-controllable variables: Banker and Morey (1986) introduced "non-controllable" variables in DEA modelling to account for those input indicators that impact outputs, yet are beyond the control of individual DMUs. On this basis, it would be more appropriate to compare those DMUs with similar fixed variables. In policing studies, the socio-economic and demographic conditions in police force areas are typical non-controllable variables; therefore, under this model, they should be contrasted with similar peer forces.
4. Ordinal variables: Cook et al. (1993, and 1996) incorporated inputs and outputs of ordinal variables, which are fundamentally qualitative, not quantitative measures. Such an approach may be of help in a policing study using survey data, as questionnaire results usually provide ranking order.

By combining basic DEA with these variations, a more technical measurement of police efficiency may be achieved.

3.5. Indicator and environmental factor selection

By reviewing the previous indicators in the UK and novel ones put forward in non-UK studies, this research obtains an overall view of input and output variable selection combined with the three measures (the managerial efficiency measure, response/reactive efficiency measure, and proactive/preventative efficiency measure) highlighted in the Demonstration Project (Home Office, 2001).

However, the world is changing: the National Police Chief's Council (2017, p.8) stated that although the missions of policing remained constant, "globalisation and digitisation present new challenges that have increased the complexity of the police task." New threats and types of crime (i.e. cybercrime, organisational and serious crime, child-related crime, domestic abuse, terrorism) should be prioritised both in policing and when measuring policing. In response, new indicators representing new challenges and new priorities should be considered in the modelling. Besides, public confidence offers another lens through which police performance can be assessed. Those indicators illustrating public confidence can be added in as DEA variables or used to conduct an independent analysis.

As Drake and Simper (2005b) suggested, impacts from environmental factors could be evaluated in either DEA or external regression (econometric) models. Referring to Spottiswoode (2000), environmental factors, such as number of young men, stock of goods available to be stolen, and changes in consumer expenditure, also warrant inclusions in new DEA models.

It should be noted that comparability between police forces is of the utmost importance in this paper. The rationale here is that inefficient forces want to learn from efficient forces, they should look for a role model within their "peer family", as these forces will operate in similar socio-economic contexts. For example, an inefficient police force operating in an area with high unemployment and economic instability may struggle to draw lessons from an efficient police force in a relatively prosperous area with low unemployment. Although previous studies have suggested that the environmental factors could be treated as elements in the DEA models or external elements regression models, the later analysis in this paper does not directly incorporate environmental factors in the DEA. Instead, to conduct the measurement, the 43 police forces are grouped into several families according to their socio-economic and demographic characteristics. By doing so, the DEA scores (biased by the environmental factors) can then be compared within the relevant police family, allowing for lessons to be learned from police forces operating under similar conditions.

Although previous studies have put forward a range of external factors that could affect crime data, the further analysis in this paper will narrow its focus to a few comprehensive and representative variables that remain constant over time, such that each police force remains in a fixed family over time. Adopting such an approach is also important to ensure comparability between forces and also across different years. In the next chapter, a comprehensive indicator, the Indices of Multiple Deprivation 2015, is introduced to help group forces. This includes constant socio-economic factors, such as education, employment and health, in a series of regressions and selected for clustering analysis. The exclusion of other environmental factors (e.g. number of young men, consumer spending) introduces bias in the grouping of forces. The risk of such an approach is that those factors contributing to crime and policing may be overlooked. However, this will not have a major impact as most demographic and socio-economic variables are relevant, even endogenous, to the variables in the Indices of Multiple Deprivation. The purpose of grouping police forces is to provide a rough picture for similar forces to follow, not to predict crime data precisely; therefore, it is not necessary to exhaust all possible important factors when searching for those that may work.

3.6. Data support

Three types of data are accessible: official recorded data, survey data and social media data.

(1) Official recorded data

Official recorded data are available from the Office for National Statistics, including the socio-economic and demographic conditions of local areas, recorded crime data, and policing administrative data. The official data are directly taken from the government and police forces, meaning that they are comprehensive and can be systematised. The recorded crime data are annually or quarterly published for different types of crime. Additionally, the annual data are separately published and broken down by police force area level. Though this data has always been the first choice in police studies, they are not always as reliable as is expected.

Clarke and Hough (1984) pointed out that not all crimes are recorded by the police for various reasons: some victims do not report crimes, some crimes are not witnessed, and crimes may not be recorded due to the limitations of the police workforce. The ratios of recorded crimes to actual crimes vary across different crime categories. Therefore, to some extent, the official recorded data do not accurately reflect the actual criminal conditions of a police area. As a result, a supplementary dataset is required in this efficiency research to show the true extent of the crimes committed in England and Wales.

In section 4.3 (below) data interpretation will provide examples of crimes that are not reported to the police. In the Crime Survey for England and Wales 2015/16, Of the 10594 incidents in England and Wales, the police only attended 31% (3243) (the police did not attend 48% (5038) cases and the relevant information is not available for 21% of cases 2225). Interestingly, the two most common responses to "why not report" were "the cases are too trivial" and "he police could not do anything". This is problematic as it is difficult to ensure the reliability of the efficiency assessment when crime data may be under-reported. For present purposes, crime reporting is not only a factor influencing crime recording, but is also likely to be an endogenous element of efficiency. A number of researchers (e.g. Rader, 2017; Tarling & Morris, 2010) have shown that, at the individual level, if a resident has more trust in the police, they are more likely to report crimes. This may also be partly explained by the response "the police could not have done anything" in the last example. Therefore, if a police force has performed poorly and residents in that area have less trust in it, they may choose not to report the offences committed against them. As a result, the recorded data will give the misleading impression that there is less crime. This paper will conduct a further empirical analysis of the relationship between reporting, public trust and efficiency.

(2) Survey data

Crime survey data is mainly available from the Crime Survey for England and Wales (CSEW), which is an annual survey[14] on the crime experiences of interviewees derived through systematic sampling methods. The data present a more accurate picture of the actual crimes committed, as "hidden crimes" may be revealed in interviews. Thanks to CSEW, it is technically possible to estimate the actual crime before assessing the efficiency of police forces. However, although CSEW sampling is designed to adequately cover every police force area, the open dataset is not broken down by police force area. This is a barrier to adjusting the recorded data to the estimated actual data for each police force area.

Despite the weaknesses of recorded crime data mentioned above, there are many reasons why CSEW data is preferable in this research (Hales, 2018):

(a) When comparing the "comparable subset" of crimes before 2000, the police recorded data always records fewer crimes than the CSEW data;

(b) The recorded crime growth was stimulated by the introduction of the National Crime Recording Standard (NCRS) in 2002, though this has proven to be erosive where the NCRS has not been emphasised.

(c) When police performance and crime reduction are prevailing priorities, police are incentivised to not record crimes when possible.

[14] Before 2012, the survey was known as the British Crime Survey. It was carried out in 1982, 1984, 1988, 1992, 1994, 1996, 1998 and 2000. From 2001 onwards, it became an annual survey.

Therefore, the recorded crime data are not as reliable as the CSEW data (though the latter also has its own problems).

The other view of efficiency assessment pertains to public confidence. The CSEW interviews include content about satisfaction with the local police, which can be used in the efficiency assessment. In addition to the CSEW, local police forces completed the Victim Satisfaction Survey[15] on public confidence, as required by the Home Office and guided by the Survey Technical Advisory Group. What's more, in 2015/16 and 2016/17, the HMIC commissioned a third party to survey the public and consider the results in the PEEL assessment (Ipsos MORI, 2017).

(3) Social media data

Social media data can be extracted from social media platforms like Facebook and Twitter. For instance, by monitoring and analysing comments about policing and safety issues, public confidence in the police can be evaluated. In contrast to the systematic surveys mentioned above, data from social media cannot avoid bias as samples are drawn from those who post related comments or share experiences on social media platforms targeted by research. Clearly, those who do not express options online are fully excluded from the sample. Another problem is that anonymity creates doubts about the reliability of the data.

However, the tremendous potential of social media data means it is a good option when analysing public trust. Firstly, the data is updated in real-time, as opposed to quarterly or annually. Secondly, new crime and serious safety events are hot topics discussed on social media platforms, although most participants are neither victims nor witnesses. This feature fills in a gap since victim surveys are mainly interested in those experience involved in crime. Finally, accessible comprehensive information (like account handles and accurate post time) is helpful for tracking public views on a specific safety event.

[15] See an example at https://discover.ukdataservice.ac.uk/catalogue/?sn=7084 .

With the support of new forms of data, police efficiency can be measured more accurately.

3.7. Conclusion

The first three sections of this chapter reviewed how DEA models have been used to assess police efficiency in English and Welsh studies and summarised the selection of variables in British and international studies. Various suggestions were put forward relating to the selection of inputs and outputs and the treatment of environmental factors. It then moved on to discuss the controversy surrounding the use of DEA in measuring police efficiency. Some researchers pointed out the weaknesses of DEA and proposed other approaches for measuring efficiency; regardless, other researchers proposed solutions and further considerations to better apply DEA. Sections 3.4 to 3.6 explored developed methods in DEA, optional environmental factors, and the more innovative data that can be used. To ensure comparability within the family of police forces, this research will use environmental factors as external factors, rather than directly incorporating the variables in the DEA. Moreover, as many crimes go unreported to the police, this paper will consider using survey data and other new types of social media data instead of recorded crime data.

Below are empirical research questions to be developed in chapters 4-6.

1. In order to build an efficiency measurement system, which environmental factors are worth using to group police forces together? What inputs and outputs are representative? This question involves the selection of variables, the use of survey data and the assessment of the relationship between any variables.
2. How can the efficiency models be implemented and explained? How can the scale efficiency and pure technical efficiency results be explained? How can police forces be compared within their ‘families’ and over different years? This will involve DEA models and their interpretation.
3. Which police forces performed better than others during the period of austerity? Which forces improved their services? How have these forces been affected by budget cuts? This is a general picture of the results and their interpretation in the circumstances of budget reduction.
4. In the analysis of effectiveness, what kind of resource allocation can be shown to be related to performance? This will be explored using the regression method and detailed inputs corresponding to police functions will be evaluated.
5. When analysing public trust in policing, what kind of resource allocation is related

to performance? Is there a difference in public trust between victims and non-victims? This requires both regression analysis and testing the difference between samples.

6. Is there any new data other than the traditional survey data from the CSEW that can be used to assess public confidence in the police? How does this data work and how does it differ from traditional survey data? This can draw on social media data and provide a different perspective on public trust.

7. Is there a relationship between efficiency, effectiveness and public trust in the police? How and why is this the case? This requires an analysis that takes into account both the model results and the real world.

The empirical research based on these questions begins with the efficiency assessment in chapter 4.

4. Efficiency assessment

This chapter includes the DEA analysis based on police-recorded data from 2015/16 featuring the selected input and output indicators. The spatial variations among police force areas are discussed in terms of socio-economic factors and demographic factors, all of which are outside of the control of the police. As noted previously, similar police force areas are clustered in groups to allow for a comparison of their efficiency scores.

This chapter is structured as follows: Section 4.1 presents a simple DEA based on police-recorded data from 2015/16. Section 4.2 implements a method for clustering the police forces into groups to allow for the interpretation and comparison of DEA scores within peer groups; Section 4.3 introduces how the CSEW data can be utilised in outcome measures and outlines the variables required by DEA models. Section 4.4 presents the main DEA scores and 4.5 then discusses them within the specific police families. Section 4.6 discusses the scale efficiency scores and scale of police forces and Section 4.7 finally concludes this chapter.

4.1. Basic model using police-recorded data

Firstly, to determine the feasibility of employing DEA models in police performance research, the present research builds an initial model using recent data for England and Wales featuring two inputs and two outputs. The relevant indicators and data are listed below:

Input 1: Police workforce
Data: Total number of police officers, staff, community support officers, designated officers and special constables by police force area (sampled on 31st March 2016).

Input 2: Police expenditure
Data: Police service expenditure by police force area for the year ending 31st March 2016. Data are extracted from the Group Comprehensive Income and Expenditure Statement sections in the PCC's Statement of Accounts.

Output 1: Violent crimes
Data: Total number of violent crimes, including violence with injury and violence without injury, by force area for the year ending 31st March 2016.

Output 2: Non-violent crimes
Data: Total number of non-violent crimes by force area for the year ending 31st March 2016, including theft from the person, bicycle theft, shoplifting, all other theft offences, criminal damage and arson, domestic burglary, non-domestic burglary, vehicle offences, drug offences, fraud offences, homicide, miscellaneous crimes against society, possession of weapons offences, public order offences, robbery, and sexual offences

Though all previous British studies have used the number of crimes as either an input (see Thanassoulis, 1995) or an output variable (see Simper & Drake, 2000), the present research continues to use it as an output variable. This is appropriate as this research aims to examine how the police budget reductions have impacted the reallocation of policing resources and how this in turn has impacted efficiency. Data on resources, such as workforce (i.e. number of policing staff), are controlled by the police and can reflect the strategies used by police forces to cut costs. Additionally, though the number of crimes is set as an output variable to reflect the outcomes of policing, it cannot represent the full range of services delivered by the police. If the number of crimes was to be included as an input variable in this study, it could not accurately reflect the resources or situations that the police can control, amend, and reallocate.

The data for Input 1 and the two outputs are taken from the ONS. The decision-making units (DMUs) consist of the 43 police forces in England and Wales. The DEA model estimates the relative efficiency scores for all DMUs to illustrate whether they utilised their inputs efficiently and which forces better utilised their inputs than others. Table 4.1 lists the efficiency scores of 43 police forces in 2015/16. In this table, the score "1" means fully efficient overall, technical and scale efficiency. According to Drake and Simper (2000), when the return of scale assumption is "constant", it does not eliminate the impact of scale and the results represent "overall efficiency". Meanwhile, if the assumption is "variable", the impact of scale is removed, such that what is referred to as "pure technical efficiency". The corresponding "scale efficiency" score is the ratio of "overall efficiency" to" pure technical efficiency".

Table 4.1. DEA results of the initial model, data in 2015/16.

Police force	Overall efficiency	Pure technical efficiency	Scale efficiency
Avon and Somerset	0.856	0.893	0.959
Bedfordshire	0.793	0.906	0.876
Cambridgeshire	**1.000**	**1.000**	**1.000**

Cheshire	0.643	0.674	0.954
Cleveland	**1.000**	**1.000**	**1.000**
Cumbria	0.609	**1.000**	0.609
Derbyshire	0.708	0.708	**1.000**
Devon and Cornwall	0.561	0.600	0.935
Dorset	0.900	**1.000**	0.900
Durham	0.747	0.908	0.823
Dyfed-Powys	0.446	0.896	0.497
Essex	**1.000**	**1.000**	**1.000**
Gloucestershire	0.722	0.981	0.736
Greater Manchester	0.955	**1.000**	0.955
Gwent	0.724	0.888	0.815
Hampshire	**1.000**	**1.000**	**1.000**
Hertfordshire	0.865	0.867	0.998
Humberside	0.877	0.885	0.991
Kent	0.825	0.828	0.996
Lancashire	0.785	0.793	0.989
Leicestershire	0.811	0.819	0.990
Lincolnshire	0.835	0.986	0.848
London, City of	0.169	**1.000**	0.169
Merseyside	0.747	0.769	0.972
Metropolitan Police	0.660	**1.000**	0.660
Norfolk	0.640	0.771	0.830
North Wales	0.558	0.721	0.774
North Yorkshire	0.606	0.706	0.859
Northamptonshire	0.779	0.876	0.889
Northumbria	0.833	0.851	0.979
Nottinghamshire	0.801	0.811	0.988
South Wales	0.765	0.773	0.990
South Yorkshire	0.950	0.985	0.965
Staffordshire	0.940	**1.000**	0.940
Suffolk	0.813	0.925	0.879
Surrey	0.635	0.660	0.961
Sussex	0.733	0.739	0.991
Thames Valley	0.773	0.801	0.965
Warwickshire	0.768	**1.000**	0.768
West Mercia	0.764	0.814	0.939
West Midlands	0.761	0.805	0.945
West Yorkshire	0.937	**1.000**	0.937
Wiltshire	0.723	0.911	0.794

As shown in Table 4.1, in terms of overall efficiency scores, four police forces are fully efficient: Cambridgeshire, Cleveland, Essex, and Hampshire. Of the 43 forces, 12 police attain pure technical efficiency: Cambridgeshire, Cleveland, Cumbria, Dorset, Essex, Greater Manchester, Hampshire, City of London, Metropolitan Police, Staffordshire, Warwickshire, and West Yorkshire. Additionally, five police forces are fully efficient in scale: Cambridgeshire, Cleveland, Essex, Hampshire, and Derbyshire.

Although the two London police forces (City of London and Metropolitan Police) have low overall efficiency scores (0.169 and 0.660), they are fully efficient when scale economics is disregarded (i.e. pure technical efficiency scores of 1.000). Moreover, it is worth noting that Greater Manchester scored well for both pure technical efficiency and scale efficiency.

Figure 4.2 (below left) illustrates the relationship between workforce and scale efficiency in each police force's dataset. In this figure, City of London has the smallest scale (workforce=1177), while Metropolitan Police has the largest (workforce=47188). When these two outliers are removed, Figure 4.2 (below right) shows more a visible relationship: middle-scale forces attained higher scale efficiency than those small or large-scale forces.

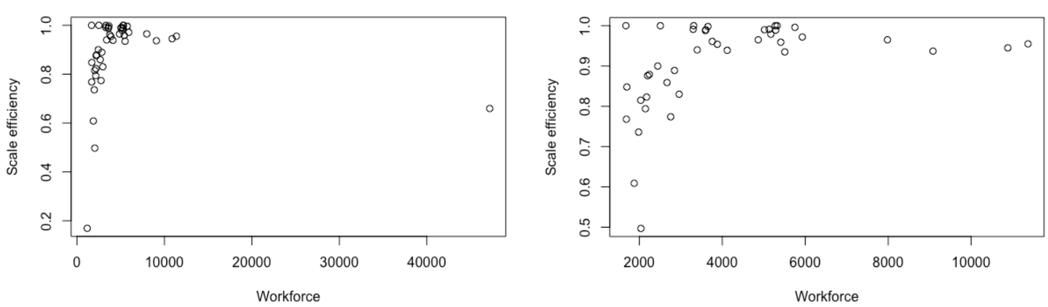

Figure 4.2. Workforce - Scale efficiency relationship with and without outliers.

In this way, pure technical efficiency and scale efficiency can be achieved through DEA models. However, as police force areas differ in socio-economic and demographic characteristics, they are not truly comparable. Those environmental factors that influence crime and policing conditions but are beyond the control of the police are discussed in section 4.2, whilst the use of survey data and the construction of variables are interpreted in section 4.3.

The initial model has two shortcomings that should be highlighted: The first is that the two inputs overlap in terms of staff payments, as total expenditure for each force also includes salaries and remuneration for all staff. The second is that the two outputs are the number of crimes, not crime rates; as a result, these outputs will be heavily impacted by the size of the population the police force area covers. Even if the Metropolitan Police (the force responsible for the largest population) were to perform perfectly in crime prevention, its number of crimes cannot be less than that in the City of London (the force responsible for the smallest population). From this perspective, crime rates would be better outputs than the number of crimes, especially in relation to a multi-year analysis.

4.2. Exogenous factors

The basic DEA model does not consider socio-economic and other variations between different police force areas; for the purposes of translating policing resources to outcomes, all areas are assumed to have the same conditions. However, there are many exogenous factors that fall beyond the control of police forces. Based on the empirical analysis of English and Welsh data, Carr-Hill et al. (1979) studied seven socio-demographic factors that influence criminal activities in different areas: the number of immigrants, female population, neighbourhood context, unemployment rate, social class, youth population, and family background. Later, Willis (1983), in a more in-depth piece of research, tested a statistical model for police resources, outcomes, and non-controllable factors. In this model, income, inequality, unemployment and population density were strongly correlated with the level of offence. To address concerns about the variations between different areas when assessing police efficiency in England and Wales, Thanassoulis (1995) proposed dividing the police forces into groups based on the socio-economic condition of the areas they are responsible for policing. Furthermore, he illustrated the unfeasibility of using the index of deprivation as an input variable: the index measurement only reflected the ranked level of each area, not the actual ratio-scale deprivation (e.g. 30% deprivation of economics).

To model the variations in exogenous factors, this section starts with the measurement of English Indices of Deprivation 2015 to understand the socio-economic factors and how they relate to police forces ’efficiency. As explained in section 3.5, this research focuses on a select few comprehensive, representative variables that remain constant over time, meaning that each police force remains in a fixed family over the analysis period. This is also important for comparability between forces and across years. Based on the above, the present research uses a comprehensive indicator—the Indices of Multiple Deprivation 2015—to group forces. This approach includes constant socio-economic factors (i.e. education, employment, and health) in a series of regressions and selects them for clustering analysis. The exclusion of other environmental factors (e.g. youth population or family background, as mentioned by the literature above) introduces bias in the grouping of forces. However, the purpose of grouping police forces is to provide a rough picture of similar forces and allow for comparison, not to predict crime data precisely. Therefore, it is not necessary to undertake an exhaustive search of all possible important factors that may work. Another advantage of using an integrated index is that it helps reduce dimensions: where there are too many variables to include but only 39 units to group, clustering analysis will be ineffective.

This section then examines two other factors not included in the Indices of Multiple Deprivation—inequality and the proportion of immigrants in the population—to determine whether they should be considered environmental factors. Finally, this section attempts to eliminate spatial variation by clustering police forces families according to the representative exogenous factors. Unfortunately, the Welsh and English indices of deprivation are not measured in the same way. Therefore, four Welsh forces are excluded from the following analysis (though they are included in the final comparison).

(1) Indices of Deprivation

The English Indices of Deprivation is a series of official statistics that capture the multiple dimensions of socio-economic deprivation of 32844 Lower-layer Super Output Areas (LSOA) in England. The measurement features seven domains: income; employment; education, skills and training; health and disability; crime; barriers to housing and services; and living environment. As the Indices of Deprivation are not published annually, the most recent version after 2010 was the English Indices of Deprivation 2015[16] (Smith et al. 2015) where most data are from 2012/13, and some data such as employment status are from the 2011 Census. Due to these data limitations, the socio-economic condition of each area is assumed to be constant during the 2011 to 2015 period, thus allowing for comparison with the DEA model based on data from 2011 to 2017. The measurement of domains and a summary of indicators are listed below (Smith et al. 2015):

- Income deprivation domain: measures the proportion of the population that is of low-income status. The indicator is that an individual is in receipt of low-income allowance and benefits.
- Employment deprivation domain: measures the proportion of the working-age

[16] Data available from: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015 Accessed at [17/05/2019]

population who are unable to work due to unemployment, sickness, disability, or caring responsibilities. The indicator is that an individual is in receipt of unemployment, disability, or caring allowance.

- Education, skill and training deprivation domain: measures the lack of qualifications and skills amongst children, youths, and adults. The indicators include the attainment of pupils, absence from education, and proportion of adults who have no or few qualifications.
- Health deprivation and disability domain: measures the deprivation in quality of life in terms of both physical and mental health. The indicators include the morbidity and illness rates recorded for various health problems.
- Crime domain: measures the risk of being a victim in a prescribed geographical area. Indicators aggregate the crime rates for all 45 types of crime.
- Barriers to housing and services domain: measures the geographical and financial barriers to accessing housing and key services. Geographical indicators include the distance from a post office, supermarket, primary school, and GP surgery; financial indicators measure household space, homelessness, and housing affordability.
- Living environment deprivation domain: measures the quality of the living environment, both indoors and outdoors. Indicators include housing in poor conditions, poor air quality, and elevated road traffic accident rates.

Although each area is scored for all seven domains, only the income and employment scores are indicative of the actual proportion of the population that is deprived (the scores of the remaining five domains are not directly representative of deprivation in a given population). PFAs with higher scores experience more severe deprivation than those with lower scores. In the English Indices of Deprivation 2015, the seven domains are aggregated to calculate the Index of Multiple Deprivation (IMD), which also included corresponding weights[17]. The 32844 small areas were then ranked according to their IMD scores. As an aggregated index including a crime domain, IMD cannot be

[17] Weights for IMD calculation: income 22.5% , employment 22.5%, education skills and training 13.5%, health and disability 13.5%, crime 9.5%, barriers to housing and services 9.5%, living environment 9.5%.

directly applied to identify which factors influence criminal activities, as this may give rise to endogeneity problems. However, as the research report (Smith et al. 2015) suggested, a modified IMD could be applied by removing the crime domain and any weakly crime-correlated domains.

Firstly, scores in seven domains for each police force area (PFA) are calculated. The score for each PFA is the population-weighted[18] average of all LSOA scores within the PFA in question. The 39 PFAs 'scores are summarised in Table 4.2. As can be seen, the two London police areas (Metropolitan Police and City of London) are outliers, most likely due to the nature of policing the capital city, as well as their extremely large and small sizes, respectively.

Next, the Pearson's correlation between each two domain scores is calculated and hypothesis testing is carried out to determine whether the coefficient is different from 0. The correlation coefficients for PFAs including and excluding London police areas are shown in Tables 4.3 and 4.4, respectively. In the tables, a correlation coefficient value marked with an asterisk "*" indicates that the p-value is less than 0.05, such that the correlation is significantly different from 0, while a value without the asterisk represents an insignificant correlation. In both tables, Crime is strongly correlated with Income, Employment, Education and Health, though no correlation was found with Barriers and Living (-0.5 < correlation coefficient < 0.5, or p-value > 0.05). Notably, the two London outliers make little difference to the correlation test as the main relationship does not change.

From the correlation test, it is concluded that Crime exhibits the strongest correlation with Income (0.7), followed by Employment (0.58), Education (0.57), and Health (0.49). Meanwhile, Income, Employment, Education and Health are strongly correlated with each other (most coefficients are approximately 0.8 or higher). On this basis, Income should be taken as a core factor when socio-economic conditions are discussed in conjunction with Crime. Moreover, the Income Deprivation factor does not measure

[18] For the employment domain, the weight is the working-age population. For the remaining six domains, the weights are the total population within LSOA.

total household income or the distribution of income in a given area. Instead, it represents the proportion of the population that is low-income, without providing further information on the rest of the income distribution. In this way, it is more of a measurement of poverty in an area. As the data sources for Income cover a part of the unemployment statistics, it is reasonable that Income is strongly correlated with the Employment factor.

Table.4.2. Summary of domain scores for 39 PFAs in England.

	Min.	Median	Mean	Max.
Income	0.059 (London, City of)	0.132 (Lincolnshire)	0.135	0.218 (Merseyside)
Employment	0.047 (London, City of)	0.111 (Kent)	0.115	0.192 (Merseyside)
Education	4.069 (London, City of)	23.004 (Durham)	21.961	33.778 (South Yorkshire)
Health	-1.030 (Suffolk)	-0.183 (Metropolitan)	-0.037	1.078 (Merseyside)
Crime	-1.220 (London, City of)	-0.186 (Warwickshire)	-0.156	0.561 (Metropolitan)
Barriers	13.18 (Merseyside)	21.29 (Avon and Somerset)	21.14	30.74 (London, City of)
Living	6.866 (Durham)	19.778 (Dorset)	20.613	48.252 (London, City of)

Table 4.3. Correlation coefficients between domains, English PFA samples including Metropolitan and City of London.

	Income	Employment	Education	Health	Crime	Barriers	Living
Income	1.00*						
Employment	0.97*	1.00*					
Education	0.77*	0.80*	1.00*				
Health	0.90*	0.96*	0.74*	1.00*			
Crime	0.70*	0.58*	0.57*	0.49*	1.00*		
Barriers	-0.45*	-0.58*	0.49*	-0.62*	-0.33*	1.00*	
Living	-0.02	-0.08	-0.21	0.01	0.15	0.36*	1.00*

*p-value < 0.05.

Table 4.4. Correlation coefficients between domains, English PFA samples excluding Metropolitan and City of London.

	Income	Employment	Education	Health	Crime	Barriers	Living
Income	1.00*						
Employment	0.98*	1.00*					
Education	0.82*	0.8*	1.00*				
Health	0.91*	0.96*	0.74*	1.00*			
Crime	0.67*	0.57*	0.59*	0.50*	1.00*		
Barriers	-0.48*	-0.56*	-0.28	-0.62*	-0.39*	1.00*	
Living	0.19	0.18	0.22	0.25	0.15	0.05	1*

*p-value < 0.05.

After selecting the correlated factors influencing crime in this measurement, the following formula is used to calculate a modified IMD (MIMD) score for each PFA:

$$MIMD_i = 22.5\%Income_i + 22.5\%Employment_i + 13.5\%Education_i + 13.5\%Health_i,$$

where *i* is the PFA. The initial weights for each domain in IMD were proposed by Smith et al. (2015): income 22.5% , employment 22.5%, education skills and training 13.5%, health and disability 13.5%, crime 9.5%, barriers to housing and services 9.5%, and living environment 9.5%. In an MIMD, weights preserve the original proportional relationship between domains; however, as three domains have been removed, they do not add up to 1. Once the scores for each domain are exponentially transformed, all the values of different domains are measured in a standardised system and can thus be aggregated[19]. The correlation between MIMD and Crime (exponentially transformed score) is tested again using the Pearson method, revealing a significant relationship (correlation coefficient 0.634 and a p-value below 0.001).

Figure 4.3 illustrates the moderately strong, positive association between MIMD and the Crime domain. Thus, the factor MIMD can be employed as a comprehensive socio-economic measure of social-economic status.

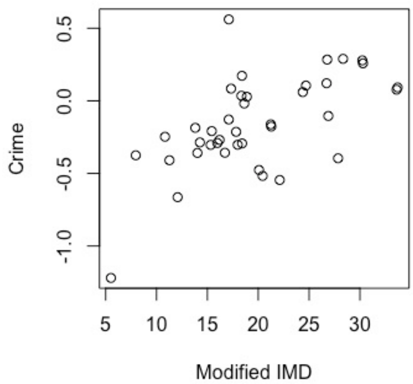

Figure 4.3. Relationship between Modified Index of Multiple Deprivation and Crime, 39 PFA samples in England.

[19] Data available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/467776/File_9_ID_2015_Transformed_domain_scores.xlsx Accessed at [17/05/2019]

(2) Income inequality

Income inequality is also a factor worth analysing, as is reflected by the substantial body of research confirming its significant effect on crime levels (Hsieh & Pugh, 1993; Kelly, 2000; Fajnzylber et al. 2002; Brush 2007). Different methods can be used to quantify income inequality: the Gini coefficient for nationwide inequality; the proportion of the population with income less than 60% of the median; standard deviation; or a simple indicator of the mean divided by the median. Although there are many published datasets about income and wealth inequality for nationwide or income surveys within a local area, the whole income distribution at the police force area level is unavailable for England and Wales. Moreover, the published official data on average household income in small areas are not sufficiently precise to estimate income inequality between individual households. For example, in their mixed-effect regression study on inequality and crime rates, Whitworth (2012) estimated and employed the Gini coefficient to measure inequality for both Crime and Disorder Reduction Partnerships (CDRPs) and PFAs, based on 2004/05 mean household income in each Middle-Layer Super Output Area (MSOA). When estimating the Gini coefficients for local areas in this manner, the use of mean household income treats all households in a given MLSO as same-income households, as the mean values do not reveal the distribution of household income within an MLSO. Thus, this method of Gini estimation is more of a measure of income inequality between MLSOs within the PFA (or CDRP), as opposed to an accurate measure of the difference between low- and high-income households. In this research, income inequality is found to have a significantly positive impact on crime rates (i.e. crime rates increase).

At this point, a simpler measure of inequality is introduced. This research calculates the standard deviation of Income domain scores in the Indices of Deprivation 2015 within each PFA as an alternative inequality indicator. As described above, the Income domain scores measure the proportion in receipt of low-income-related allowances and benefits. Notably, this Inequality factor also measures the poverty variations among small areas (LSOA) within a PFA, not the difference between low- and high-income groups. The standard deviation measure uses the same level of information as the local Gini estimation: both use only a single value (property ratio and mean income, respectively) to represent the income of a small area, not the entire income distribution. Additionally, there is no need to use the population weights of LSOAs in the standard deviation calculation because LSOAs consist of homogenous, evenly-sized areas containing approximately 1500 people (Smith et al., 2015). In this measurement, the most equal PFA is Surrey (sd.= 0.0478), the most unequal is Cleveland (sd.=0.1496) and the median is Northamptonshire (sd.=0.0877). The correlation coefficient between the Inequality and Crime domain scores is 0.540, and the p-value is less than 0.001. These results suggest that inequality within a PFA may be positively associated with crime level.

(3) Immigration

Immigration is another commonly mentioned factor in criminal econometric models. Though classic studies regard immigration as an impact factor, more recent research (Reid et al., 2005; Bell et al, 2013) has found little to no evidence of the relationship between immigration and crime. The English research mentioned above (Whitworth, 2012) also considered immigrants as a social-demographic explanatory variable in the mixed-effect regression using the indicator of non-white population). Interestingly, the results showed that immigrants had a significant positive association with high crime rates. In their recent review featuring both qualitative and quantitative research, Ousey and Kubrin (2018) concluded that researchers observed a relationship between immigration and crime whilst others did not. Moreover, study designs were found to have a more important impact on the research results.

The designs of immigration measure, crime measure, unit of analysis, destination context and longitudinal approach vary across the research that has been carried out to date. The most frequently used immigration measure is the percentage of the population that is foreign-born, though the results are different. Allen and Cancino (2012) found that the percentage of foreign-born had a negative association with juvenile crime in urban counties, but not rural counties, based on a set of 18-year data sampled in the Texas borderlands. However, in this study, ethnic heterogeneity was found to be positively associated with juvenile crime. Elsewhere, based on an empirical model in the rural U.S., Deller and Deller (2010) also measured immigration by the foreign-born population as a proportion of the total population, remarking that immigration is significantly positively correlated with the crime rates of seven types of crime.

Another American study in Chicago carried out by Graif and Sampson (2009) indicated that the foreign-born percentage of the population is unrelated or even inversely related to household homicide rates. Later, covering established and new destination cities in the US, Ramey (2013) found a positively relationship between the proportion of immigrants (especially recent immigrants) and violent crime rates. The problem with a single, whole measure of immigrants such as these, is that it neglects differences between groups of immigrants. It should be pointed out that other studies have focused on the impact of recent immigration (Nielsen et al. 2005; Stowell & Martinez 2007; Martinez et al. 2008) or immigration of particular ethnicities (Martinez, 2000; Shihadeh & Barranco, 2010, 2013).

This section now moves on to construct a migration factor to capture the variation in immigration conditions among English PFAs. Long-term immigration estimation data are published annually by the ONS at the Local Authority District (LAD) level. This research uses the data from 2013, which are the most consistent with the Indices of Deprivation 2015 data. Migration inflows and outflows are recorded at the LAD level; however, it is hard to identify whether the flows are inside or outside the PFA. As such, migration flow data are not available at the PFA level. Fortunately, long-term international immigration data are available, which may be the sum of all LADs within the same PFA[20]. Additionally, as this section is seeking a constant representation of PFA's socio-demographic conditions for later analysis of police forces in 2011-2017, the model does not consider short-term international immigration. There are two sets of data published by the ONS that involve long-term international immigration: non-UK-born and non-British estimates. This research chooses the "non-UK born estimate" indicator to represent the immigration proportion because it shows a stronger correlation with Crime domain scores in Pearson's correlation testing. Then the formula is Immigration = (non-UK born estimate) / (resident population)(note that this data is not available for City of London because its total population estimate in 2013 is only 6000).

[20] Data available from: https://www.ons.gov.uk/file?uri=/peoplepopulationandcommunity/populationandmigration/migrationwithintheuk/datasets/localareamigrationindicatorsunitedkingdom/current/publicviewmastercopylocalareamigrationindicatoraugust2018.xlsx

In this measurement, the PFA with the highest Immigration value is Metropolitan (0.359), while the lowest is Derbyshire (0.027) and the medians are Humberside (0.061) and West Mercia (0.067). Correlation testing of Immigration and Crime shows returned a coefficient value of 0.42 and a p-value below 0.01. Thus, at the PFA level, crime level and long-term international immigration may be positively correlated. Figure 4.4 illustrates the relationship between Immigration and the Crime domain, from which it can be seen that Metropolitan is the clear outlier.

(4) Linear regression analysis

To test the relationship between Crime, MIMD, Inequality, and Immigration, a multiple linear regression method is applied to analyse the 37 PFA samples (excluding City of London and Metropolitan). The dependent variable is Crime and the covariate includes MIMD, Inequality and Immigration. The first linear model shows that it is not appropriate to include Inequality and MIMD in the same covariate due to the phenomenon of collinearity. In response, the second linear model removes Inequality as a factor. The latter model produces more convincing results as all the coefficients of covariates become significant (see Table 4.5 below).

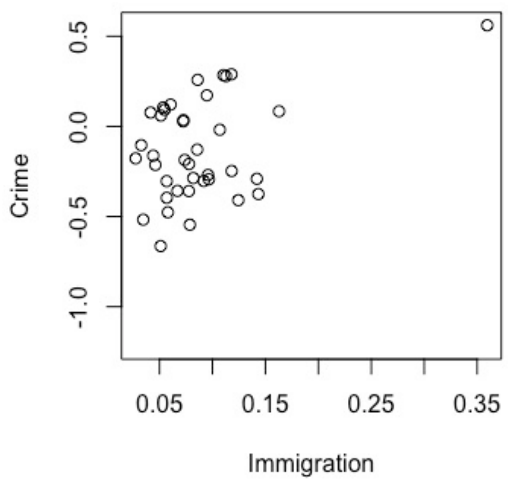

Figure 4.4. Relationship between Immigration and Crime, 38 PFA samples in England.

Table 4.5. Linear regression: Crime ~ MIMD + Immigration.

Coefficients:	Estimate	Std. Error	p-value
(Intercept)	-0.980207	0.119563	1.17e-09
MIMD	0.029614	0.004715	3.30e-07
Immigration	2.958405	0.537981	3.53e-06

Returning to the construction of the variables, the raw scores for the crime domain in each small area LSOA is measured using an aggregate crime rate of 45 types of crime (i.e. the raw dataset does not include an actual crime rate). After aggregating the crime domain for all LSOAs in the same police force areas, the Crime variable represents the deprivation score for PFAs (again, not an actual crime rate). The value of Crime is between -1 to 1; the higher the value, the greater the possibility of being victimised in a given police force area. In Table 4.5, the coefficients of MIMD are 0.0296 and 2.9584, which are diverse. This is a reasonable result because MIMD is a score that ranges from five to fifty. Moreover, Immigration is a real proportion of immigrants (non-UK born and long-term, to be specific) that only takes values between zero and one. The positive coefficient 0.0296 of MIMD means that if the deprivation of an area worsens from 30 to 31 and the Crime score increases by 0.0296. Meanwhile, the positive Immigration coefficient of 2.9584 means that if the proportion of immigrants in a police force area increases by 1%, the value of Crime will increase by 0.029584. This indicates that both MIMD and Immigration play an important role in the model.

The linear covariates can explain 54% (Adjusted R-squared) of the variation in Crime. Meanwhile, the two exogenous factors, MIMD and Immigration, both form significant (p-values of the coefficients are less than 0.001) and positive associations with high crime levels. Also, the whole linear model is significant (the F-statistic's p-value is less than 0.001). These results give rise to the issue of how it can be demonstrated that for this dataset at least, an understanding of Immigration is necessary to explain variations in Crime.

In response, another linear model Crime ~ MIMD was constructed. However, when Immigration is removed, the model only explains only 46% (Adjusted R-squared) of the variations in Crime. Hence, it can be concluded that adding Immigration into the linear relationship helps to explain the criminal environment. The model results set out in Table 4.5 do not mean that it is only non-UK-born immigrants who commit crimes or that immigrant populations increase crime rates. To be precise, immigrants' preferences for where to live in the UK are shaped by a range of factors, including job opportunities, social amenities, and cultural diversity, some of which are not included as IMID indicators. For present purposes, the Immigration variable is a demographic indicator pertaining to a defined area that is a composite representation of the socio-economic conditions underpinning it.

Based on the above discussion, this section concludes that Modified IMD and Immigration could be the exogenous factors that explain the uncontrollable conditions for policing among PFAs.

(5) Cluster Analysis

Figure 4.5 presents the socio-economic and immigration conditions of PFAs in England (the City of London is excluded due to missing data). As two factors are identified above, it is feasible to cluster police forces based on these two dimensions to allow for police forces with similar conditions in the same police family to be compared. The Metropolitan force is the apparent outlier and as such should be excluded from the cluster analysis. The K-means method is applied to calculate the center and scale, whilst the number of clusters (k) is set as 5. The values for these two dimensions are scaled before clustering. Figure 4.6 visualises the clustering results using different colours for different groups. It can be gathered from the figure that police forces in the same family have more similar levels of immigration and MIMD than police forces in other families.

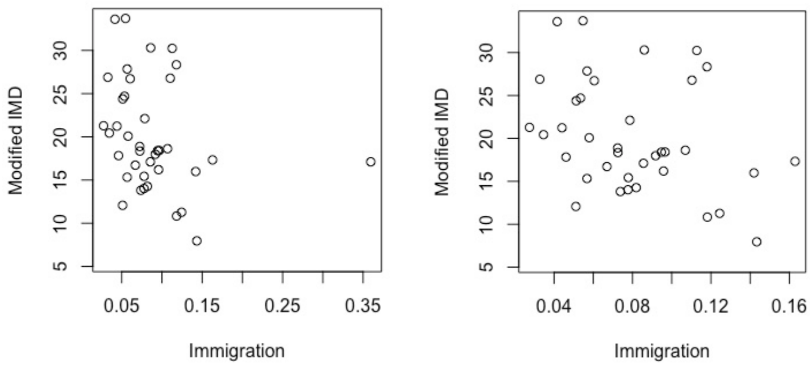

Figure 4.5. Socio-economic and immigration conditions of PFAs in England, including and excluding Metropolitan respectively.

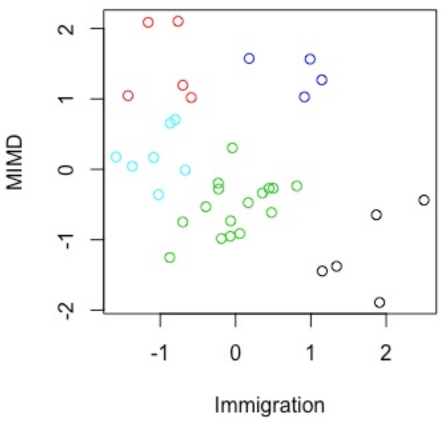

Figure 4.6. Clustering results, PFAs in England, excluding Metropolitan Police and City of London. Values are pre-scaled before clustering.

The members of each police force group are listed in Table 4.6. Due to missing data, the City of London is removed from further analysis and assigned to Group 0. Group 1 is the Metropolitan Police, which will be discussed in further analysis. Group 2 includes four Welsh police force areas' these are excluded from the clustering analysis because the Welsh and English deprivation data are not standardised. As this precludes comparison of the data, the relationship between environmental factors and crime is not examined in the Welsh data. Nevertheless, it is still reasonable to group all Welsh forces together, as their performance can be compared with their efficient peers (if there are any). Group 3 (the black points in Figure 4.6) has a high proportion of immigrants and a low MIMD (low deprivation); conversely, Group 4 (the red points in Figure 4.6) has a low proportion of immigrants and a high MIMD (high deprivation). Group 5 (the green points) feature the family consisting of the most police forces, which has a low-to-middle proportion of immigrants and a low-to-middle MIMD. Group 6 (the purple points) has a middle proportion of immigrants and a high MIMD, whereas Group 7 (the light blue points) has a low proportion of immigrants and a middle MIMD.

Regarding the extent to which crime levels vary between forces within a single family, for all 37 forces (the two London forces are excluded) the overall standard deviation in Crime is 0.328. The standard deviations for Groups 3-7 are 0.1963, 0.217, 0.215, 0.014, and 0.238 respectively. These are acceptable as the standard deviations in groups are all substantially lower than the overall standard deviation, indicating that the Crime values tend to be concentrated within each family. Group 6 exhibits extreme convergence in Crime, with a standard deviation of just 0.014. This could be due to the fact that the deprivation and immigration variables are highly similar for forces in this family.

Table 4.6. Police force family allocation according to socio-economic and immigration factors, England and Wales.

Group 0 (1 force)	London, City of	
Group 1 (1 force)	Metropolitan Police	
Group 2 (4 force)	Dyfed-Powys Gwent	North Wales South Wales
Group 3 (5 forces)	Bedfordshire Cambridgeshire Hertfordshire	Surrey Thames Valley
Group 4 (5 forces)	Cleveland Durham Humberside	Merseyside Northumbria
Group 5 (16 forces)	Avon and Somerset Devon & Cornwall Dorset Essex Gloucestershire Hampshire Kent Leicestershire	Norfolk North Yorkshire Northamptonshire Suffolk Sussex Warwickshire West Mercia Wiltshire
Group 6 (4 forces)	Greater Manchester South Yorkshire	West Midlands West Yorkshire
Group 7 (7 forces)	Cheshire Cumbria Derbyshire Lancashire	Lincolnshire Nottinghamshire Staffordshire

Below, the most notable similarities among the police forces in each family in terms of size, geography, and socio-economic status are highlighted. A map of the police force area in England and Wales, marked by the group number, is included in Appendix I.

Group 1: Metropolitan Police

This group consists of only one police force. It is the largest force in England and Wales, featuring the most prosperous economy and diverse culture.

Group 2: Welsh police force areas

Wales is a predominantly rural country, with large areas of open countryside and a relatively small number of large urban areas. Compared to England, Wales has a much lower urbanisation rate and a higher ageing rate. According to the 2011 Census, 19% of the Welsh population can speak Welsh, compared to only 1% in England.

Group 3: Southeast and diverse areas

The five police force areas in this group are all located in the southeast of England and border each other. Additionally, they are either adjacent or close to the Metropolitan Police and enjoy prosperous economies and less social deprivation. The distinctive feature of this area compared to other neighbouring areas (i.e. Group 5) in the southeast of England is that there are many more immigrants.

Group 4: Northern and deprived areas

The five police force areas in this group are all located in the north of England. They are all former industrial areas that have undergone economic restructuring over the past several decades. The populations in these areas have high levels of unemployment and low levels of education and skills. This group is distinguished from its neighbouring areas (i.e. North Yorkshire in Group 5 and Lancashire in Group 7) by its deprivation and poor socio-economic conditions.

Group 5: Typical areas

This group includes most police forces that are neither affluent nor deprived, nor are they in an area with very high or low numbers of immigrants. It includes all the southern coastal areas in England and some central and northern areas, encompassing a mix of urban and rural areas.

Group 6: Large-size areas

This group includes the four of the largest police forces in terms of police workforce and population in the area (‘largest’ in this sense does not refer to the land size of the area). The forces in the group are located in the central and northern parts of England, covering both large urban areas and their surrounding towns.

Group 7: Central-northern areas

Five of the seven forces in this group border each other in central England, whilst the other two are adjacent but to the north. They have a relatively low level of ethnic diversity and a relatively higher proportion of older residents than other parts of the UK. This group is a cluster of the force areas with the lowest level of international immigrants and they are less deprived than Group 4. Additionally, they differ from other neighbouring forces in the central region (i.e. Group 6) in that their population size is normal.

This section discusses how to group forces by referring to socio-economic indicators and explains its results. The groups will repeatedly be referred to in the following sections when performance is compared within force families.

4.3. CSEW data and variable selection

In section 4.1 recorded crime data from the police are used to produce a DEA model designed to measure the efficiency of the 43 English and Welsh police forces. In light of the inaccuracies of police-recorded crime data (discussed in section 3.6), CSEW data is introduced to accurately capture the crime level in England and Wales. Variables are selected from the CSEW dataset to represent various aspects of police performance at the police force level, whilst other variables relevant to the workforce and policing expenditure are retained from the official data. Once the variables have been selected, the annual efficiency measurements for the years 2011/12 to 2017/18 can be calculated using the DEA method.

(1) Feasibility of CSEW data

Since 2011/12, the Crime Survey for England and Wales (CSEW) has gathered data from over 40000 core samples annually, with at least 1000 interviews conducted in each police force area (except for the City of London due to its size). In addition to the adult samples aged 16 to 59, the survey data also includes children aged 10 to 15, though the children sample is much smaller than the adult group. For example, in 2011/12, only 4000 children were sampled for the dataset). Broadly speaking, response rates are high (e.g. 75% in 2011/12). To eliminate the bias stemming from non-responses, the data provider advised weights to be used to adjust future analysis.

For all adults aged 16 to 59, the main questionnaire consists of several modules, such as the demographic characteristics of the individual and household, experience of crime in the previous 12 months, and attitude to the police and the criminal justice system (CJS). Some modules are posed to all respondents, whilst others are posed to randomly allocated sub-samples. In addition, those who confirm that they had experienced criminal incidents are directed to a further victimisation form, which elicits further details of every incident and the associated contact with the police. Address sampling for adults uses a combined method featuring clustered and unclustered sampling to reduce the over-sampling problem and the effect of demographic characteristics. Finally, where adults are in the sample pool, children are randomly selected from their households.

Further steps have been taken to reduce sampling bias. To be precise, every individual, household, and incident is paired with a weight (e.g. IndivWg*t* for individuals, HhdWgt for households and weight for incidents in 2011/12), which is estimated on the basis of socio-demographical diversity, intentional over-sampling of certain groups, and non-response impact. To derive a more accurate picture of crime levels or public confidence, crime levels should be calculated in conjunction with either an individual or household type of weight. This will depend on whether the problem is individual- or household-related. Moreover, for victim cases, the clear-up rate should be calculated in association with the incident weight.

It should be noted that CSEW 2011/12 recorded all the interviews conducted between April 2011 to March 2012, whilst the questionnaire asked about all victimisation experiences that took place in the 12 months prior to the interview. For example, on 15th July 2011, the interview asked the respondent if they had experienced any personal violence between 1st July 2010 and 30th June 2011. Hence, the data in CSEW 2011/12 covers the period from April 2010 to February 2012. Figure 4.7 shows the reference period covering one year of CSEW interviews (March is the only month that all interviews cover). According to the time period design, the CSEW 2011/12 results are most comparable with recorded crime and administrative data from Oct 2011 to Sep 2012.

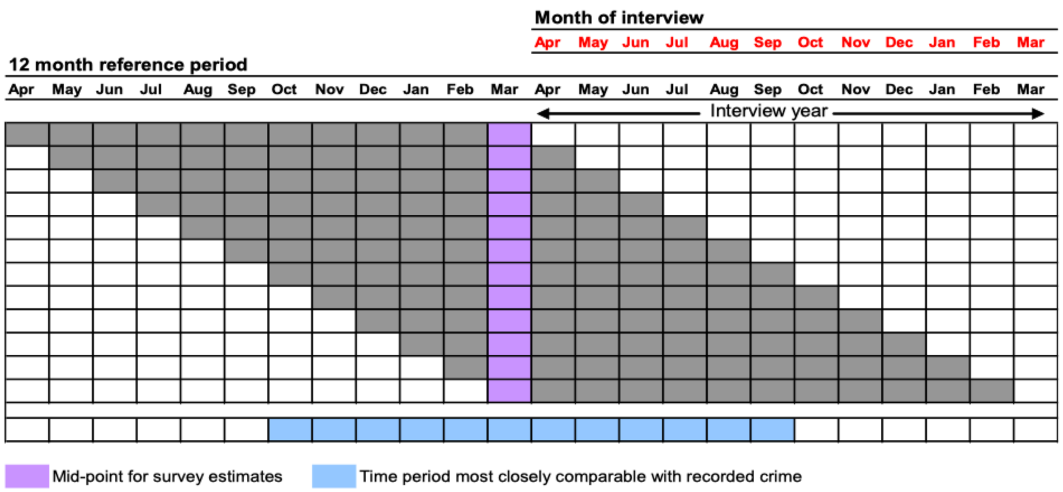

Figure 4.7. Reference period in one year of CSEW interviews

Regarding the coverage of offence types, CSEW covers most categories recorded by the police, including actual offences and “attempted” offences, though homicide and “possible” incidents are excluded. There are also screening questions about household incidents and individual incidents included in the questionnaire; the former ask about household property loss, while the latter focus on personal property and violence. Every respondent has a unique case identifier paired with the LSOA code, from which the location can be determined.[21] Crucially, this code allows for respondents and their answers to be linked to a police force area, thus allowing the crime rates and public confidence in policing to be estimated.

It should be stressed that although the police-recorded data are more accessible, the CSEW crime data still warrant analysis. Take CSEW 2015/16 as an example: the victimisation form featured the question "Did the police come to know about the matter?" Of the 10594 incidents in England and Wales, the police only attended 31% (3243) (the police did not attend 48% (5038) cases and the relevant information is not available for 21% of cases 2225). Table 4.7 illustrates how the "the police come to know" ratio varies by crime type, with "vehicle stolen" receiving the most attention and "online fraud" receiving the least. Where the answer to the above questions was "no", the next question was "Why not?". Respondents were then provided with 19 choices, from which they could select those that were applicable to their case. Figure 4.8 shows the five most common answers to this question. Specifically, some cases were not reported because the victims thought the case was trivial, whilst, in others, the victims did not believe the police could have done anything.

[21] The location information is available when the data provider agrees to grant it. Access can be applied for through the UK Data Services' Secure Lab.

Table 4.7. "The police come to know" ratio in 2015/16, England and Wales.[22]

	Crime category	Crime type	Ratio
1	Motor	vehicle was stolen or driven away without permission	94.59%
2		something was stolen off or out of vehicle	39.82%
3		vehicle was tampered with or damaged	29.77%
4		bicycle was stolen	49.07%
5	Household property	Someone got into current residence to steal/try to steal (movers)	79.11%
6		Someone got into current residence and caused damage (non movers)	72.30%
7		Someone tried to get into current residence to steal/cause damage	53.03%
8		Something was stolen out of current residence	31.94%
9		Something was stolen from outside current residence	33.89%
10		Something was damaged outside current residence	48.95%
11	Personal property	Something was stolen out of hands, pockets or bag	58.52%
12		Someone tried to steal anything from hands, pockets or bag	78.49%
13		Something has been stolen from a cloakroom, office etc.	81.77%
14		Personal items have been deliberately damaged	48.28%
15	Personal violence	Someone has deliberately used force/violence on adult respondent	30.01%
16		Someone has threatened to damage things/use force or violence	27.31%
17		Adult respondent has been sexually assaulted or attacked	43.29%
18		Member of household has used force or violence on adult respondent	49.81%
19	Cybercrime	Fraud or cybercrime involved in any incidents mentioned at non-fraud screeners	20.07%
20		Personal information or account details used to obtain money or buy goods or services	21.44%
21		Tricked or deceived out of money or goods in person, by telephone, or online	26.49%
22		Someone tried to trick or deceive you out of money or goods in person, by telephone, or online	52.14%
23		Someone stole personal information or details held on computer or in online accounts (e.g. e-mail, social media)	39.05%
24		Computer or other internet-enabled device has been infected or interfered with e.g. by a virus	32.05%

Data source: Crime Survey for England and Wales, 2015/16.

[22] The CSEW survey was conducted on a household basis, so it does not include crimes against people living in institutions or against the homeless.

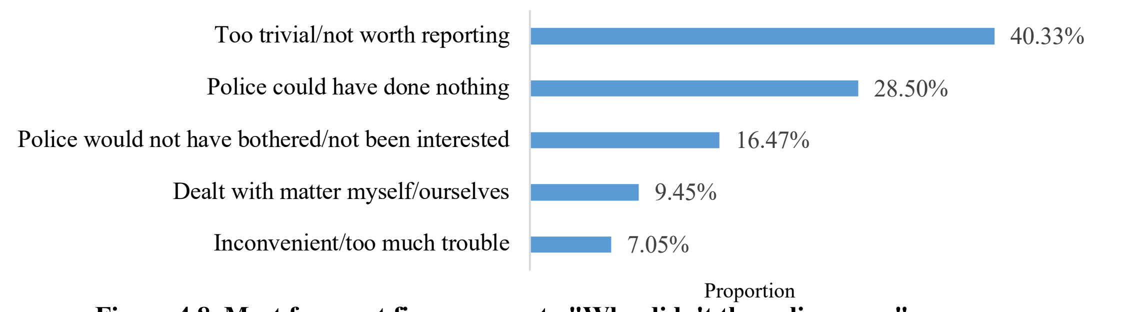

Figure 4.8. Most frequent five answers to "Why didn't the police come", England and Wales, 2015/16.

Data source: Crime Survey for England and Wales, 2015/16.

Comparisons between CSEW data and police-recorded data highlight further evidence of hidden crime. Taking sexual offences as an example, Figure 4.9 shows the difference between the crime rates of sexual offences in England and Wales from 2011/12 to 2017/18. The police-recorded crime rate is calculated as the number of recorded crimes divided by the mid-year population estimates; contrastingly, CSEW crime rates are calculated as the number of incidents divided by the number of respondents with the paired individual weights. This result implies there has always been a large amount of hidden sexual offences not recorded by the police.

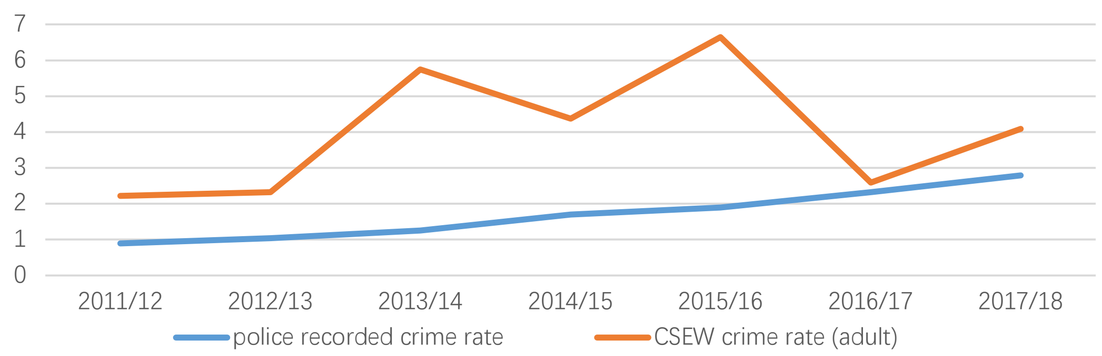

Figure 4.9. Crime rate (per 1000 population) estimation of sexual offences

Data source: Police recorded crime, and mid-year population estimates, ONS and CSEW 2011/12 to 2017/18.

It is important to introduce the CSEW data into the research as they are not merely replicating the same information as is represented in the police-recorded crime rates. However, in addition to the sampling and weighting bias issues, the CSEW data have limitations. Firstly, CSEW includes only a small number of child participants. In England and Wales in 2011/12, only about 4000 children aged 10 to 15 were included, and no child under 10 was included. As a result, the CSEW data may not reflect the full extent of crimes against children. Secondly, the CSEW survey was conducted on a household basis, so it may not reflect crimes against people living in institutions or the homeless, and also miss corporate fraud. A more detailed discussion of the questionnaire issues and the consistency of questions will be discussed in relation to the selection of variables. Importantly, all these potential problems should be accounted for when interpreting the DEA models.

(2) CSEW questionnaire and variables

This section selects representative variables to measure police performance. The police duties and selected indicators in previous research were discussed in sections 1.2 and 3.1. When assessing whether a given police force performs its duties well in the present research, three outputs are considered: residents' fear of crime; residents' experiences of crime; and policing activities following an incident.

a) Fear of Crime

In CSEW 2011/12 to 2017/18, Fear of Crime (FC) is assessed by a series of questions posed to the module C and D samples by the question "How worried are you about (different types of crime)? [1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not worried at all]". An aggregate value of worry for all individuals is also required in this study. If an average is taken, this entails transferring the ordinal category to a numeric variable that has realistic meaning with any rational value between 1 and 4. This is reasonable because it does not change the order of worry level – smaller values still indicate a greater degree of concern – and the difference between any two values can represent a variation in worry level. At the same time, this is problematic as all types of crime are treated with the same importance, which is most likely not how individuals perceive crime. There is also a limitation of the scale with no neutral values; for example, a value of 2 indicates a positive for worry whilst a value of 3 indicates a negative for worry. There are no available options for those participants who want to express that they are neither worried nor unworried, which may lead to bias at the individual level. After averaging the data, a value of 2.5 is treated as a neutral response to worrying in the present research ("neither worried nor unworried"), whilst all values larger than 2.5 will be treated as negative for worry (relatively unworried).

Building on the above, Fear of Crime in a police force area (PFA) is calculated by finding the average of all residents' worry values for each type of crime. It only counts for those types of crime that appear in each year's survey. It should be pointed out that personal items being stolen from the home, things being stolen from the home, things being stolen from outside the home, online crime, and personal details being used without permission are not included when calculating FC in PFAs. In addition, "being physically attacked because of skin colour, ethnic origin or religion" is a measure of crime motivated by hate for ethnic reasons, which may overlap with "being physically attacked by strangers", and is therefore also removed from the calculation.

Table 4.8 shows the changes in Fear of Crime in England and Wales by crime crimes. Most values for Fear of Crime are in the 2.5-3.5 range, indicating the respondents are not very worried. Meanwhile, respondents are least worried about being physically attacked because of skin colour, ethnic origin or religion". However, the score for worried about personal details being used without permission, which was introduced in 2014/15, is substantially greater than any other type of crime.

Table 4.8. Fear of Crime by crime type in England and Wales, 2011/12 to 2017/18.

	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18
home being broken into	2.64	2.63	2.67	2.70	2.69	2.72	2.69
mugging and robbery	2.83	2.82	2.87	2.88	2.88	2.91	2.88
car been stolen	2.80	2.93	2.96	2.99	2.98	2.97	2.96
things been stolen from car	2.81	2.87	2.91	2.91	2.93	2.93	2.90
rape	3.21	3.22	3.26	3.28	3.25	3.28	3.26
being physically attacked by strangers	2.89	2.86	2.90	2.93	2.93	2.95	2.91
being physically attacked because of skin colour, ethnic origin or religion	3.40	3.42	3.41	3.44	3.43	3.41	3.38
personal items being stolen from home		2.68	2.75				
things being stolen from outside home		2.78	2.87				
online crime			2.70	2.69	2.63	2.70	2.70
personal details being used without permission				2.23	2.22	2.27	2.29
Average of violent offence	2.89	2.88	2.92	2.95	2.94	2.97	2.94
Average of all crime excl. cyber	2.86	2.89	2.93	2.95	2.94	2.96	2.94

Data source: Crime Survey for England and Wales, 2011/12 to 2017/18.

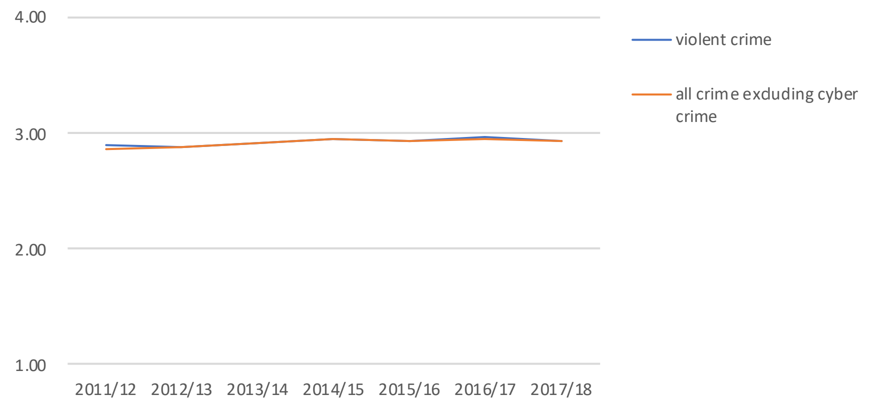

Figure 4.10. Fear of crime in England and Wales.
1=very worried; 2 = fairly worried; 3 = not very worried; 4=not worried at all.

Data source: Crime Survey for England and Wales, 2011/12 to 2017/18.

The average worry values for violent offences[23] and average worry values for all crimes (crime excluding cybercrime[24]) between 2011/12 to 2017/18 were less than 3. Figure 4.10 shows two almost flat albeit slightly increasing trend lines for Fear of Crime. During the 2011/12 to 2014/15 and 2015/16 to 2016/17 periods, the values increased, meaning that respondents became less worried about crime during this time. By way of contrast, in the periods between 2014/15 to 2015/16 and 2016/17 to 2017/18 values fell, indicating that respondents became more worried about crime.

To reduce the effect of redundant and incomparable variables discussed above, when analysing the data at the police force level, this research defines Fear of Crime as the average value of fear of one's home being broken into, mugging and robbery, car being stolen, things being stolen from car, rape, and being physically attacked by strangers. The values of Fear of Crime (FC) at the police force level are calculated and summarised for 2011/12 to 2017/18 below.

It should be noted that the definition of Fear of Crime affords equal weight to each type of crime (i.e. it treats the fear of each type of crime as being of equal importance). Equal weighting is counterintuitive because violence is typically viewed by the public as more

[23] Here the "violent crime" includes home being broken into, mugging and robbery, rape, and being physically attacked by strangers in Table 4.8.

[24] Here the "all crime excluding cybercrime" includes home being broken into, mugging and robbing, car being stolen, things being stolen from car, rape, and being physically attacked by strangers in Table 4.8.

serious than theft. However, equal weighting is feasible because fear of crime has two parts of inherent importance: one is the possibility of being victimised, and the other is the level of harm. One type of crime may have a high prevalence and a low level of harm, whilst another may be less prevalent but with a higher level of harm. In this research, it is difficult to attach different weights to different types of crime as the information on these two dimensions is vague in the survey. The other reason for equal weighting is that although violence tends to cause more fear and worry amongst the public, it is difficult to quantify the difference between personal crime and property crime. For this reason, this research does not provide each category with a distinct weight.

Table 4.9. Description of Fear of Crime at the police force level from 2011/12 to 2017/18.

Year	Max	Median	National average	Min	Standard deviation
2011/12	3.24 (North Yorkshire)	2.985	2.86	2.78 (West Midlands)	0.063
2012/13	3.15 (Cumbria)	2.90	2.89	2.65 (West Midlands)	0.106
2013/14	3.32 (Dyfed-Powys)	2.99	2.93	2.70 (West Midlands)	0.135
2014/15	3.33 (Dyfed-Powys)	2.99	2.95	2.74 (West Midlands)	0.110
2015/16	3.14 (Cleveland)	2.98	2.94	2.80 (Greater Manchester)	0.123
2016/17	3.24 (North Yorkshire)	2.985	2.96	2.78 (West Midlands)	0.116
2017/18	3.30 (Dyfed-Powys)	2.98	2.94	2.70 (West Midlands)	0.128

Data source: Crime Survey for England and Wales, 2011/12 to 2017/18.

Higher Fear of Crime values indicate that respondents are less worried about crime. Table 4.9 shows that residents in West Midlands are the least fearful of crime in most years. Further analysis of Fear of Crime at the police force level is presented in Chapter 5 on police effectiveness. It should be pointed out that the" national average" column is the result of averaging the individual-level data, not the simple average of all police forces.

b) Crime Rate

All respondents were asked a series of questions investigating whether they had experienced any type of crime in the past 12 months and how many times it occurred during this time. Two groups were asked about household property crimes: 1. Those who were living at their current address one year ago; 2. Those who were living at another address one year ago. In order to compare the national and local results of household crime in the present research, hose samples that were living in another address one year ago were removed as their experience of household crime did not reflect the corresponding area. Cybercrime experiences were recorded in the 2015/16 survey, such that the summarised crime rates including cybercrime are not comparable with rates in years before 2015.

There is another controversial point in the questionnaire: household crimes are presumed to occur in the respondent's place of residence, while personal crimes are not. For example, though respondents living in Avon and Somerset might have been mugged in London in the previous 12 months, this incident is recorded in Avon and Somerset as this is where they reside and are sampled. When attempting to look at crime level data in England and Wales on a national level, this is unproblematic; however, this research measures crime levels at the police force area level. For present purposes, it is assumed that most crimes reported occurred in the area in which they were reported, such that the possibility of suffering crimes outside the area is omitted.

The Crime Rate for each type of crime is calculated as the weighted mean of the times it occurred. As discussed above, the individual or household weight attached to it depends on the crime type. Not all crime rates can be reduced to a total rate because some types are individual-based whilst others are household-based. There are 24 types of crime mentioned in the questionnaire, which are also listed in the third column of Table 4.7. In this study, the Crime Rate is calculated for all crime types and then totalled for four categories: motor and household property crime, personal property crime, personal violent crime, and cybercrime. Figure 4.11 shows the Crime Rate trends between 2011/12 and 2017/18: the four studied crime rates generally charted a decreasing trend over the period, though personal violent crime increased from 2014 to 2017.

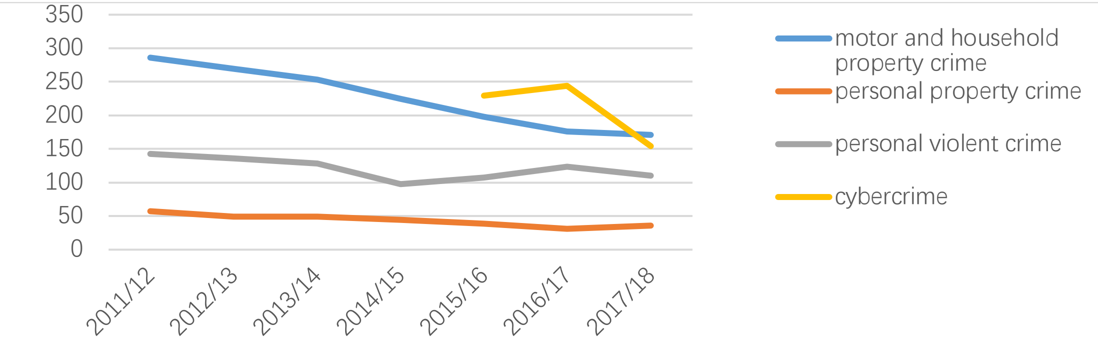

Figure 4.11. Crime rates in England and Wales, per 1000 population.

Data source: Crime Survey for England and Wales, 2011/12 to 2017/18.

The variable Crime Rate (CR) is divided into four variables representing different categories:

Crime Rate 1 (CR1): Total crime rate for motor and household property crimes in Table 4.7.

Crime Rate 2 (CR2): Total crime rate for personal property crimes in Table 4.7.

Crime Rate 3 (CR3): Total crime rate for personal violent crimes in Table 4.7.

Crime Rate 4 (CR4): Total crime rate of cybercrimes in Table 4.7 (excludes "Someone tried to trick or deceive you out of money or goods in person, by telephone, or online" as it produced outliers).

In the Data Envelopment Analysis model, as cybercrime is not comparable across the whole period, CR4 is removed. Only CR1, CR2 and CR3 are calculated for the DEA models. A Crime Rate breakdown between 2011/12 and 2017/18 is detailed below.

As can be seen from the table, some points have a value of 1000 per 1000 population, which means that the original values of crime rates in these police force areas are greater than 1000 per 1000 population. These values could be caused by biased sampling or biased weighting; therefore, they are treated as outliers and replaced by 1000 for further analysis. There are three outliers in the study period across 42 police forces: one point in 2012/13 and two points in 2013/14.

As discussed in section 3.2, the higher the values are, the better the decision-making unit performs. However, in the real-world policing assessment logic, the higher the crime rate is, the worse the police force performs. On this basis, the crime rate should be defined in another way:

Safety Rate 1 (SR1) = 1000 – Crime Rate 1;

Safety Rate 2 (SR2) = 1000 – Crime Rate 2;

Safety Rate 3 (SR3) = 1000 – Crime Rate 3.

After this transformation, it is feasible to include Crime Rates as the DEA model outputs.

Table 4.10. Description of Crime Rate at the police force level from 2011/12 to 2017/18, per 1000 population.

Year-Crime Group	Max	Median	National average	Min	Standard deviation
2011/12- Crime rate 1	509	276.5	286	151	83.92
2011/12- Crime rate 2	120	55	57	26	19.14
2011/12- Crime rate 3	289	128	143	64	56.34
2012/13- Crime rate 1	1000	261.5	270	124	153.84
2012/13- Crime rate 2	117	41	49	14	19.82
2012/13- Crime rate 3	366	134	136	48	83.38
2013/14- Crime rate 1	1000	201.5	253	62	205.91
2013/14- Crime rate 2	80	43	49	12	15.24
2013/14- Crime rate 3	291	123	128	34	72.45
2014/15- Crime rate 1	1000	193	225	41	157.74
2014/15- Crime rate 2	194	35	45	14	32.31
2014/15- Crime rate 3	273	89	98	43	45.46
2015/16- Crime rate 1	439	185	197	56	83.33
2015/16- Crime rate 2	70	31.5	39	11	13.63
2015/16- Crime rate 3	301	96.5	108	42	51.46
2016/17- Crime rate 1	326	155	176	64	55.98
2016/17- Crime rate 2	60	26.5	31	12	12.51
2016/17- Crime rate 3	308	105.5	113	45	69.1
2017/18- Crime rate 1	279	155	171	67	48.71
2017/18- Crime rate 2	71	28	35	2	15.77
2017/18- Crime rate 3	238	113.5	107	29	44.55

Data source: Crime Survey for England and Wales, 2011/12 to 2017/18.

c) Clear-up Rate

Clear-up Rate (CLR) pertains to" clear up", which is measured by a series of questions on the victimisation form (only answered by victims_:
"Did the police come to know about the matter? [yes; no]". For those who answered the police came to know, responders were asked "Did the police find out or know who did it? [yes; no; not yet; not know]". Then for those who answered the police found out or knew who did it, responders were asked "What action, if any, did the police take against the person who did it? [1 = Charged them; 2 = Gave them a caution; 3 = Gave them a fine (or Penalty Notice for Disorder); 4 = Made them do something to make amends for the matter (e.g. apologise to the victim or do voluntary work in the

community); 5 = Some other action (SPECIFY); 6 = No action (yet) taken against the offender; 7 = Don't know]"[25]. The last two questions exclusively appear in the long-type form, not its short-type counterpart.

Each type of crime defines:

(1) Know Rate as the proportion of "yes" responses to the first question, which represents the ratio of cases delivered to the police;

(2) Findoff Rate as the proportion of "yes" responses to the second question, which represents the ratio of cases in which the offender was found relative to all cases delivered to the police; and

(3) Charge Rate as the total proportion of responses answering 1-5 for the third question[26], which represents the ratio of cases in which the police took an action when the offender was known. It should be emphasised that although the police are responsible for improving the charge rate, this variable is beyond their control to some extent. For example, decisions by the prosecution and courts also influence whether offenders are charged.

All rates are calculated in conjunction with the incident weights. Cybercrime rates are not available when calculating Findoff Rate or Charge Rate because victims of this crime category were not directed to the long-type form. Thus, this research defines:

Clear-up Rate (CLR) = Know Rate × Findoff Rate × Charge Rate.

Figure 4.12 presents the trends exhibited by Clear-up rate, Findoff rate, and Charge rate between 2011/12 and 2017/18 for personal violence and all types of crimes excluding cybercrime in England and Wales. The clear-up rate of all crimes excluding cybercrime fluctuated slightly over the period, while the clear-up rate of personal violence fluctuated more significantly. Changes in the charge rates of all crimes and personal violence were similar, though the charge rate of personal violence was much higher than the average for all crimes. In contrast to the increasing findoff rate of all crimes,

[25] In 2011/12, there are only six options which do not include the fourth one.

[26] In 2011/12, Charge Rate is defined as the proportion of 1-4 for the third question.

the findoff rate of personal violence increased prior to 2014, before then decreasing to a lower level than at the outset of the sampling period.

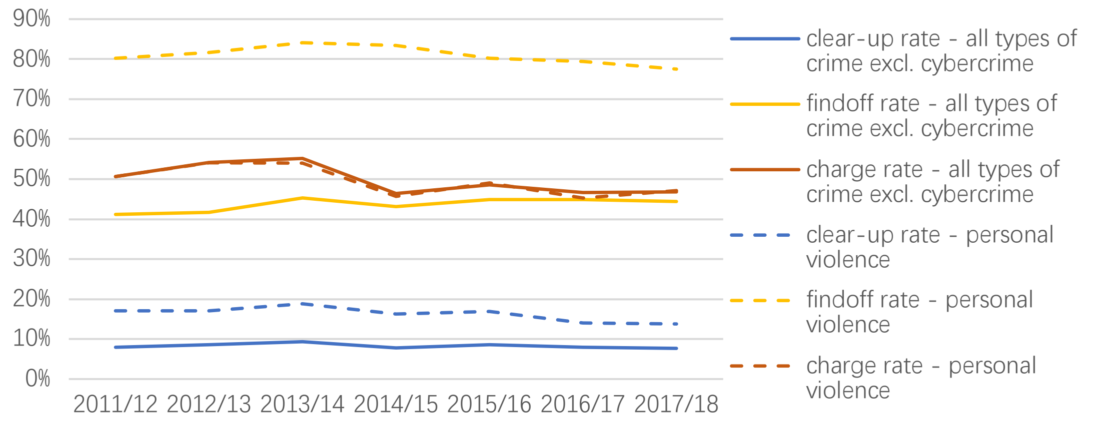

Figure 4.12. Clear-up rates in England and Wales.

Data source: Crime Survey for England and Wales, 2011/12 to 2017/18.

As the clear-up rates of personal violence are much larger than those of all crimes, this research divided the overall variable Clear-up Rate (CLR) into two variables:

Clear-up Rate of Property Crime (PCLR); and
Clear-up Rate of Violent Crime (VCLR).

The CLR, PCLR and VCLR values are calculated at the police force area level, based on which a summary of the clear-up rates is provided below. Although clear-up rates of property crime are 0 in some police forces, these values are not considered outliers. Table 4.10 also shows that the crime rates for violent crime are significantly greater than that for property crime.

Thus, the output variables for use in the DEA efficiency models are Fear of Crime, Safety Rate 1, Safety Rate 2, Safety Rate 3, Clear-up Rate, Clear-up Rate of Property Crime, and Clear-up Rate of Violent Crime.

Table 4.11. Description of Clear-up Rate at the police force level from 2011/12 to 2017/18.					
Year-Crime Group	Max	Median	National average	Min	Standard deviation
2011/12- CLR	0.18	0.085	0.080	0.03	0.037
2011/12- PCLR	0.092	0.033	0.030	0.006	0.017
2011/12- VCLR	0.317	0.169	0.171	0.034	0.071
2012/13- CLR	0.26	0.079	0.086	0.029	0.048
2012/13- PCLR	0.096	0.036	0.036	0.007	0.021
2012/13- VCLR	0.595	0.1465	0.171	0.034	0.113
2013/14- CLR	0.294	0.0775	0.093	0.029	0.052
2013/14- PCLR	0.122	0.0345	0.038	0	0.024
2013/14- VCLR	0.477	0.163	0.188	0.037	0.098
2014/15- CLR	0.237	0.072	0.078	0.02	0.047
2014/15- PCLR	0.097	0.025	0.026	0	0.021
2014/15- VCLR	0.45	0.1555	0.162	0.016	0.1
2015/16- CLR	0.166	0.093	0.086	0.021	0.038
2015/16- PCLR	0.095	0.0305	0.030	0	0.024
2015/16- VCLR	0.393	0.1535	0.169	0.03	0.086
2016/17- CLR	0.181	0.072	0.080	0.013	0.038
2016/17- PCLR	0.106	0.0395	0.035	0	0.026
2016/17- VCLR	0.274	0.1285	0.140	0.027	0.07
2017/18- CLR	0.257	0.069	0.077	0.014	0.054
2017/18- PCLR	0.106	0.0245	0.027	0	0.022
2017/18- VCLR	0.447	0.1075	0.138	0.01	0.089

Data source: Crime Survey for England and Wales, 2011/12 to 2017/18.

(3) Workforce and expenditure data

Police resources are treated as input variables in the DEA efficiency models. Two aspects of resources are selected: workforce and expenditure. This choice was inspired by previous research indicating that frontline workforces improve police effectiveness (Draca et al., 2008; Sindall & Sturgis, 2013). The responsibilities of the police workforce can be divided into two roles: frontline and support. To eliminate the overlapping impact of workforce and remuneration, the cost input only covers non-staff costs to ensure its representativeness, meaning that staff payments are not considered input variables.

Input variable 1: Frontline Workforce (FW)

Prior to 2015/16, the workforce function statistics split the workforce into four prominent roles: operational support, business support, operational frontline, and other. From 2014/15 onwards, a new function framework was introduced to explain the six new main roles of the police: visible operational frontline, non-visible operational frontline, frontline support, business support, national, and others. The old and new framework statistics are not comparable due to their dissimilar function definitions.

However, workforce data for 2014/15 are published under both the old and new function frameworks, meaning that the year 2014/15 with the years that preceded it and those that came after. In this research, for 2011/12 to 2014/15 (old), Frontline Workforce is defined as the total number of operational frontline staff, while for 2014/15 to 2017/18, Frontline Workforce is defined as the total number of visible operational frontline and non-visible operational frontline staff. It should be noted that when constructing the Workforce variable for a territorial police force, the function of national policing is removed. As a result, the national policing workforce is not included in Frontline Workforce or Support Workforce (introduced below).

Input variable 2: Support Workforce (SW)

In this research, for 2011/12 to 2014/15 (old), Support Workforce is defined as the total number of operational support and business support staff, while for 2014/15 (old) to 2017/18, Frontline Workforce is defined as the total number of frontline support and business support staff, excluding the national policing function.

The values are calculated at the police force level. The summary of Frontline Workforce (FW) and Support Workforce (SW) is listed below. Due to the population size and force scale, the max and min in the table always reflect the values of Metropolitan Police and Lincolnshire, respectively.

Table 4.12. Description of Frontier Workforce and Support Workforce at the police force level from 2011/12 to 2017/18, full-time equivalent.

Year	Max	Median	Mean	Min	Standard deviation
2011/12 FW	37062	2680	3892	1140	5556
2011/12 SW	11123	896	1226.4	304	1651
2012/13 SW	35779	2648	3801	1150	5373
2012/13 FW	10351	858	1162.9	238	1534
2013/14 SW	35404	2567	3744	1119	5307
2013/14 FW	8335	813	1069.3	189	1245
2014/15 (old) FW	35542	2460	3702	1139	5326
2014/15 (old) SW	8352	795	1069.0	245	1245
2014/15 (new) FW	32799	2474	3619	1251	4904
2014/15 (new) SW	7606	741	994.0	188	1145
2015/16 FW	31223	2444	3455	1206	4654
2015/16 SW	6543	694	930.4	182	985
2016/17 FW	29881	2398	3417	1194	4465
2016/17 SW	5936	757	931.7	198	906
2017/18 FW	29121	2447	3394	1076	4350
2017/18 SW	6051	780	982.7	244	918

Source: Police workforce England and Wales statistics, GOV.UK.

Input variable 3: Non-Staff Cost (NSC)

Values of non-staff cost at the police force level are available from each police force's Account of Statement for each year. The Non-Staff Cost at the police force level during the whole period is summarised below.

Table 4.13. Description of Non-Staff Cost at the police force level from 2011/12 to 2017/18, £000.

Year	Max	Median	Mean	Min	Standard deviation
2011/12	815795	39614	65224	18917	121243
2012/13	829634	44319	66576	20605	122603
2013/14	672515	42802	63368	21375	99481
2014/15	656763	45690	62004	21522	97044
2015/16	672374	44285	65737	21243	99269
2016/17	717410	38943	58933	16877	106904
2017/18	1283027	79868	117170	34967	189745

Source: Her Majesty's Inspectorate of Constabulary and Fire & Rescue Services (HMICFRS), Value for money profile.

After preparing the inputs and outputs for each year's DEA efficiency model from 2011/12 to 2017/18 respectively, section 4.4 will run DEA models to assess the efficiency of the police forces.

4.4. DEA model using CSEW data

Firstly, all of the indicators selected in section 4.3 are included in the DEA model: frontline workforce-FW, support workforce-SW, non-staff costs-NSC, fear of crime-FC, safety rate of motor and household property crime-SR1, safety rate of personal property crime-SR2, safety rate of personal violence-SR3, clear-up rate for property crime-PCLR, clear-up for personal violence-VCLR. Constant or variable assumptions for return to scale are used to obtain efficiency, pure technical, and overall efficiency scores. DEA models are constructed for each year as opposed to using a pooling context including all years. The rationale here is that this research does not require a relative efficiency score estimated from the comparison between Avon and Somerset in 2011/12 and Bedfordshire in 2012/13, for example.

"Output-oriented" models are used here instead of "input-oriented" as the first aim of this research is to recognise those police forces with a greater output (i.e. higher clear-up rates, lower crime rates) when working with limited inputs. Where a piece of research seeks to recognise those police forces who save more resources given the level of output, an "input-oriented" model should be chosen instead.

The DEA scores of the 42 police forces in 2011/12 are listed below. In this table, an efficiency score of 1 means that the police force has achieved full efficiency in this measure.

Overall efficiency scores are calculated by the DEA models based on the constant assumption of return to scale, whilst pure efficiency scores are the results including the variable assumption. Pure efficiency is associated with the scores that eliminate the impact of scale. For example, Metropolitan, the largest police force in England and Wales, has an efficiency score of only 0.04, though its pure efficiency score is 0.98 after the model removes the scale factor. However, Table 4.14 reveals two problems: (1) Of the 42 police forces, more than 20 are estimated as having full efficiency; (2) All pure efficiency scores range between 0.97-1.00, which is a very narrow range. These two problems may be a barrier in the assessment process where police forces seem to exhibit similar performance.

Table 4.14. DEA results of 42 police forces in 2011/12.

Police force	Pure Efficiency	Overall efficiency
Avon and Somerset	1.00	0.45
Bedfordshire	0.99	0.93
Cambridgeshire	1.00	0.83
Cheshire	1.00	0.64
Cleveland	1.00	1.00
Cumbria	1.00	0.94
Derbyshire	0.98	0.60
Devon and Cornwall	0.99	0.40
Dorset	0.98	0.81
Durham	1.00	0.88
Dyfed-Powys	1.00	1.00
Essex	1.00	0.42
Gloucestershire	1.00	1.00
Greater Manchester	1.00	0.19
Gwent	1.00	0.93
Hampshire	0.99	0.38
Hertfordshire	0.98	0.59
Humberside	1.00	1.00
Kent	1.00	0.37
Lancashire	0.98	0.41
Leicestershire	1.00	0.68
Lincolnshire	0.97	0.93
Merseyside	0.93	0.38
Metropolitan Police	0.98	0.04
Norfolk	0.99	0.81
North Wales	1.00	1.00
North Yorkshire	1.00	0.81
Northamptonshire	1.00	0.93
Northumbria	1.00	0.82
Nottinghamshire	0.97	0.60
South Wales	0.99	0.50
South Yorkshire	1.00	0.49
Staffordshire	0.99	0.63
Suffolk	1.00	1.00
Surrey	0.98	0.54
Sussex	1.00	0.42
Thames Valley	0.99	0.28
Warwickshire	1.00	1.00
West Mercia	0.99	0.57
West Midlands	0.97	0.21
West Yorkshire	0.99	0.26
Wiltshire	1.00	0.95

These two problems stem from the large number of variables compared with the number of decision-making units; as a result, in a nine-dimension space, more than 20 decision-making units are estimated as “frontier points”, thus indicating full efficiency. In response, this research focuses on small subsets of the selected variables.

After carrying out the linear correlation analysis of FC, SR1, SR2, SR3, CLR, PCLR, and VCLR at the police force level for each year, it is found that: (1) VCLR is significantly statistically correlated with CLR in each year (p-values < 0.001), which means that most clear-up incidents are violent crimes; (2) Except for 2011/12 and 2016/17, FC is significantly statistically correlated with at least one other variables in each year (p-values < 0.05). Table 4.11 shows that the standard deviation of PCLR is significantly small than that of VCLR, indicating that police forces have more similar clear-up rates for property crime than violent crime. Based on the above, consideration is given as to whether FC should be removed. The three crime rate variables, SR1, SR2 and SR3, cannot be used to calculate aggregated crime rate values, as they are calculated according to different crime weights in the CSEW statistics. SR1 is based on household weights, whilst SR2 and SR3 are based on individual weights. To reduce dimensions, the values of SR2 and SR3 are totalled to define a new variable, Safety Rate 4 (SR2 + SR3), representing the safety rate of personal crime. Among the three clear-up rate variables (CLR, PCLR and VCLR) VCLR is more representative if only one is allowed to be retained.

The revised DEA model is now conducted with six variables: SR1 (safety rate of household property crime per 1000 population), SR4 (safety rate of personal crime per 1000 population), VCLR (clear-up rate of violent crime), FW (frontline workforce, full-time equivalent), SW (support workforce, full-time equivalent), and NSC (non-staff cost, £000).

DEA scores of pure efficiency for 42 police forces (with the impact of the scale factor eliminated) from 2011/12 to 2017/18 are listed below.

Table 4.15. DEA pure efficiency scores of 42 police forces, 2011/12 to 2017/18.								
Police force	2011/12	2012/13	2013/14	2014/15 old	2014/15 new	2015/16	2016/17	2017/18
Avon and Somerset	0.990	0.945	0.940	0.995	0.995	0.968	0.983	0.971
Bedfordshire	0.989	0.860	1.000	1.000	1.000	0.989	1.000	0.974
Cambridgeshire	1.000	0.961	0.965	0.943	0.943	0.973	0.936	0.932
Cheshire	1.000	0.988	0.988	0.971	0.971	0.959	0.975	1.000
Cleveland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Cumbria	1.000	1.000	1.000	1.000	0.988	1.000	0.977	1.000
Derbyshire	0.919	0.817	0.926	0.998	0.998	0.982	0.927	0.993
Devon and Cornwall	0.953	0.971	0.967	0.921	0.921	1.000	1.000	0.969
Dorset	0.949	1.000	0.961	0.954	0.954	0.986	1.000	1.000
Durham	0.978	0.997	1.000	1.000	1.000	1.000	1.000	1.000
Dyfed-Powys	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Essex	0.978	0.984	0.916	0.955	0.955	0.979	0.990	0.937
Gloucestershire	1.000	0.930	1.000	1.000	1.000	1.000	1.000	0.959
Greater Manchester	1.000	0.969	0.967	0.966	0.966	0.962	0.986	0.954
Gwent	0.994	1.000	0.897	0.937	0.937	0.905	1.000	1.000
Hampshire	0.954	0.942	0.967	0.998	0.998	0.982	0.964	0.941
Hertfordshire	0.973	0.980	0.973	0.996	0.996	0.992	0.994	0.953
Humberside	1.000	0.953	0.943	0.987	0.986	0.950	0.991	0.954
Kent	0.986	0.890	0.971	0.959	0.959	0.952	0.986	0.942
Lancashire	0.966	0.938	0.966	0.930	0.930	0.963	0.973	0.992
Leicestershire	0.965	0.915	0.910	0.995	0.995	1.000	0.983	0.918
Lincolnshire	0.962	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Merseyside	0.930	1.000	0.934	1.000	1.000	0.987	0.961	0.915
Metropolitan Police	0.927	0.945	0.953	0.966	0.966	0.943	0.932	0.958
Norfolk	0.978	0.994	0.957	0.992	0.992	0.944	0.992	1.000
North Wales	1.000	1.000	0.938	1.000	1.000	0.997	0.969	1.000
North Yorkshire	0.973	1.000	0.986	0.994	0.994	0.979	0.927	0.986
Northamptonshire	0.937	0.939	0.936	0.983	0.983	0.935	1.000	0.949
Northumbria	0.952	0.909	0.969	0.986	0.980	0.989	0.953	0.998
Nottinghamshire	0.962	0.977	0.946	0.996	0.997	0.862	0.986	0.978
South Wales	0.985	0.955	0.908	0.942	0.942	0.967	0.968	0.956
South Yorkshire	0.992	1.000	0.890	0.895	0.895	0.974	0.920	0.917
Staffordshire	0.964	0.932	0.976	0.979	0.979	1.000	0.985	1.000
Suffolk	1.000	1.000	1.000	1.000	1.000	0.955	0.964	0.968
Surrey	0.965	0.991	0.986	0.937	0.937	0.940	0.997	0.941
Sussex	1.000	0.919	0.942	0.934	0.934	1.000	0.853	0.960
Thames Valley	0.993	0.951	0.899	0.961	0.961	0.968	0.992	0.959
Warwickshire	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
West Mercia	0.984	0.977	1.000	0.988	0.988	0.990	1.000	0.963
West Midlands	0.938	0.928	0.852	0.969	0.969	0.957	0.952	0.939
West Yorkshire	0.986	0.966	0.919	1.000	1.000	0.958	0.986	0.939
Wiltshire	1.000	0.974	0.924	0.976	0.979	0.988	0.972	0.941

The only two differences between the 2014/15 new workforce function framework model and the 2014/15 old function framework model are that Cumbria's score decreases from 1 to 0.988, and Nottinghamshire's increases from 0.996 to 0.997. Moreover, Cumbria performed at full efficiency for most years (except 2016/17). In later research, 2014/15 refers to the new workforce function framework.

For each year, Pearson's correlation analysis is conducted on the ratio of frontline workforce over support workforce and the efficiency score, which returns p-values that are all greater than 0.20. Thus, it can be concluded there is no statistical evidence that pure efficiency is linearly correlated with the frontline-support workforce allocation. If all seven years are considered in a pooling context, the scatter plot Figure 4.13 seems to present a positive linear relationship between Frontline/Support Workforce and Pure Efficiency as follows. Pearson's correlation testing also provides a significant result in this context (correlation coefficient = 0.13, p-value = 0.02). However, outliers in both two variables are observed in this figure. If the correlation test removes the outliers (eight points for Frontline/Support Workforce and five points for Pure Efficiency), the scatter plot does not support any linear relationship (see Figure 4.14). At the same time, Pearson's correlation testing does not support any significant linear correlation between Pure Efficiency and Frontline/Support Workforce (correlation coefficient = 0.05, p-value = 0.40). Therefore, no matter how pure efficiency is compared within the same year or over the years, there is no statistical evidence to support the linear relationship between pure efficiency score of a police force and its frontline allocation.

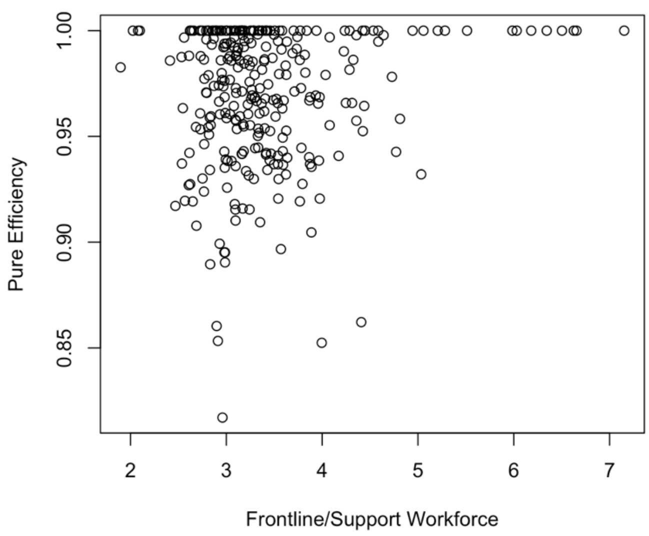

Figure 4.13. Scatter plot for Frontline/Support Workforce and Pure Efficiency, with outliers.

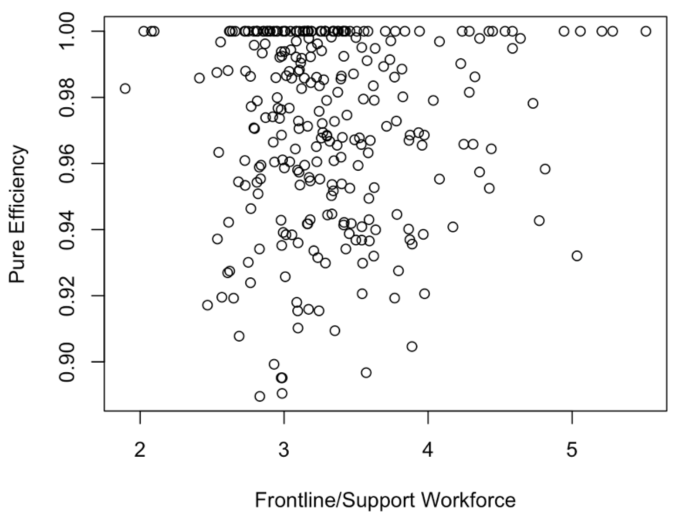

Figure 4.14. Scatter plot for Frontline/Support Workforce and Pure Efficiency, without outliers.

Next, Pearson correlation analysis is carried out on the efficiency scores and each input and output at the police force level for each year. For the correlation test results between scores and the sum of Crime Rate 2 and 3, the p-values are all less than 0.001. Thus, it is concluded that a police force's efficiency score is significantly statistically correlated with the crime rate of personal crime (CR2+CR3). To be precise, a larger number of crimes per 1000 population relates to a lower pure efficiency score. However, it is interesting to note that the household crime rate is not always associated with pure efficiency scores over the years. The crime rate of household crime has a significantly statistically negative relationship with the pure efficiency score (p-values < 0.05) in 2011/12, 2013/14, and 2017/18. Meanwhile, the clear-up rate of violent crime exhibited a significantly statistically negative relationship with the pure efficiency score (p-values < 0.05) in 2016/17 and 2017/18. That is to say, in 2017/18, both the crime rate and clear-up rate are negatively related to the pure efficiency score (i.e. a higher crime rate and clear-up rate are associated with a lower efficiency score).

It is briefly necessary to unpack the counterintuitive relationship between efficiency and the clear-up rate. Firstly, the crime and clear-up rates may be positively related. This could be due to how the workforce is allocated, as police force areas with a larger workforce that can be put to work on crime prevention may have less manpower to dedicate to investigating crimes. Secondly, the construction of the clear-up rate has a shortcoming, in that the charge rate, a multiplier of the clear-up rate, is beyond the control of the police. Even if the criminal was found by the police, decisions taken by the prosecution and the courts will influence the charge rate.

None of the input variables are significantly statistically correlated with pure efficiency in any year (p-values are all greater than 0.2). In Chapter 5, more regression methods are drawn on to further investigate the relationship between efficiency and input-output variables, as opposed to just the pair-wise relationship here. Unsurprisingly, since DEA is not a linear method to picture the linear correlation between variables, no input or output terms remain positively or negatively correlated with the efficiency scores at all times. As dictated by how DEA models work, changes in any input or output may lead to an increase in efficiency scores through the evaluation of the vector weights. Further analysis will be carried out in Chapters 5 and 6 to identify the drivers of efficiency scores.

In the next section, the police force classification discussed in section 4.2 is used to control for a similar environment amongst different police forces. The results in Table 4.15 are then analysed in detail within each of the police force families.

4.5. Environmental factors and police force family

Section 4.2 introduced a classification method to group police forces based on selected socio-demographic factors: Indices of Multiple Deprivation (only England) and Immigrants. According to Table 4.6, the pure efficiency scores can be presented by group as below:

Group 1: (Metropolitan only: The largest force in England and Wales with the most prosperous economy and diverse culture)

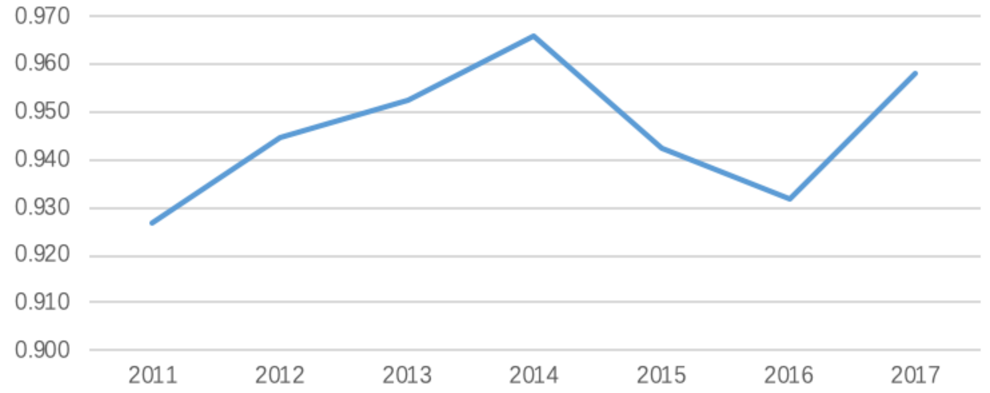

Figure 4.12. Pure efficiency of Metropolitan Police from 2011/12 to 2017/18.

The first group contains only the Metropolitan Police force. It never achieves full efficiency, fluctuating between 0.927 to 0.966. Efficiency increased during the austerity period from 2011-14 and decreased from 2015/16, whilst the efficiency score in 2017/18 was far greater than in 2016/17 and 2011/12.

Group 2: (Welsh police forces: Large areas of open countryside and a relatively small number of large urban areas with a much lower urbanisation rate and a higher ageing rate)

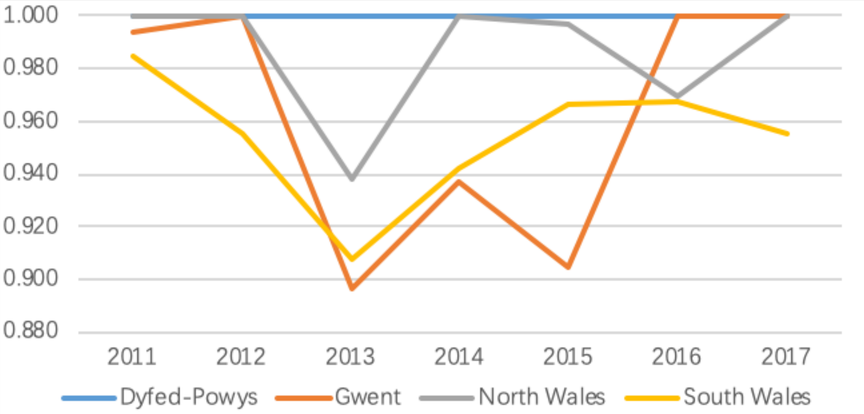

Figure 4.13. Pure efficiency of Welsh Police from 2011/12 to 2017/18.

Group 2 features all of the Welsh police forces. Welsh police force areas are not classified together with the English police force areas as the two countries calculate the Index of Multiple Deprivation environmental factor using different statistical systems (discussed above). As revealed by Figure 4.13, one police force remained fully efficient during the whole period: Dyfed-Powys. Other police forces fluctuated during the austerity period, with their efficiency in 2014/15 decreasing relative to 2011/12.

Group 3: (Southeastern and diverse areas: Adjacent to or not far from London with a prosperous economy and less social deprivation)

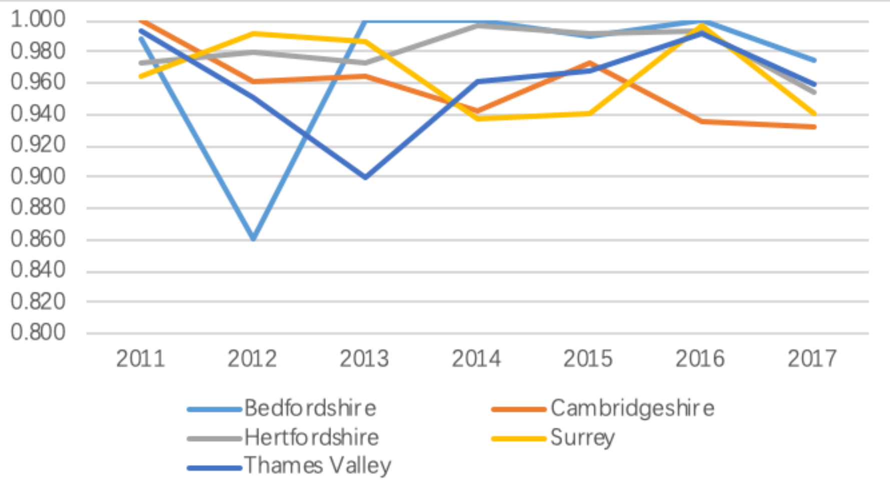

Figure 4.14. Pure efficiency of group 3 police forces from 2011/12 to 2017/18.

In Group 3, no police forces maintained full efficiency, whilst two police forces never achieved full efficiency: Bedfordshire (2012/13, 2013/14, and 2016/17), and Cambridgeshire (2011/12). Except for Hertfordshire and Bedfordshire, the police forces performed less efficiently in 2014/15 than in 2011/12.

Group 4: (Northern and deprived areas: Former industrial areas that have undergone economic restructuring over the past several decades; the population has high levels of unemployment and low levels of education and skills)

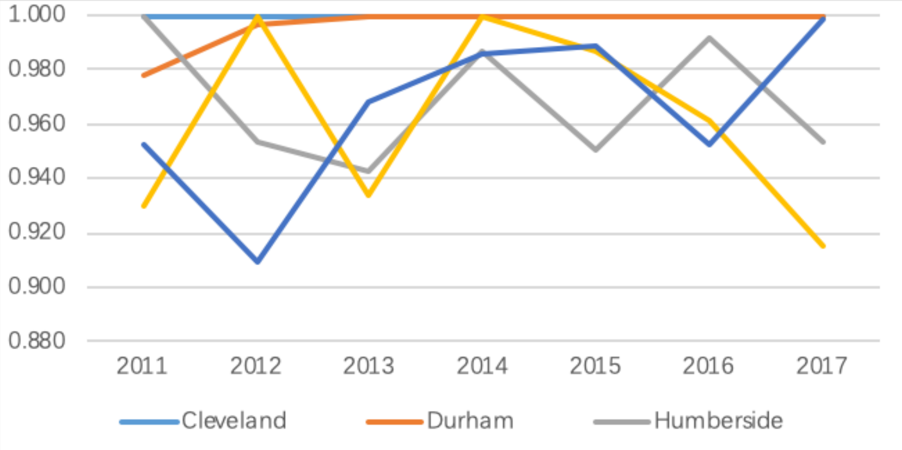

Figure 4.15. Pure efficiency of group 4 police forces from 2011/12 to 2017/18.

In Group 4, Cleveland maintained full efficiency during the whole period. Durham improved its efficiency from 0.978 in 2011/12 to 1 in 2013/14, whilst Northumbria's pure efficiency increased from 0.952 to 0.998 during the seven years although in 2012/13 and 2016/17 it decreased. Humberside and Merseyside exhibited significant fluctuations and made no pure efficiency improvements during the austerity period or the whole period.

Group 5: (Typical areas: Neither affluent nor deprived, not in an area with the highest or lowest levels of immigrants. All southern coastal areas in England are included in this group, featuring a mix of urban and rural areas)

Group 5 is too large to be presented in a multiple-line chart. Instead, Table 4.16 lists the pure efficiency scores and notes the changes between 2011-2015 and 2011-2017, respectively. Warwickshire is the only force that maintained full efficiency across the study period. Devon & Cornwall, Dorset, Hampshire, and Leicestershire improved by a larger margin during the austerity period than other police forces, whilst Kent, Norfolk, and Suffolk decreased by a larger margin over the austerity period.

Table 4.16. Pure efficiency of group 5 police forces from 2011/12 to 2017/18.

	2011	2012	2013	2014	2015	2016	2017	2011-15 change	2011-17 change
Avon and Somerset	0.990	0.945	0.940	0.995	0.968	0.983	0.971	-0.022	-0.018
Devon and Cornwall	0.953	0.971	0.967	0.921	1.000	1.000	0.969	0.047	0.017
Dorset	0.949	1.000	0.961	0.954	0.986	1.000	1.000	0.037	0.051
Essex	0.978	0.984	0.916	0.955	0.979	0.990	0.937	0.001	-0.041
Gloucestershire	1.000	0.930	1.000	1.000	1.000	1.000	0.959	0.000	-0.041
Hampshire	0.954	0.942	0.967	0.998	0.982	0.964	0.941	0.028	-0.013
Kent	0.986	0.890	0.971	0.959	0.952	0.986	0.942	-0.034	-0.044
Leicestershire	0.965	0.915	0.910	0.995	1.000	0.983	0.918	0.035	-0.047
Norfolk	0.978	0.994	0.957	0.992	0.944	0.992	1.000	-0.034	0.022
North Yorkshire	0.973	1.000	0.986	0.994	0.979	0.927	0.986	0.006	0.013
Northamptonshire	0.937	0.939	0.936	0.983	0.935	1.000	0.949	-0.002	0.012
Suffolk	1.000	1.000	1.000	1.000	0.955	0.964	0.968	-0.045	-0.032
Sussex	1.000	0.919	0.942	0.934	1.000	0.853	0.960	0.000	-0.040
Warwickshire	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.000
West Mercia	0.984	0.977	1.000	0.988	0.990	1.000	0.963	0.007	-0.020
Wiltshire	1.000	0.974	0.924	0.976	0.988	0.972	0.941	-0.012	-0.059

Group 6: (Large-size areas: Four of the largest police forces located in the centre and north of England)

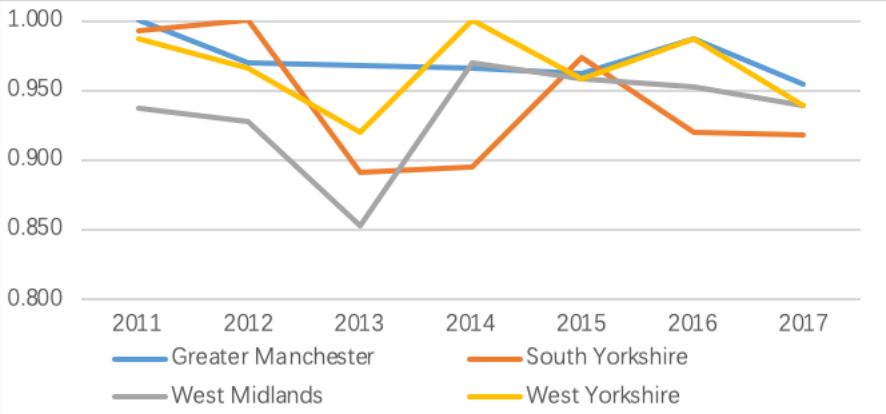

Figure 4.16. Pure efficiency of group 6 police forces from 2011/12 to 2017/18.

All police forces in Group 6 are large-scale forces none of which achieved full efficiency. Only West Midlands improved slightly during the austerity period, with all other forces performing less efficiently when comparing their 2015/16 to 2011/12 performance. All police forces performed worse from 2015/16 to 2017/18, though there was some fluctuation.

Group 7: (Central-northern areas: Relatively low level of ethnic diversity and a relatively larger ageing population)

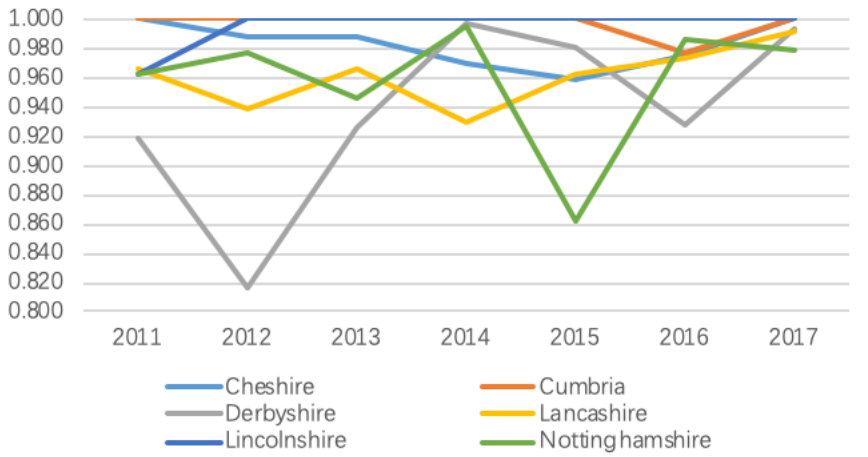

Figure 4.17. Pure efficiency of group 7 police forces from 2011/12 to 2017/18.

Group 7 contains two police forces which almost maintained full efficiency during the study period: Cumbria and Lincolnshire. Cumbria was only not fully efficient in 2016/17, whilst Lincolnshire started from inefficiency in 2011/12 and improved to full efficiency in each year after that. Meanwhile, Cheshire performed worse during the austerity period and Derbyshire significantly improved its pure efficiency from 2011 to 2015, though it decreased in 2012/13.

In conclusion, some police forces improved their efficiency during the austerity period (the years from 2011/12 to 2015/16), whilst for others, it decreased; For most forces, their efficiency varied quite significantly, whilst some outstanding forces remained fully efficient in each year. There are 16 police forces with lower efficiency scores in 2014/15 than in 2011/12. Moreover, five forces scored the same as in 2011/12, and 20 forces attained improved efficiency scores in 2014/15.

In general, it can be said that most forces performed better in the efficiency assessment during the austerity period. From the perspective of the national average from 2011/12 to 2014/15, the Fear of Crime value increased from 2.86 to 2.95, indicating that respondents became less worried about crime. At the same time, crime rates for household property crime, personal property crime, and personal violence fell from 286, 57, and 143 to 225, 45, and 98 per 1000 population, respectively. The clear-up rates of total crime slightly decreased from 8 to 7.8 per 100 cases. Meanwhile, the resources (frontline workforce, support workforce, and non-staff costs) input into the policing system continually decreased.

Thus, though the clear-up rates fell slightly, there is a clear trend of increasing outputs and decreasing inputs. Generally speaking, police forces in England and Wales became more efficient during the austerity period, which is consistent with the Coalition government's expectations: crime did not go up even though police force budgets were cut. It is worth noting that in terms of clear-up rates, most police forces in England and Wales did not improve their clear-up rates between 2011/12 and 2014/15, whilst there was a sharp decrease in the clear-up rates for many police forces, especially in the first three years of the study period. Clear-up rates of violent crimes reflect a substantial portion of urgent and controllable tasks that the police have to deal with; on this basis, a fall in clear-up rates reflects the negative impact of austerity to some extent.

From the analysis above, outstanding police forces (i.e. those that maintained full efficiency or continually increased their efficiency) and the forces that decreased a lot are highlighted below:

Table 4.17. Selected police forces for further analysis.

	Outstanding police forces	Forces which decreased a lot
Group 1	only Metropolitan	
Group 2	Dyfed-Powys	South Wales
Group 3	Bedfordshire	Cambridgeshire
Group 4	Cleveland, Durham, Northumbria	Humberside
Group 5	Warwickshire Devon & Cornwall, Dorset Hampshire and Leicestershire	Kent, Norfolk and Suffolk
Group 6	West Midlands	South Yorkshire
Group 7	Cumbria, Lincolnshire, Derbyshire	Cheshire

Next, according to Table 4.17, the selected outstanding and declining areas, respectively, are compared by referring to the values of the three input variables (FW-frontline workforce, SW-support workforce, NSC-non-staff cost) and three output variables (SR1-safety rate of motor and household property crime, SR4-safety rate of personal crime, VCLR-clear-up rates for personal violence) included in the DEA models. Subsequently, by learning from the outstanding areas, this research will propose some aspects in which the declining areas had room for performance efficiency improvement.

Table 4.18. Output and Input variable comparison of Metropolitan Police from 2011/12 to 2017/18.							
	2011	2012	2013	2014	2015	2016	2017
Efficiency	0.927	0.945	0.953	0.966	0.943	0.932	0.958
SR1	680	719	787	738	761	841	824
SR4	1765	1824	1846	1861	1822	1778	1876
VCLR	167	158	143	180	128	153	81
FW	37062	35779	35404	32799	31223	29881	29121
SW	11122	10351	8335	7606	6543	5936	6051
NSC	815795	829634	672515	656763	672374	717410	1283027

The pure efficiency of the Metropolitan Police increased between 2011/12 and 2014/15. Meanwhile, Safety Rate 1 increased and Safety Rate 2 increased from 2011/12 to 2013/14, while Clear-up Rate for Violence decreased. Frontline Workforce decreased across the entire period and Support Workforce followed a similar trend before 2017/18. Non-Staff Cost increased slightly after 2011/12 before decreasing sharply. From 2014/15 to 2017/18, Non-staff Cost increased to almost double its initial value, with the corresponding pure efficiency exhibiting a decreasing trend.

The pure efficiency scores of the Metropolitan Police are not comparable with other forces as it operates in a more complex criminal environment and undertakes more national policing tasks.

Table 4.19. Output and Input variable comparison of Welsh Police forces from 2011/12 to 2017/18.								
	Variable	2011	2012	2013	2014	2015	2016	2017
	Efficiency	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Dyfed-Powys	SR1	726	789	870	722	856	690	523
	SR4	1663	1912	1852	1882	1923	1911	1839
	VCLR	280	55	331	80	240	48	88
	FW	1383	1423	1458	1397	1340	1382	1428
	SW	433	425	407	393	401	410	413
	NSC	18917	20605	21375	22520	21243	16877	34967
South Wales	Efficiency	0.985	0.955	0.908	0.942	0.942	0.967	0.968
	SR1	790	907	755	893	850	875	842
	SR4	1844	1839	1757	1810	1866	1864	1854
	VCLR	181	292	247	131	130	134	131
	FW	3457	3443	3676	3602	3503	3535	3634
	SW	1219	1281	1163	1138	1056	1085	1145
	NSC	53512	53856	56956	58413	52158	47205	91074

In the Welsh police force group, Dyfed-Powys and South Wales are compared: Dyfed-Powys maintained full efficiency during the whole period, whilst South Wales did not.

Moreover, South Wales performed less efficiently in 2013/14 than in 2011/12, before making efficiency improvements from 2013 onwards.

In most of the years studied, South Wales had a larger Safety Rate of household property crime than Dyfed-Powys, though it has a smaller Safety Rate of personal property and violent crime. The Clear-up Rate for Violence in Dyfed-Powys fluctuated between 48 and 280 per 1000 incidents, while in South Wales it decreased since 2012/13 from 292 to 131.

Frontline Workforce in Dyfed-Powys fluctuated before 2015 and Support Workforce did not increase. A similar trend to this can be seen in the South Wales data: From 2011/12 to 2014/15, Frontline Workforce has increased accompanied by fluctuation, while Support Workforce has been decreasing. Although the police funding in 2011-15 was reduced, Non-Staff Cost increased during the austerity period for both police forces. From 2016/17 to 2017/18, Non-Staff Cost almost doubled for both police forces.

All inputs in South Wales were greater than Dyfed-Powys each year, though some outputs were smaller. The worst performance variable in South Wales is SR4. When considering how to improve pure efficiency in South Wales in the future, based on Dyfed-Powys, controlling expenditures and improving safety rates for personal property and violent crime may help to increase pure efficiency scores.

Table 4.20. Output and Input variable comparison of group 3 police forces from 2011/12 to 2017/18.

	Variable	2011	2012	2013	2014	2015	2016	2017
Bedfordshire	Efficiency	0.989	0.860	1.000	1.000	1.000	0.989	1.000
	SR1	750	694	805	778	880	872	867
	SR4	1653	1578	1816	1859	1867	1805	1883
	VCLR	131	167	76	309	38	200	72
	FW	1487	1447	1355	1481	1410	1412	1478
	SW	513	460	445	432	382	414	506
	NSC	22788	43919	23292	21522	22855	17493	40130
Cambridgeshire	Efficiency	1.000	0.961	0.965	0.943	0.943	0.973	0.936
	SR1	840	647	582	888	817	826	827
	SR4	1742	1793	1861	1789	1878	1770	1812
	VCLR	151	227	37	220	130	117	33
	FW	1787	1799	1759	1766	1765	1680	1746
	SW	598	558	553	492	467	432	482
	NSC	31384	30039	32070	45994	43937	27480	56955

In Table 4.20, two representatives in Group 3 (Southeastern and diverse areas) are selected: Bedfordshire (for efficient performance) and Cambridgeshire (for decreasing efficiency). Except for 2016/17, Bedfordshire was fully efficient from 2013/14 to 2017/18. In 2012/13, its performance was less efficient than 0.9, which was the lowest in this group. The Lower Safety Rate of personal property and violent crime (1578) and much higher Non-Staff Cost (43919) might explain why Bedfordshire was less efficient than Cambridgeshire in 2012/13. Cambridgeshire was fully efficient in 2011/12, with all inputs and outputs exceeding those of Bedfordshire. This confirms the output-oriented DEA models prioritise output in the calculation process.

To improve the pure efficiency of Cambridgeshire in the future, the force should focus on improving the safety rate for motor and household property crime and the clear-up rate for personal violence as these two areas performed far worse in most inefficient years.

Table 4.21. Output and Input variable comparison of group 4 police forces from 2011/12 to 2017/18.

	Variable	2011	2012	2013	2014	2015	2016	2017
Cleveland	Efficiency	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	SR1	714	776	776	723	795	725	857
	SR4	1868	1915	1889	1880	1893	1874	1959
	VCLR	107	189	39	16	104	263	196
	FW	1581	1460	1440	1409	1360	1320	1356
	SW	304	322	227	197	220	267	246
	NSC	32842	50757	49158	49550	49165	26452	84524
Northumbria	Efficiency	0.952	0.909	0.969	0.986	0.980	0.989	0.953
	SR1	667	637	833	692	859	885	880
	SR4	1782	1757	1868	1888	1903	1806	1932
	VCLR	148	106	98	40	33	76	180
	FW	1929	1846	1905	3966	3780	3709	3581
	SW	575	619	624	1037	990	1023	1076
	NSC	55631	53799	55886	53478	50984	51291	78074
Humberside	Efficiency	1.000	0.953	0.943	0.987	0.986	0.950	0.991
	SR1	780	719	357	572	777	730	857
	SR4	1854	1841	1826	1893	1834	1921	1843
	VCLR	216	85	161	139	258	96	52
	FW	2697	2663	2584	2423	2104	2237	2333
	SW	988	894	857	713	632	599	700
	NSC	28363	35737	36071	46733	48426	24125	88696

In Table 4.21, the selected police forces in Group 4 (Northern and deprived areas) are Cleveland (fully efficient), Northumbria (improved during the austerity period), and Humberside (decreased during the austerity period). Northumbria performed worse in 2012/13 than in 2011/12, though it improved between 2012 and 2016/17. The Safety Rate of both crime groups in Northumbria increased from 2012/13 to 2015/16. However, Clear-up Rate sharply fell before 2016/17. Notably, both Workforce functions increased significantly in 2014/15, thus avoiding a negative impact on the efficiency score. Non-Staff Cost fluctuated between a range of £55,000-56,000, though it decreased by the end of the austerity period.

For Humberside, pure efficiency decreased during the austerity period, though there were some improvements in 2014/15. An extremely low value of 357 for Safety Rate for household property crime was recorded in 2013/14, which may have contributed to Humberside's low efficiency score. Both Workforce functions gradually decreased before 2017/18, while Non-Staff Cost increased during the austerity period.

Compared to Cleveland, during the austerity period, Northumbria's clear-up rate for personal violence was sometimes better, whilst the two types of safety rates were the worst performing terms. In the post-austerity period, the clear-up rates fell below Cleveland's, which can most likely be attributed to the delayed impact of austerity (e.g. overwhelming workload and limited resources undermined the well-being of the workforce and the effect would be exposed in the long term). Thus, to improve Northumbria's pure efficiency in the future, attention should first be paid to crime prevention. Later, when sufficient funding is available, the police should maintain clear-up rates to prevent a possible delayed effect from the austerity.

Again, compared to Cleveland, Humberside's performance trends were similar to those of Northumbria. In the austerity period, the safety rates were the main difference between the inefficient and efficient forces. In the post-austerity period, the clear-up rates of inefficient forces revealed some shortages compared to their efficient counterparts. Thus, in order to improve Humberside's pure efficiency moving forward, the force should focus on crime prevention whilst its budget is limited; later, when more funding is available, the force should maintain clear-up rates to prevent a possible delayed effect from the austerity.

Table 4.22. Output and Input variable comparison of group 5 police forces from 2011/12 to 2017/18.							
	Variable	2011	2012	2013	2014	2015	2016	2017
Devon and Cornwall	Efficiency	0.953	0.971	0.967	0.921	0.921	1.000	1.000
	SR1	766	850	863	854	939	897	858
	SR4	1775	1677	1861	1760	1836	1881	1861
	VCLR	175	128	97	59	200	274	208
	FW	4047	3922	3935	3860	3804	3669	3682
	SW	1091	1124	1111	971	991	856	936
	NSC	65605	63084	61280	62408	62156	57793	109125
Suffolk	Efficiency	1.000	1.000	1.000	1.000	1.000	0.955	0.964
	SR1	608	749	902	0	870	839	857
	SR4	1838	1872	1908	1858	1823	1861	1771
	VCLR	289	216	184	450	104	155	94
	FW	1586	1612	1666	1573	1454	1456	1517
	SW	568	522	532	479	457	473	460
	NSC	23520	27446	26696	25299	29506	25507	49668

Table 4.22 compares the variables of two representative police forces in Group 5 (typical areas: Devon & Cornwall and Suffolk). The efficiency of Devon & Cornwall progressively decreased during the austerity period, whereas Suffolk maintained full efficiency. From 2016/17, Devon & Cornwall achieved full efficiency while Suffolk decreased to an inefficient level.

Suffolk had an outline of SR1 in 2014/15 and the value imported into the model is zero. Although Suffolk performed worse in terms of Safety Rate for household property crime in most years between 2011/12 to 2015/16, its Safety Rate for personal property and violent crime was higher than Devon & Cornwall before 2015/16. SR4 seems to exert a greater influence on the efficiency scores in this group. Meanwhile, Clear-up Rate for violent crime in Suffolk was better than that in Devon & Cornwall during the years between 2011/12 and 2014/15.

Frontline, Support Workforce, and Non-Staff Cost in Devon & Cornwall decreased during the austerity period. At the same time, Non-Staff Cost in Suffolk increased, even though Workforce was charting a decreasing trend.

For Devon & Cornwall, compared to the performance of Suffolk, preventing personal property and violent crimes and improving clear-up rates for personal violence will help to close the gap in the outcome performance of the two forces. It should be highlighted that Suffolk became inefficient but Devon & Cornwall became efficient during the post-austerity period. Even so, non-staff costs increased sharply, the workforce did not recover to its level at the beginning of the study period, and Devon & Cornwall's outcome performance was worse than that of Suffolk. This indicates that for Suffolk, going forward, the three outcome variables are all of importance in its efforts to improve pure efficiency.

In Table 4.23, two representative police forces are selected from Group 6 (Large-size areas) for analysis: West Midlands (slightly improved during the whole period) and Greater Manchester (steadily decreased). West Midlands and Greater Manchester performed less and less efficiently from 2011/12 to 2013/14. In both police forces, Safety Rate for household property crime decreased significantly in 2012/13.

Table 4.23. Output and Input variable comparison of group 6 police forces from 2011/12 to 2017/18.

	Variable	2011	2012	2013	2014	2015	2016	2017
West Midlands	Efficiency	0.938	0.928	0.852	0.969	0.969	0.957	0.952
	SR1	721	300	683	788	747	843	818
	SR4	1786	1792	1652	1866	1852	1831	1832
	VCLR	141	34	248	104	158	143	133
	FW	9090	8859	8606	8281	7743	7863	7481
	SW	2396	2217	2221	2084	1777	1777	1886
	NSC	119177	97434	100044	115808	107777	99367	206199
Greater Manchester	Efficiency	1.000	0.969	0.967	0.966	0.966	0.962	0.986
	SR1	841	621	720	825	795	845	837
	SR4	1806	1864	1874	1855	1856	1912	1859
	VCLR	248	305	139	105	246	164	55
	FW	8624	8959	8609	8161	7314	7167	7215
	SW	2616	2317	2175	2423	2154	2222	2122
	NSC	125343	114753	130489	121674	126090	121345	240968

In West Midlands, both crime groups' Safety Rate followed an increasing trend during the study period, though there were some fluctuations between 2013/14 and 2015/16. The Clear-up Rate of violent crime fluctuated between 34 and 248 per 1000 incidents, whilst Frontline and Support Workforce decreased from 2011/12 to 2016/17. Non-Staff Cost did not change much during the austerity period, though it doubled in 2017/18 based on the previous year. In Greater Manchester, the two Safety Rates changed very little, while the Clear-up Rate of violent crime decreased from 2011/12 to 2014/15. Although it later returned to the initial level of 246 per 1000 incidents in 2015/16, it then sharply decreased to 55 in 2017/18. Similar to West Midlands, both Workforce functions decreased most years during the study period, with Non-Staff Cost nearly doubling in 2017/18.

There is no“ efficient peer” in this large-scale force family. The better force, Greater Manchester, outperformed West Midlands in terms of safety rates; however, in terms of clear-up rates for personal violence, Greater Manchester sometimes performed worse than West Midlands. Thus, for West Midlands to bolster its efficiency in the future, it should focus on improving safety rates for two categories of crime.

Table 4.24. Output and Input variable comparison of group 7 police forces from 2011/12 to 2017/18.

	Variable	2011	2012	2013	2014	2015	2016	2017
Lincolnshire	Efficiency	0.962	1.000	1.000	1.000	1.000	1.000	1.000
	SR1	568	683	713	784	701	674	762
	SR4	1775	1793	1807	1877	1880	1934	1815
	VCLR	200	91	97	44	175	83	147
	FW	1500	1257	1229	1251	1206	1194	1234
	SW	518	238	189	188	182	198	244
	NSC	27302	22810	44630	43793	42766	17054	81661
Cheshire	Efficiency	1.000	0.988	0.988	0.971	0.971	0.959	0.975
	SR1	849	783	873	820	812	880	933
	SR4	1857	1909	1908	1859	1847	1863	1871
	VCLR	63	66	53	277	197	97	238
	FW	2545	2518	2426	2498	2674	2694	2695
	SW	975	994	868	805	761	784	852
	NSC	39957	41010	41936	42426	44928	36840	63710

Table 4.24 compares two representative police forces in Group 7 (Central-northern areas): Lincolnshire (most efficient) and Cheshire (efficiency decreased during the austerity period). Lincolnshire achieved full efficiency in every year except 2011/12, whereas Cheshire was only fully efficient in 2011/12, after which point it gradually decreased until it then began to increase in 2017/18.

Lincolnshire improved its Safety Rate for household property crime from 2011/12 to 2014/15 and the Safety Rate for personal property and violent crime from 2011/12 to 2016/17, though the Clear-up Rate of personal violent crime decreased during the austerity period. Both Workforce functions gradually fell, though Non-Staff Cost fluctuated within a large range. Cheshire improved its Clear-up Rate of personal violent crime during the whole period. Similarly, both Workforce functions decreased during the austerity period while Non-Staff Cost roughly remained the same.

Cheshire police force covers a larger area than Lincolnshire, which means that it has more frontline, support workforce, and non-staff costs. Cheshire performed better in safety rates of motor and household property crime in most years than Lincolnshire, though it exhibited lower safety rates of personal property and violent crime and clear-up rates in some years. Thus, in the future, Cheshire needs to improve its safety rates of personal crime and clear-up rates of personal violence to elevate its pure efficiency.

In Section 4.5, the DEA pure efficiency scores are discussed with reference to police force families for the years 2011/12 to 2017/18. In this way, efficient and inefficient police forces are able to compare input and output variables. The above discussion has offered some ways specific forces can improve efficiency scores; it is now necessary to look into how these relate to tangible steps the place can take. Chapter 5 will investigate how workforce allocation and function are associated with fear of crime, crime rates and clear-up rates. It will then propose further suggestions for how police forces can reduce crime and improve their clear-up capacity.

In the next section, scale efficiency scores implying the optimised scale are discussed.

4.6. Scale efficiency with CSEW data

As discussed in chapter 3, when the return of scale assumption is "constant", it does not eliminate the impact of scale and the results represent "overall efficiency". Meanwhile, if the assumption is "variable", the impact of scale is removed, such that what is referred to as "pure technical efficiency". The corresponding "scale efficiency" score is the ratio of "overall efficiency" to" pure technical efficiency", and expresses whether the size of the decision making unit (DMU) is optimal.

After the overall efficiency and pure efficiency scores are calculated, the scale efficiency scores can be derived for the 42 police forces from 2011/12 to 2017/18. This section exclusively focuses on those police forces with full efficiency in scale within each family. Table 4.25 presents the input resources of fully efficient scale police forces from 2011/12 to 2017/18.

As the forces have scale efficiency scores of 1 (i.e. perfect efficiency), the allocation of Frontline Workforce, Support Workforce and Non-staff Cost in Table 4.25 provides an optimised solution of scale in each group. The values for full Workforce efficiency are far below the median of all police forces that year (except for North Yorkshire which exceeded the median of all police forces in 2012/13), whilst most values for fully-efficient Non-Staff Cost are far less than the median of all police forces (except Cleveland in 2012/13 and Lincolnshire from 2013/14 to 2015/16).

Group 1 (only Metropolitan Police) and Group 6 (the four largest forces) have no police forces performing at full scale efficiency. In Group 2, only Dyfed-Powys achieved full scale efficiency during the study period. In Group 3, Bedfordshire performed efficiently in two years. In Group 4, Cleveland and Durham were referred to as the optimized scale in different years. In Group 5, Warwickshire, one of the smallest forces, remained fully efficient on scale across the study period. In response, large-scale police forces in this group can consider restricting their forces by dividing them into smaller workforce groups. Cumbria and Lincolnshire are the two police forces in Group 7 achieving full scale efficiency scores in some years.

Groups 1 and 6 contain five of the largest police forces in England and Wales. Table 4.26 presents their scale efficiency scores for 2011/12 to 2017/18.

Table 4.25. Input resources of the police forces with full scale efficiency, 2011/12 to 2017/18.

	Police Force (police group number)	Frontline Workforce	Support Workforce	Non-Staff Cost
2011/12	Cleveland (4)	1581	304	32842
	Dyfed-Powys (2)	1383	433	18917
	Warwickshire (5)	1140	386	29555
2012/13	Cleveland (4)	1460	322	50757
	Cumbrian (7)	1300	477	28915
	Dyfed-Powys (2)	1423	425	20605
	Gwent (2)	1817	509	24181
	Lincolnshire (7)	1257	238	22810
	North Yorkshire (5)	4014	1364	32438
	Warwickshire (5)	1150	383	31034
2013/14	Cumbria (7)	1351	469	26349
	Dyfed-Powys (2)	1458	407	21375
	Lincolnshire (7)	1229	189	44630
	Warwickshire (5)	1119	284	24961
2014/15	Bedfordshire (3)	1481	432	21522
	Durham (4)	1563	555	21858
	Dyfed-Powys (2)	1397	393	22520
	Gloucestershire (5)	1301	435	26932
	Lincolnshire (7)	1251	188	43793
	Suffolk (5)	1573	479	25299
	Warwickshire (5)	1640	274	24202
2015/16	Cumbria (7)	1353	517	29358
	Durham (4)	1584	619	22156
	Dyfed-Powys (2)	1383	433	21243
	Gloucestershire (5)	1421	517	28714
	Lincolnshire (7)	1500	518	42766
	Warwickshire (5)	1140	386	27296
2016/17	Bedfordshire (3)	1412	414	17493
	Cleveland (4)	1320	267	26452
	Durham (4)	1495	515	23881
	Dyfed-Powys (2)	1382	410	16877
	Gloucestershire (5)	1197	438	26774
	Gwent (2)	1398	330	22663
	Lincolnshire (7)	1194	198	17054
	Northamptonshire (4)	1522	463	17668
	Warwickshire (5)	1241	279	22980
2017/18	Cleveland (4)	1356	246	84524
	Cumbria (7)	1158	557	44190
	Dorset (5)	1598	789	50625
	Dyfed-Powys (2)	1428	413	34967
	Warwickshire (5)	1076	373	47951

Table 4.26. Scale efficiency of police forces in group 1 and group 6, 2011/12 to 2017/18.

	2011	2012	2013	2014	2015	2016	2017
Greater Manchester	0.187	0.265	0.179	0.195	0.184	0.180	0.187
Metropolitan Police	0.038	0.036	0.043	0.045	0.043	0.049	0.052
South Yorkshire	0.417	0.478	0.422	0.428	0.422	0.436	0.415
West Midlands	0.196	0.214	0.224	0.203	0.212	0.198	0.226
West Yorkshire	0.241	0.330	0.237	0.257	0.231	0.227	0.274

Table 4.26 shows that the scale efficiency of the Metropolitan Police remained below 0.3 during the study period, whilst the scale efficiency of the five large-scale police forces did not exceed 0.5. It reveals that large-scale police forces have extremely low scale efficiency. In Chapter 5, panel regression analysis between workforce scale and scale efficiency scores will be used to shed light on their relationship to support the finding that large-scale police forces tend to have low scale efficiency. It should be noted that although the national policing function has been removed from the workforce calculation, some distortions remain in the construction of the variables. For example, the workforce dealing with crimes against children and cybercrime is not included in the results, meaning that these valuable tasks are not included in the efficiency assessment. An exclusion such as this may affect not only pure efficiency, but also the accountability of scale efficiency.

The policy conclusion that might be drawn from this finding is counterintuitive: large police forces should be divided into smaller ones to achieve greater efficiency. In 2005 and 2006, there was a major debate about police force mergers (Godfrey, 2007). The then Home Secretary, the Rt Hon Charles Clarke MP, proposed a super-force plan that aimed to reduce the number of police forces from 43 to 24, achieved by merging small-scale forces. The rationale underpinning this plan was that small forces are poorly-equipped to tackle serious cross-border crime and organised crimes. Additionally, in this dynamic policing landscape, larger, merged forces are more effective in conducting intelligence and investigation operations.

However, many took issue with this suggestion, arguing that the merger programme would be costly and that effective policing relies on community identity in local areas; this public engagement would be lost in centrally managed merged forces. Loveday (2006b) proposed a three-tier policing system as an alternative to "superforces": local BCUs are responsible for neighbourhood policing, territorial forces for serious crimes and other functions, and national agencies for cross-border crime and terrorism.

Although the merger programme was halted in 2006, during the austerity period, police forces were encouraged to collaborate with neighbouring forces to tackle inter-regional or serious organised crime, and share resources and services to cut costs. HMIC (2012; 2013) assessed how the collaboration among 43 forces proceeded: 18 forces achieved savings of more than 10% through collaboration, though eight forces only realised savings of less than 2% by collaborating with peer forces.

Therefore, this study on scale efficiency does not support the merging of small police forces. Instead, in line with previous policy, it is suggested that forces should enhance collaboration to improve the efficiency with which they use the resources available to them. The assessment of scale efficiency in this research does not account for the effect of collaboration as the available data are not labelled as being the product of collaboration. An evaluation of the impact of collaboration on scale efficiency is also needed in the future.

4.7. Conclusion

This chapter discussed the use of Data Envelopment Analysis models with CSEW data, conducting an empirical assessment of 42 police forces for the period 2011/12 to 2017/18. Although police-recorded crime data is more accessible to researchers, crime survey data is more accurate as it includes hidden crime. By analysing the proportion of incidents that were known to the police out of all crimes experienced by respondents to the CSEW in 2015/16, it was found that the proportion of "police know" responses for different categories of crime ranged from 20.7% to 94.6%. The estimate also indicates that no more than 50% of violent crimes were reported to the police.

Before running the DEA models, environmental factors were discussed. There are uncontrollable factors in the process of transforming policing resources into outcomes, and police forces in different areas have to carry out their duties in different socio-demographic conditions. It would be unfair to simply compare crime rates as an outcome of policing between different police forces, as there are environmental factors that affect crime rates. To properly examine the relationship between immigrants, deprivation, inequality, and crime rates, this research uses the Index of Multiple Deprivation (excluding its crime domain) and an immigrant variable to classify police forces. 37 police forces (excluding the City of London, Metropolitan Police, and four Welsh forces) were classified in two-dimensional space and grouped into five police force families: including the Metropolitan Police and the four Welsh forces, there are seven police force families in total.

After an initial DEA model was carried out using recorded crime data for 2015/16, the research selected and calculated outputs using CSEW data. Firstly, Fear of Crime, Crime Rate and Clear-up Rate were taken as output variables, whilst Frontline Workforce, Support Workforce and Non-Staff Cost were taken as input variables for the DEA model. The first model with the CSEW data used nine variables: Fear of Crime, Safety Rate of household property crime, Safety Rate of personal property crime, Safety Rate of personal violent crime, Clear-up Rate for property crime, Clear-up Rate for violent crime, Frontline Workforce, Support Workforce, and Non-Staff Cost. However, the high dimension of the assessment model produced unreliable results, with more than half of the decision units being fully efficient. Thus, some dimension reduction was required.

Due to the significant correlation between Fear of Crime and other output variables, and the positive relationship between the total Clear-up Rate and Clear-up Rate for violent crime, the revised DEA model contained just six variables: Safety Rate for household property crime, Safety Rate for personal property and violent crime, Clear-up Rate for violent crime, Frontline Workforce, Support Workforce, and Non-Staff Cost. Seven DEA models were run for 42 police forces using CSEW data from 2011/12 to 2017/18. The pure efficiency score of a police force represents its efficiency without the impact of scale. Through Pearson's correlation testing, it was found that values of Safety Crime for personal property and violent crime exhibit a significant statistical correlation to the pure efficiency scores at the police force level, while Clear-up Rate and Safety Rate for household property crime have an unstable association – sometimes significant but sometimes not – with the pure efficiency scores across the whole study period. There is no significant relationship between the pure efficiency score and the allocation ratio of Frontline Workforce over Support Workforce.

Fully efficient and inefficient police forces were then compared within police force families. In each group, two or three forces were selected as representative examples to compare their input and output values over the whole period. Some forces were fully efficient from the offset, whilst others improved during the austerity period or performed worse than in 2011/12. This research compares the changes in input and output values of each force over the years, and also analyses the difference between efficient, better, and worse forces, respectively.

Finally, the comparison provided schematic examples for each group: by comparing with the fully efficient police forces within the group, it identified which aspects of input-output variables an inefficient police force should improve in the future. Advice was then offered for the "worse" forces on how to improve their pure efficiency scores in terms of input and output variables. The recommendations were not reflected in all variables: some inefficient forces generally performed better on one variable but worse on another compared to their efficient peers in the family, whilst some outcome variables appeared to be better in the austerity period though they decreased in the post-austerity period. This part of the analysis contributes to the application of DEA models combined with the environmental factors, thus allowing inefficient forces to learn which aspect of the input-output data has room for improvement in the real environment of their own peer family.

There are some limitations to the efficiency assessment done by DEA models with the CSEW data. The problems of CSEW include the following: the data do not reflect crimes against children under 15, crimes against people living in institutions or against the homeless, financial crime or business fraud. Additionally, there is a small possibility that the personal crimes registered in the responses did not actually occur in the police force area in which the respondent resides. Although the CSEW introduced questions on cybercrime in 2015/16, cybercrime is removed from the assessment for comparability in this research. Meanwhile, the construction of clear-up rate inevitably contains factors beyond the control of forces such as decisions by the prosecution and courts that can affect charge rates. Therefore, due to many limitations, it cannot be said that the assessment of police efficiency in this research covers all the services provided by the police and selects all representative indicators that should be considered in the implementation of DEA. In terms of DEA results, those police forces with lower scores performed inefficiently. However, this could be because they had to dedicate resources to solving the problems of children or the homeless , which are not measured by the models.

The DEA also calculated scale efficiency to determine how the scale of a police force affects overall efficiency. The findings showed that large-scale police forces achieved extremely low scale efficiency scores each year. Groups 2, 3, 4, 5, and 7 contain small-scale police forces that attained full efficiency scores. Their workforce and expenditure could be referred to as the optimised scale within the group. This finding is counter to the rationale for the contentious "merging forces" proposals of 2006.

In general, it can be said that most forces performed better in the efficiency assessment during the austerity period; at the national level, the improved outputs and reduced policing resources suggest that police forces in England and Wales became more efficient, which is consistent with the Coalition government's expectations. However, the general decline in clear-up rates especially in the first three years implies that austerity negatively impacted the tasks that the police have to deal with after a crime has been committed.

In addition to the limitations of variables and data already discussed above, there is still one point worth discussing here: efficiency is assessed by looking at value for money, which entails measuring how a police force translates resources into performance with a limited budget. Due to the wider public sector budget cuts, value for money is a goal worth pursuing. However, blindly focusing on value for money will lead to the neglect of some local policing services that are expensive yet still important. For example, assisting children and the disabled often requires more resources than assisting adults healthy. Finally, an assessment system based on value for money would lead the police to focus more on tasks that are easy and inexpensive to complete, which again reflects the impact of austerity.

5. Analysis of effectiveness

Following the efficiency assessment and examination of the DEA results, this chapter analyses those policing outcomes that acted as output variables in the DEA models described above. As the main policing outcomes, variables such as Fear of Crime, Crime Rate and Clear-up Rate – all measured using self-reported victimisation data – will be compared both across the sampled years and within each police force family. Further details, such as crime rates by crime categories, reporting rate, and detection rate, shed light on more performance amongst the 43 English and Welsh police forces. In addition to investigating the associations among these indicators using regression models, correlation analysis is also carried out to determine the forces' effectiveness and measure their efficiency. This research is chiefly interested in the frontline workforce and its impact. With this in mind, this chapter unpacks the workforce data relating to three functions: (1) Responses; (2) Neighbourhoods; and (3) Intelligence and Investigation. Panel regression models for the 42 police force individuals and seven-year time series will be employed to investigate whether the workforce aspect of these functions affects any outcome indicators.

This chapter is structured as follows: section 5.1 describes and compares policing outcomes based on the survey data both at the police force area level and within police families. Section 5.2 discusses the relationship between effectiveness, workforce scale, and scale efficiency, whilst section 5.3 probes the relationship between frontline allocation, visibility, and crime rates. Sections 5.4-5.6 examine three different functions of the frontline workforce (responses, neighbourhoods and intelligence and investigation workforce) and their possible impact on effectiveness. Finally, section 5.7 provides a conclusion.

5.1. Outcome comparison

Though section 4.5 compared the resources and outcomes of the police forces in the years after the DEA scores were released, further details pertaining to policing outcomes are of interest. The Fear of Crime variable was initially introduced into the efficiency assessment framework, though it was later removed due to the requirement of dimension reduction and its correlation with other output variables. Nevertheless, this study still seeks to address the following questions: (1) Did Fear of Crime change during the austerity period and if so, how?; (2) Compared to the others in its group, which police forces area have alleviated worries about crime to the greatest extent?; (3) Which aspect of resources has the greatest impact on Fear of Crime?

Only the first two questions are answered in this section, though it also explores Fear of Crime and how it is reflected in Pure Efficiency after Fear of Crime is compared within groups. This is necessary to determine how it relates to the DEA models. The outcome comparison of crime rates and clear-up rates on the basis of self-reported victimisation data will only entail a descriptive comparison, as they have already served as output variables in the DEA models. Accordingly, a linear explanation between them and the pure efficiency scores is unnecessary. Further multivariate analysis to account for changes and variations in outcomes will be presented in the following sections.

Variable Crime Rate plays an important role in the efficiency assessment framework: there were three crime rate categories initially included that were then aggregated into two Crime Rate variables to meet the dimension reduction requirement. In this chapter, Crime Rate is discussed in three categories: motor and household property crime, personal property crime, and personal violent crime. Specifically, the data will be analysed to determine which police forces handled more crimes during the austerity period and which handled fewer. Following the UK studies that indicate the negative relationship between the level of crime and police presence (Machin and Marie, 2005; Draca, Machin and Witt, 2008), this chapter also seeks to identify any association between the allocation of the frontline workforce and crime rates. The Clear-up Rate variable is partly represented by the Clear-up Rate of personal violent crime in the DEA efficiency assessment. This chapter goes deeper into Clear-up Rate, especially the reporting rate, which pertains to the proportion of "police come to know about the matter" across all incidents. The method of grouping police forces introduced earlier continues to be used in this chapter.

(1) Fear of Crime

Fear of Crime (FC) at the police force level is calculated as the average of the "worried" responses relating to six categories of crime: home being broken into by strangers, mugging and robbery, car being stolen, things being stolen from car, rape, and physically being attacked by strangers. Respondents were questioned on whether they were worried about other crime categories (cybercrime and things stolen from the home), though such questions were not included in the questionnaire for each of the years sampled in this study. For constituency, the Fear of Crime variable only measures the main six categories of property and violent crime. The City of London police force did not return Fear of Crime values in any year due to its small sample, which is in turn due to its small resident population. Respondents' worries in the remaining 42 police force areas are described below.

Returning back to the discussion in section 4.3, the limitation of a scale with no neutral values may introduce bias at the individual level, as values of 2 and 3 indicate positive and negative for worry, respectively. When the total data is averaged, a value of 2.5 is treated as a neutral for worry in this research, which means "neither worried nor unworried". Accordingly, all values larger than 2.5 will be treated as negative for worry (relatively unworried).

Group 1: (Metropolitan only: The largest force in England and Wales with the most prosperous economy and diverse culture)

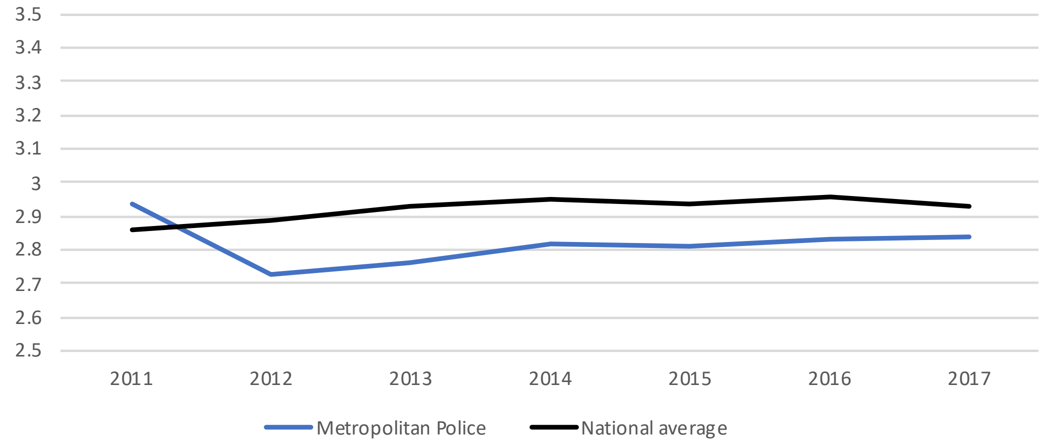

Figure 5.1. Fear of Crime of Metropolitan Police from 2011/12 to 2017/18.
1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.

The national average of Fear of Crime ranges from 2.86 to 2.96, which locates the average response between "fairly worried" to "not very worried". It should be noted that high values for Fear of Crime mean the respondents are not particularly worried about crime. Worries about crime gradually reduced between 2011/12 and 2016/17, later increasing in 2017/18. The values for Fear of Crime in Metropolitan Police are all less than the national average except in 2011/12. Figure 5.1 shows that residents in the Metropolitan Police area worried more about crimes in the main six crime categories in 2011/12 than the national average. Specifically, in 2012/13, respondents were more worried about crime than the national average. Although worries about crime in the Metropolitan Police area gradually decreased between 2012/13 and 2017/18, the score remained higher than the national average at the end of this period.

Group 2: (Welsh police forces: Large areas of open countryside and a relatively small number of large urban areas with a much lower urbanisation rate and a higher ageing rate)

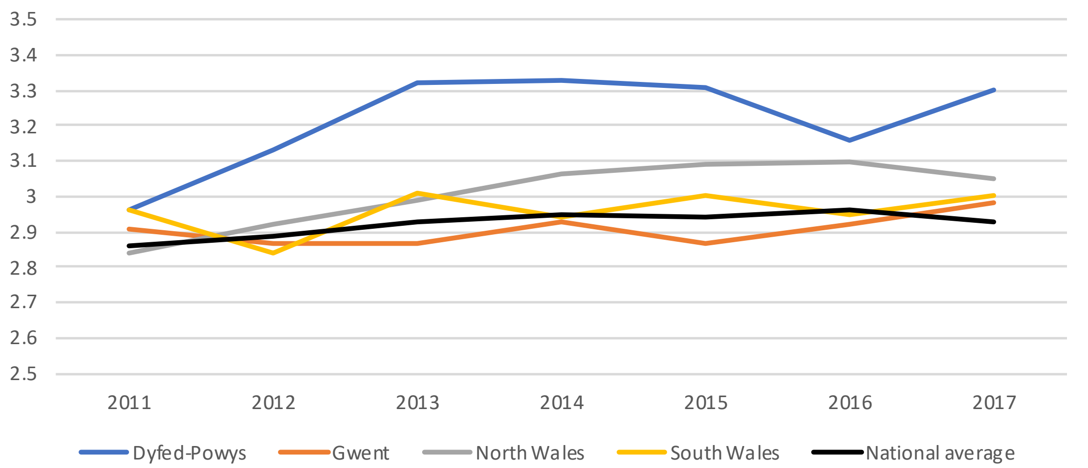

Figure 5.2. Fear of Crime of Welsh Police forces from 2011/12 to 2017/18.
1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.

Figure 5.2 presents the Fear of Crime values of Welsh police forces from 2011/12 to 2017/18. Only one police force, Dyfed-Powys, returned scores for less worried about crime than the national average during this period. Unlike other police force areas in this group, most of the values of Dyfed-Powys fall between "not very worried" and "not at all worried". This was also the only force that maintained full efficiency in each year included in the DEA assessment model. Contrastingly, Gwent was the police force area whose values all fall between "not very worried" and "fairly worried". Moreover, respondents in this area were more worried about crime than the national average from 2012/13 to 2016/17. notably, this was the least efficient force in the group. In North Wales, values for worries about crime decreased to a level far below the national average between 2011/12 and 2016/17, though they increased in 2017/18, which was consistent with the national trend. In South Wales, values for worried about crime fluctuated throughout the entire study period and showed little improvement from the 2011/12 starting point.

Group 3: (Southeastern and diverse areas: Adjacent to or not far from London with a prosperous economy and less social deprivation)

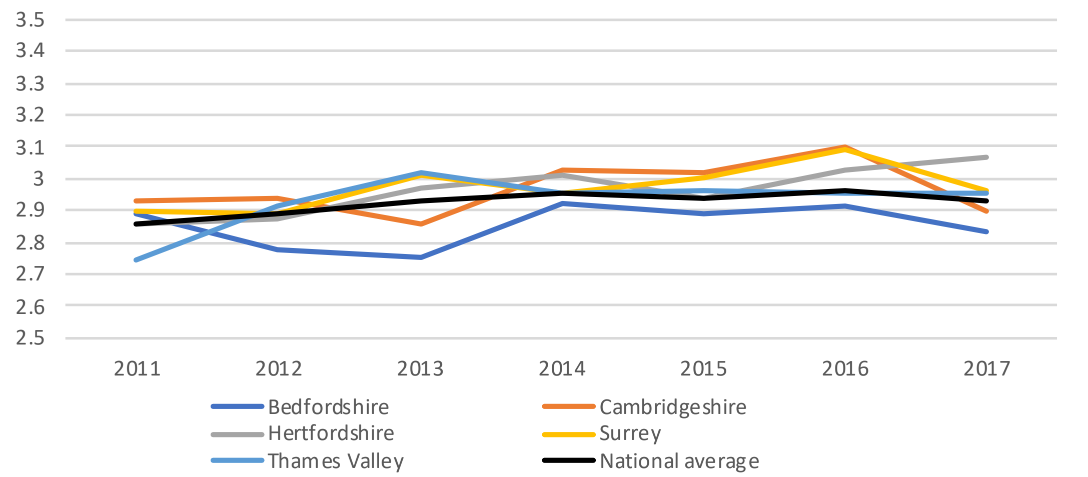

Figure 5.3. Fear of Crime of police forces in group 3 from 2011/12 to 2017/18.
1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.

Figure 5.3 plots the values of Fear of Crime of five police forces in Group 3 as well as the national average. Police forces in Group 3 show more convergence than those in Group 2. The most worried police force during the whole period is Bedfordshire (except for 2011/12), which was also the most efficient police force in the group based on the DEA assessment models. Worries about crime in Bedfordshire and Cambridgeshire increased from 2011/12 to 2013/14. This change was not consistent with other police forces and the national average in this group. Cambridgeshire saw its relative efficiency fall across the period except for 2015/16. However, the trend exhibited by Fear of Crime does not reflect any relationship with the efficiency scores. Surrey was the one police force area where the worried about crime values were less than the national average during the entire study period.

Group 4: (Northern and deprived areas: Former industrial areas that have undergone economic restructuring over the past several decades; the population has high levels of unemployment and low levels of education and skills)

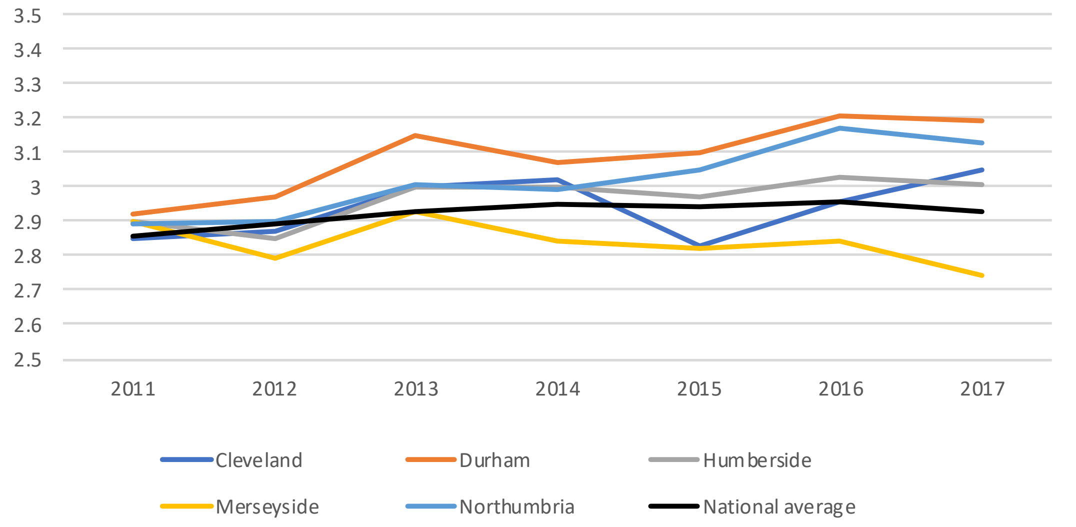

Figure 5.4. Fear of Crime of police forces in group 4 from 2011/12 to 2017/18.
1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.

Figure 5.4 plots the police forces in Group 4, which clearly demonstrate greater divergence than Group 3. The two least worried police forces, Durham and Cleveland, were less worried than the national average. Compared to 2011/12, both of their values relating to worried about crime increased during the austerity period and the whole period, from around 2.9 to more than 3.1. These two police forces were also the most efficient in the DEA assessment model, where Cleveland score 1 for each year and Durham scored 1 from 2013/14 to 2017/18. All police forces reduced their worried about crime values compared to the year 2011/12, except the most worried force, Merseyside. Merseyside has a higher score for worried about crime than the national average from 2012/13, and this score gradually increased from 2013/14 onwards.

Group 5: (Typical areas: Neither affluent nor deprived, not in an area with the highest or lowest levels of immigrants. All southern coastal areas in England are included in this group, featuring a mix of urban and rural areas)

Table 5.1. Fear of Crime of police forces in group 5 from 2011/12 to 2017/18.
(1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.)

	2011	2012	2013	2014	2015	2016	2017
Avon and Somerset	2.85	2.95	3.06	3.07	3.05	2.93	3
Devon and Cornwall	2.85	3.04	3.24	3.02	3.16	3.15	3.12
Dorset	2.82	3.12	3.13	3.12	3.09	3.12	3.07
Essex	2.86	2.93	2.87	2.84	2.95	2.88	2.81
Gloucestershire	2.86	2.94	2.95	3.11	2.94	2.87	2.77
Hampshire	2.92	2.94	3.05	3.08	3.05	3.10	3.03
Kent	2.87	2.91	2.96	2.95	2.88	2.99	3.02
Leicestershire	2.91	2.8	2.74	2.81	2.82	2.85	2.81
Norfolk	2.82	2.94	2.92	2.99	3.10	3.08	3.03
North Yorkshire	2.86	3.07	3.22	3.22	3.25	3.24	3.16
Northamptonshire	2.67	2.81	2.86	2.96	2.86	2.93	2.94
Suffolk	2.79	2.96	3.05	3.00	3.03	3.01	2.98
Sussex	2.95	2.93	3.07	3.05	3.04	3.14	3.03
Warwickshire	2.85	2.77	2.86	2.89	2.96	2.93	2.94
West Mercia	2.84	2.92	3.05	2.97	3.04	2.97	3.06
Wiltshire	2.85	2.97	2.98	2.95	2.99	3.02	3.00
National average	2.86	2.89	2.93	2.95	2.94	2.96	2.93

Table 5.1 plots the Fear of Crime values of the 16 police forces in Group 5. As the 16 lines cannot be clearly presented in the same chart, Figure 5.5 below only plots the Fear of Crime values for six representative police forces.

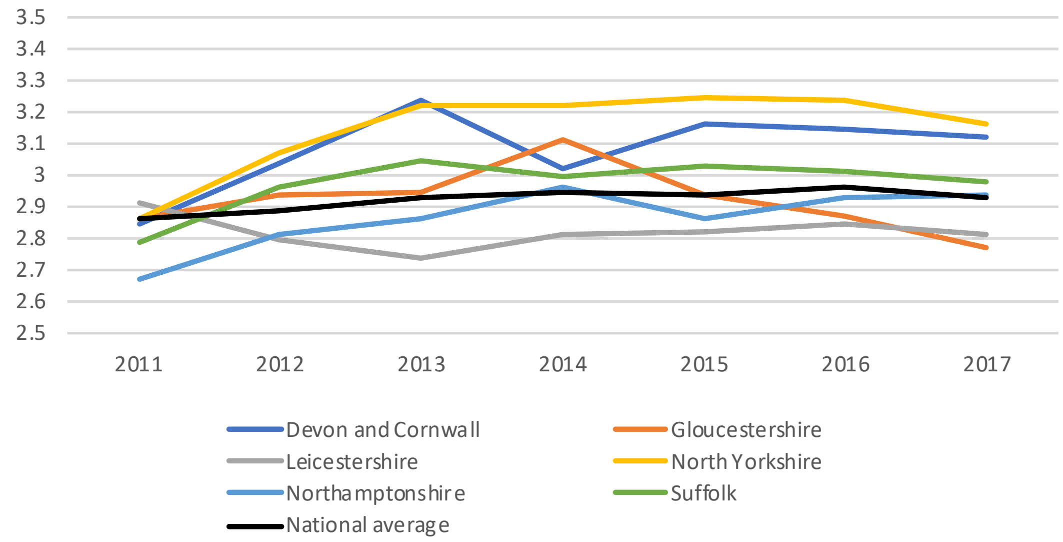

Figure 5.5. Fear of Crime of the represetative police forces in group 5 from 2011/12 to 2017/18.
1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.

In Figure 5.5, the worried about crime scores decreased during the austerity period for all police forces except Leicestershire. Devon and Cornwall, Suffolk, Northamptonshire, and North Yorkshire became less worried during the whole period. North Yorkshire was the least worried police force area in most years. North Yorkshire, Devon and Cornwall, and Suffolk also returned lower scores than the national average from 2012/13. Northamptonshire reduced its score for worried about crime from a level far above the national average in 2011/12 to one slightly below it in 2017/18. Similarly, in the DEA assessment models, it was the least efficient police force in 2011/12, only becoming fully efficient in 2016/17.

Group 6: (Large-size areas: Four of the largest police forces located in the centre and north of England)

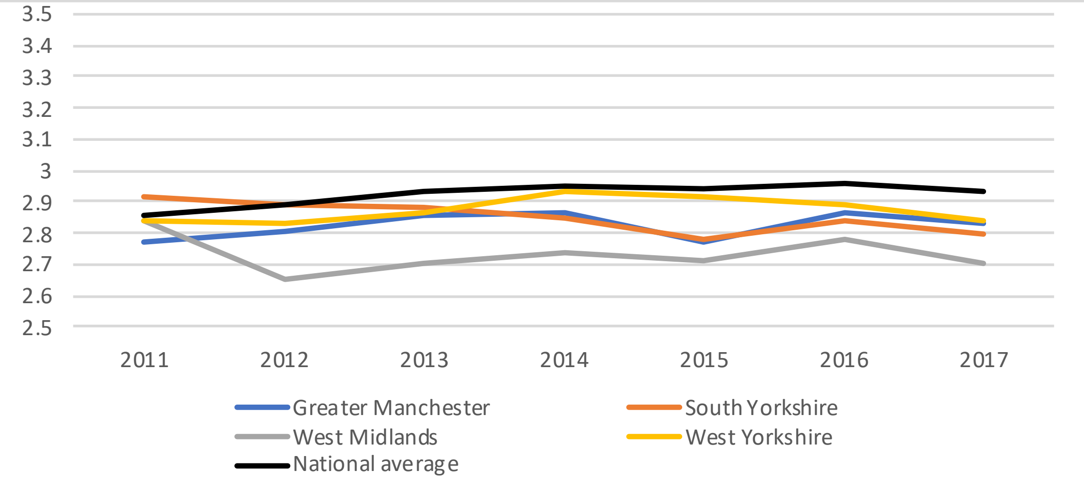

Figure 5.6. Fear of Crime of police forces in group 6 from 2011/12 to 2017/18.
1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.

Compared to Groups 2-5, the large-scale police forces in the Group 6 were almost worse than the national average: only South Yorkshire respondents were less worried about crime in 2011/12. South Yorkshire started as an area with a worried about crime score lower than the national average, though respondents became more worried than average six years later. In section 5.2, panel regression analysis will be employed to investigate whether respondents covered by large-scale police forces will be more worried about crime, and therefore, these forces will have higher scores in this regard. West Midlands was the most worried area between 2012/13 and 2017/18, with scores fluctuating around 2.7 during the period. West Yorkshire and Greater Manchester followed trends similar to the national average: worried about crime scores decreased from 2011/12 to 2014/15 and increased from 2017/18, with Greater Manchester seeing a sharp rise in its score in 2015/16.

Group 7: (Central-northern areas: Relatively low level of ethnic diversity and a relatively larger ageing population)

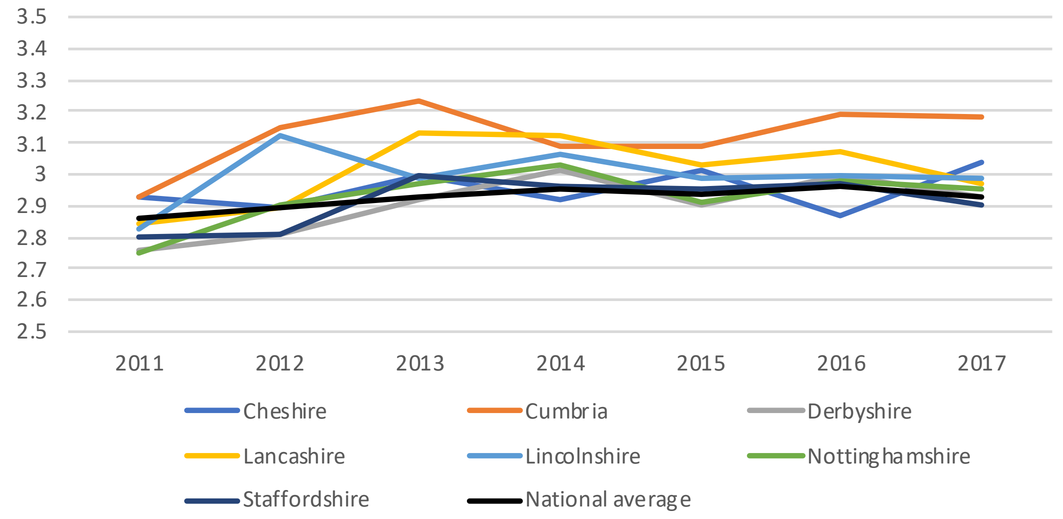

Figure 5.7. Fear of Crime of police forces in group 7 from 2011/12 to 2017/18.
1 = very worried; 2 = fairly worried; 3 = not very worried; 4 = not at all worried.

Most police force areas in Group 7 had worried about crime scores below the national average. The least worried area, Cumbria, was also one of the most efficient police forces. Interestingly, Lincolnshire, another fully efficient police force, did not consistently return scores indicating "least worried". Meanwhile, Cheshire experienced continually declining pure efficiency over the entire period, though its Fear of Crime value fluctuated in the 2.9-3.0 range, which means "not very worried".

By conducting comparisons both within groups and over the years, it can be seen that some large urban areas have always had higher scores for worried about crime than the national average. This could be due to the corresponding higher crime rates in those areas. This issue will be further investigated in the following sections. For large-size police forces, this creates a challenge of how to alleviate residents' worries about crime. Specifically, it is unclear whether increased worries are likely to stem from high perceptions of crime rates at the local level due to spatial disparities, from low visibility of the police, or from difficulties large police forces covering urban areas experience gaining public trust. These potential issues are elaborated on below and in the next chapter.

This research now moves on to compare the Fear of Crime values in the years 2011/12, 2014/15, and 2017/18. During the austerity period (2011/12 to 2014/15), the worried about crime scores decreased in most areas. Scores in Avon and Somerset, Derbyshire, Dorset, Dyfed-Powys, Gloucestershire, Lancashire, Lincolnshire, North Wales, North Yorkshire, Northamptonshire, Suffolk, Thames Valley fell by more than 0.2 during this time, whilst Dyfed-Powys was the area where worries about crime reduced the most (0.37) during this period. However, eight areas became slightly more worried: Cheshire, Essex, Leicestershire, Merseyside, Metropolitan, South Wales, South Yorkshire, and West Midlands. In the post-austerity period (2014/15 to 2017/18), only 26 police force areas reduced their worried about crime scores, fewer than in the austerity period. When looking at the study period as a whole, worried about crime values fell in most areas, though they rose in Bedfordshire, Cambridgeshire, Essex, Gloucestershire, Leicestershire, Merseyside, Metropolitan, South Yorkshire, and West Midlands.

Finally, the box plots for Fear of Crime illustrate how the worry of crime scores for each police force area are distributed, which helps to understand the broader trends as they evolve over the years. Figure 5.8 draws box plots for the Fear of Crime values in police force areas for each year. In box plots, the black lines in the box are median lines, whilst the upper and lower lines of the box represent the upper and lower quartiles, respectively. The bigger the box is, the more divergent the police force areas are. In 2011, the middle 50% of police force areas performed similarly in terms of Fear of Crime, which was concentrated in a range below 0.1. Contrastingly, in 2013 and 2016, dispersion among these areas increased. In terms of median, worried about crime values decreased below those recorded in the beginning during the austerity and post-austerity periods. Outliers were also observed in most years, which are marked as points located beyond the upper or lower whiskers. In these box plots, outliers are defined as values smaller than (lower quartile - 1.5*inner quartile range) or larger than (upper quartile + 1.5*inner quartile range). To be precise, these points are: 2011-Northamptonshire, 2012-West Midlands, 2012-Dorset, Lincolnshire, Dyfed-Powys, Cumbria, 2013-Dyfed-Powys, 2014-Dyfed-Powys, 2015-Dyfed-Powys, and 2017-Dyfed-Powys. Consistent with the group comparison described above, Dyfed-Powys was the least worried area in the majority of years. Some of these points will be removed in the following analysis.

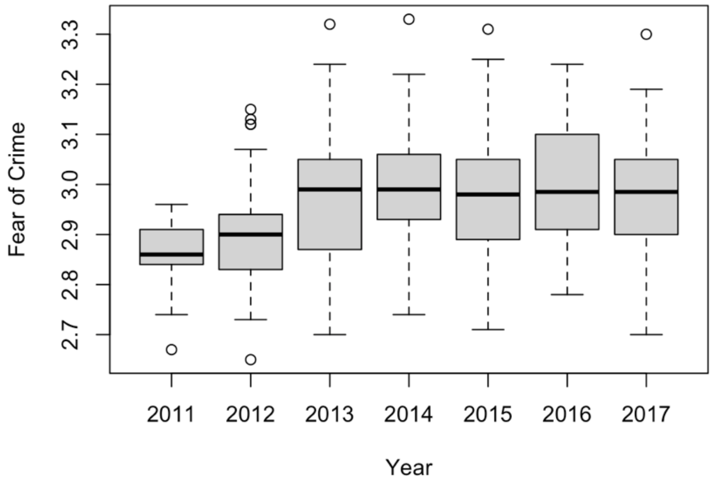

Figure 5.8. Boxplots for Fear of Crime at the level of police force area in each year. 1 = very worried. 2 = fairly worried. 3 = not very worried. 4 = not at all worried.

Some police forces maintained full efficiency and low levels of worry about crime during the period, though some fully efficient forces did not achieve consistent trends for Fear of Crime. As a result, consideration needs to be given to whether there is any relationship between the pure efficiency scores and worry about crime scores for specific police forces. To do so, the correlation in the pooling context must be tested. Pearson's correlation testing estimates the correlation coefficient as 0.27 and the p-value as less than 0.001, indicating that FC and PE form a significantly positive correlation. Linear regression can then be used to investigate the relationship between these two variables. Before carrying out the regression, the scatterplot for these two variables should first be checked. In Figure 5.9, the outliers of Fear Crime are obvious and these points will be removed in the later analysis: 2011-Derbyshire, Bedfordshire, 2012-West Midlands, 2015-Nottinghamshire, and 2016-Sussex. The outliers of Pure Efficiency have been discussed already (2013-Dyfed-Powys, 2014-Dyfed-Powys, 2015-Dyfed-Powys, and 2017-Dyfed-Powys). The scatterplot with the outliers removed is presented in Figure 5.10.

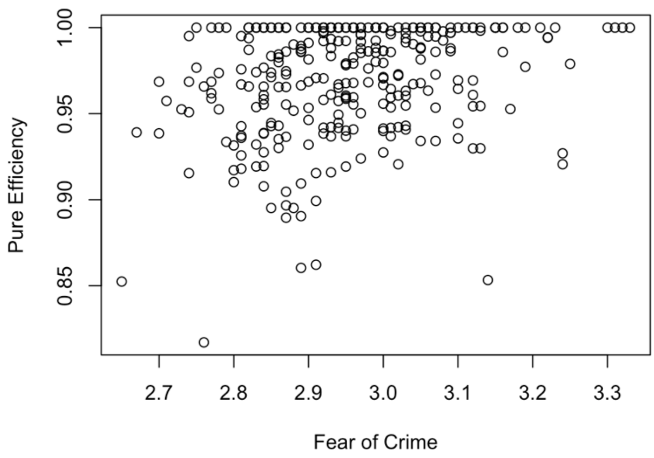

Figure 5.9. Scatterplot for Fear of Crime and Pure Efficiency with outliers.

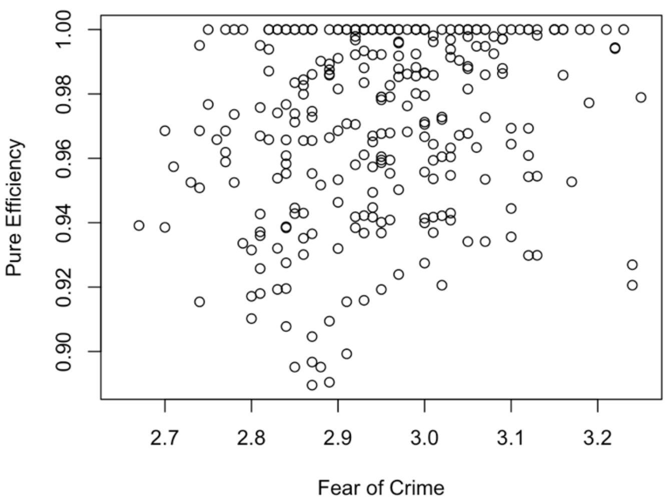

Figure 5.10. Scatterplot for Fear of Crime and Pure Efficiency without outliers.

Based on the dataset presented in Figure 5.10, linear regression is feasible. However, this set of police forces was repeatedly measured each year, which led to errors stemming from the repeated sampling of the individuals. In simple linear regression, the random error e is assumed to perform a normal distribution, such that every observation is expected to have the same intercept α. However, such an assumption is not authentic if there are repeatedly measured individuals. In this case, this research considers adding a fixed effect α_i for each individual i (i.e., a dummy variable). At the same time, the clustering of standard errors at the force level is inevitable; accordingly, the correlation in error terms within the police force area is allowed. α_i also helps to solve a problem proposed in chapter 4: police force areas operate in different socio-economic conditions and there are many hidden variables related to crime statistics lying on spatial status. Therefore, using fixed-effect individual regression eliminates the linear relationship within the individual over the years.

This research is also interested in the effect between individuals, that is, on average of time, how the explanatory variables impact the dependent variables between individuals. In this case, observations are calculated as an average over time. In the results, a larger R-squared indicate that the model explains a larger proportion of the variance in Pure Efficiency than other models. Adjusted R-squared is a modified R-squared that functions to eliminate insignificant predictors in the regression. As such, it is more reliable than R-squared, especially when used in multivariate regression models. A significant coefficient of Fear of Crime means that it forms a significant linear relationship with Pure Efficiency. This research not only uses R-squared to select the "better" model, but also determines the relationship between explanatory and dependent variables by analysing changes in the coefficients of the four models and changes in R-squared value.

To investigate the relationship between Pure Efficiency and Fear of Crime in terms of fixed effect, the two variables are considered in a panel data framework with units (police forces) $i = 42$ (excluding City of London) and time period $T = 7$, meaning that the observations $N = i \times T = 294$. If any outlier appears in the variable, their values are defined as NA. A panel regression model is then conducted with the pooling method that first treats observations as different individuals and ignores the effect of individuals or time:

$$Model\ 1: PE_{it} = \alpha_1 + \beta_1\, FC_{it} + e_{1it}$$

Also, considering the effect of repeatedly measured police forces and unobserved variables, a fixed-effect panel regression Model 2 and between-effect panel regression Model 3 were conducted:

$$Model\ 2: PE_{it} = \alpha_{2i} + \beta_2 FC_{it} + e_{2it}$$

$$Model\ 3: \overline{PE}_i = \alpha_3 + \beta_3\, \overline{FC}_i + e_{3i}$$

where PE_{it} and FC_{it} are the values of pure efficiency and fear of crime of individual i at time t; $\overline{PE}_i$, $\overline{FC}_i$ are the average values of pure efficiency and fear of crime over the years. These are taken as new variables that integrate information from each year into a single point. As a result, there is no *t* subscript included. α_{2i} is a series of dummies for each individual, which indicates that different intercepts are estimated for different individuals. Model 3 estimates the relationship on basis of individuals on the average of all years; therefore, it contains the universal intercept α_3, not the fixed effect term α_{3i}. Model 2 asks: how is *PE* related to the *FC* of a specific police force over the years? The implications of Model 2 can be described in terms of whether there is a positive, negative, or no significant relationship between *PE* and *FC* in a specific area over the years. Model 3 asks: How is a force's average *PE* over the course of all years related to the average *FC*? The implications of Model 3 can be described in terms of whether there is a positive, negative or no significant relationship between *PE* and *FC* on average over the years across the areas. Considering the fixed effect of time, this research also conducts a regression Model 4 with the effects of both individuals and time:

$$Model\ 4: PE_{it} = \alpha_{4i} + \beta_4 FC_{it} + \gamma_{4t} + e_{4it}$$

where γ_{4t} is the fixed effect – a series of dummy variables that are different for different times.

The standard errors are clustered at the police force area level. The function plm( ) from package "plm" is deployed to implement the fixed-effect model in R, choosing "individual" model for Models 1, 2 and 3 and "twoway" for Model 4. The effect parameters for Models 1, 2, and 3 are "pooling", "within" and "between", respectively. The results are presented in Table 5.2.

Table 5.2. Results of panel regression models of Pure Efficiency on Fear of Crime.

	Intercept		Fear of Crime			
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	RSq	Adj. Rsq
Pooling	0.797381 (0.042092)	2.2e-16	0.058938 (0.014254)	4.683e-05	0.056975	0.053643
Within			0.038142 (0.018891)	0.04459	0.016566	-0.15411
Between	0.703431 (0.079427)	5.678e-11	0.090095 (0.028938)	0.001757	0.2194	0.19988
Two-way			0.0039537 (0.0230912)	0.8642	0.00012421	-0.20324

From Table 5.2, it can be seen that the "two-way" model does not estimate a significant coefficient for Fear of Crime in relation to Pure efficiency as the p-value is 0.86 and the Adjusted R-Squared is less than 0 (a minus R-Squared is treated as 0). Contrastingly, the other three models all provide significant coefficients (p-values <0.05) for the explanatory variables. However, the Adjusted R-Squared in the within-individual fixed-effect regression is less than 0, indicating that Fear of Crime in this model is not able to explain much of the variance in Pure Efficiency. Furthermore, the "between" model has the largest Adjusted R-Squared, 0.132, meaning that Fear of Crime in this model can explain 13.2% of the variance in Pure Efficiency.

The between regression results and the pooling regression show that there is a cross-sectional positive relationship between Fear of Crime and Pure Efficiency. When the fixed unobserved characteristics of police force areas are accounted for, the within model estimates a smaller coefficient for Fear of Crime, indicating that the strength of the relationship is weakened. When time trend is also included, the "twoway" model determines that changes in Pure Efficiency are not related to the changes in Fear of Crime within each police force as the relationship disappears. The time-varying unobservables at the force area level may be potentially related to the dependent variable. These results are reasonable because DEA models are implemented separately for each year, such that the PE values form a series of relative values within years.

The positive coefficient (0.078) in the between model reveals a positive relationship between the two variables: if the value of *FC* in an area increases by 1 (worry reduces by 1), then the average of *PE* over the sampled years is expected to improve by 0.078. It is not easy for an area to improve its *FC* score by 1, given that the total range spans 2.5 to 3.5. Improving by 0.1 is more realistic; therefore, the average of *PE* over the years is expected to rise by 0.0078, which is not reflective of a large-sized effect. It should also be noted that this linear relationship is not actually realistic because improving *FC* from 2 (fairly worried) to 3 (not very worried) to 4 (not worried at all) means very different things in different areas and will have produced different-sized effects on average PE scores over the years.

It should be pointed out that these results indicate the following: there is no significant evidence to show the pure efficiency scores of a specific police force are related to its fear of crime over the years. On average, over the years sampled, pure efficiency scores form a positive linear relationship with the fear of crime value for all police forces. Thus, there is no inevitable relationship between pure efficiency and worried about crime in a specific area during the study period. Besides, an area with a lower worried about crime score tends to have a higher average pure efficiency score compared with others over the study period.

Taking 2017/18 as an example, Figure 5.11 illustrates the positive relationship between the fear of crime and pure efficiency scores among the 42 English and Welsh police forces.

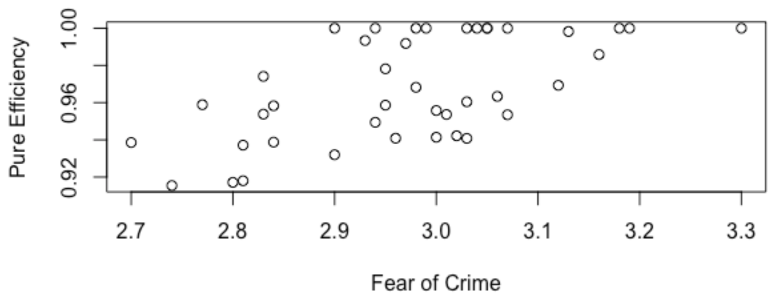

Figure 5.11. Scatterplot for pure efficiency and Fear of Crime in 2017/18.

This regression analysis exclusively investigates the possibility of a bivariate relationship, not a multivariate relationship including many explanatory variables, is that the present research is interested in the link between the worry variable and its reflection on pure efficiency because it has been removed from the DEA models. A model featuring a greater number of explanatory variables may better account for their impact on pure efficiency than bivariate regression. This possibility be explored in later sections once all the outcome variables have been prepared. Following the comparison in this section, no regression analysis between crime rates or clear-up rates and pure efficiency will be carried out. As these two outcomes serve as output variables in the DEA models, they do not form linear relationships with pure efficiency scores (which is how the DEA works). Descriptive comparisons of outcomes over the years are presented in the following analysis.

(2) Crime rates

In section 4.5, the crime rates in the 42 police force areas from 2011/12 to 2017/18 have been compared using two Safety Rates (motor household property crime, and personal property and violent crime). This section drills down into how the crime level changed in the 42 police force areas during the study period. Cybercrime data was been gathered through the survey until 2015/16; accordingly, it is not included in the DEA assessment or this section.

The respective crime rates of 18 crime categories are counted. However, due to the sampling limit, the estimated crime rates for a specific crime are less reliable than the sum. With this in mind, the Crime Rates in 18 crime categories are divided into three groups: (1) CR1, crime rates per 1000 population for motor and household property crime, including motor vehicle being theft, things being stolen from a motor vehicle, vehicle being damaged and bicycle theft, things being stolen from the home, house being damaged, and things being stolen outside the house; (2) CR2, crime rates per 1000 population for personal property crime, including things being stolen from the person or anywhere outside, and things being damaged; (3) CR3, crime rates per 1000 population for personal violent crime, including deliberate violence to the person, threat of using violence, sex assault, and violence in the household.

In contrast with the analysis of Fear of Crime, Crime Rate will not be compared to the efficiency scores as it has already been used as an output indicator in the revised DEA assessment model. The comparison between Crime Rate in police force areas examines which police forces improved or deteriorated during the austerity period, the post-austerity period, and the study period as a whole.

Figure 5.11 presents the national-level data for the study period, which shows that estimated crime rates gradually decreased in England and Wales from 2011/12 to 2017/18. Motor and household property crimes showed the greatest reduction, as the rate for this category of crimes decreased from 286 to 117 per 1000 population. Similarly, the rate for personal property crimes and personal violent crimes slightly decreased from 57 to 35 per 1000 population, and 143 to 107 per 1000 population, respectively. Despite budget reductions, three categories of crimes decreased during the austerity period, though personal violent crimes began to increase again in 2014/15.

The remarkable reduction in crime rates reflects an effective outcome of policing. However, it is important to be cautious about claiming that such reductions are exclusively the product of police efforts, as there are several factors that affect criminal circumstances that are beyond the control of the police. For example, although the DEA analysis and fixed effects regression controlled for the time-invariant unobserved factors, there are real-world time-varying factors that affect crime rates, e.g. economic status in each year and unemployed young men. Another possible explanation is that the types of crime committed have changed over time, such that new types of crime are not included in the variable produced by the CSEW, e.g., cybercrime. Therefore, the premise of this research should be cautious in noting that not all reductions in crime rates are indicative of overall police success in crime prevention.

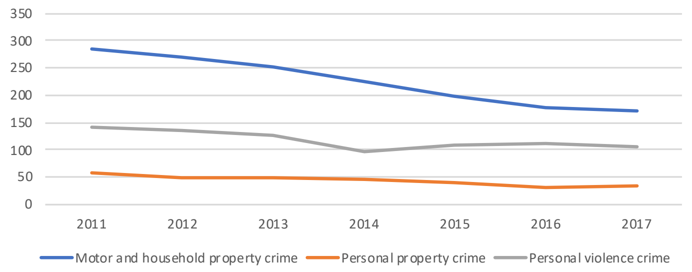

Figure 5.11. Crime rates at the national level from 2011/12 to 2017/18.

Turning to the data on police force areas, some police forces appear to have 1000 per 1000 population crime rates for motor and household property in some years (although the true values are greater than 1000, the estimation carried out for present purposes defined all values over 1000 as 1000). However, it is not realistic to say that all residents living in these areas will, for instance, have items stolen from their cars. The data are more likely to be a result of sampling bias: for example, if some respondents repeatedly suffered from multiple offences of the same type, that offence is allocated a high weight in the dataset. As a result, the corresponding estimates of crime rates may be abnormally higher than those estimates in other areas.

The distribution of crime rates at the police force area levels in each year is presented in the box plots in Figure 5.12. In terms of CR1, police force areas were more divergent in 2014/15 than 2011/12, though they were more concentrated in later years. In terms of CR2 and CR3, the data from the different police forces was less divergent in 2014/15 compared to 2011/12, though it later increased in the post-austerity period.

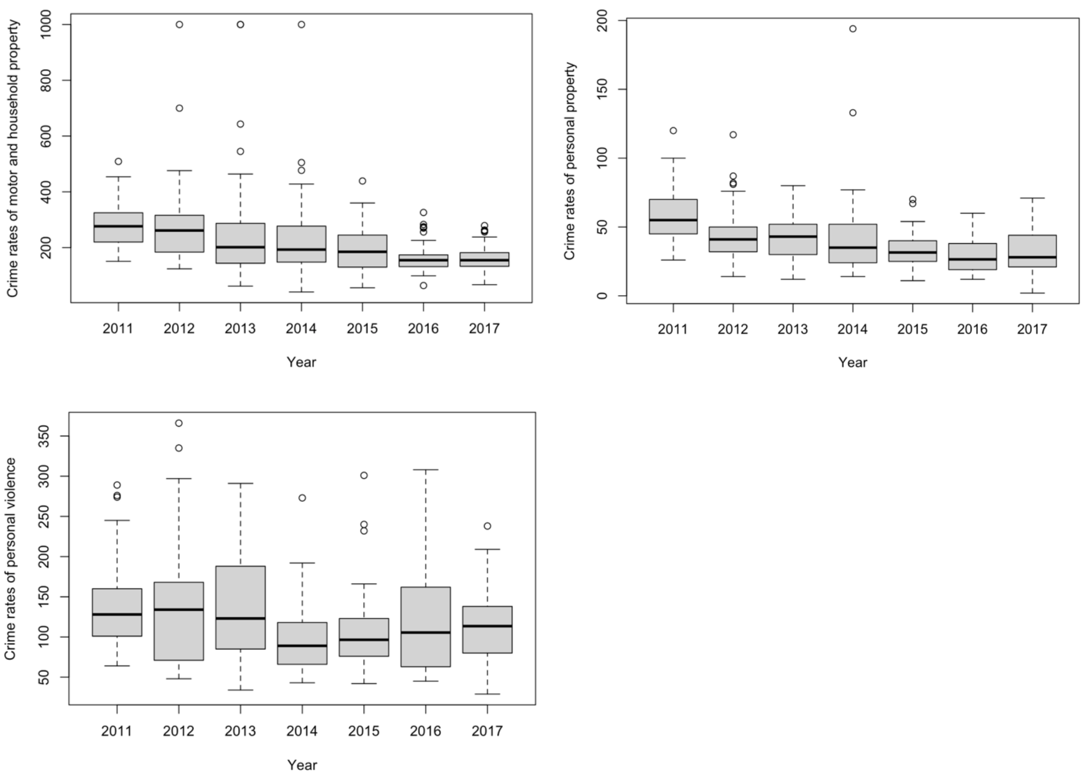

Figure 5.12. Crime rates (per 1000) of three categories at the police force level from 2011/12 to 2017/18.

Turning to whether any of the 42 police forces (excluding City of London) reduced their crimes during the austerity period, changes in crime rates (per 1000 population) are listed in Table 5.3 for each police force, with notable changes highlighted in red. During the 2011/12 to 2014/15 period, 31 police forces reduced their crime rates for motor and household property, whilst 11 forces faced rising crime rates. Norfolk performed worst, with its crime rates rising by 186 per 1000. Leicestershire experienced the greatest change, with the motor and household property crime rate decreasing by 322 per 1000, only to later increase by 76 until 2017/18.

The following areas reduced their crime rates by more than 200 per 1000: Gloucester, Hertfordshire, Leicestershire, Merseyside, Northamptonshire, Staffordshire, and Suffolk. Among these areas, only Northamptonshire continued to reduce rates during the post-austerity period, whilst the other five areas recorded more crimes over the post-austerity period (even though there was no budget reduction policy in place at the time). Among the 31 forces who reduced their motor and household property crimes rates between 2011/12 and 2014/15, only 12 succeeded in reducing crime during the post-austerity period: Cleveland, Derbyshire, Durham, Gwent, Lincolnshire, Metropolitan, North Yorkshire, Northamptonshire, Northumbria, Nottingham, Warwickshire, and West Midlands.

A similar analysis is carried out in Tables 5.4 and 5.5. Regarding personal property crime, 37 police forces reduced the associated crime rate between 2011/12 and 2014/15, with only 5 forces recording elevated crime rates. Metropolitan performed worst, with crime rates rising by 24 per 1000. Devon and Cornwall experienced the greatest change in its rates, with personal property crime decreasing by 8 per 1000, only to later increase by 70 until 2017/18. The areas in which crime rates decreased by more than 50 per 1000 were: Devon and Cornwall, Hampshire, Lincolnshire, Merseyside, Warwickshire, and West Midlands. Among these areas, crime rates continued to decrease in Warwickshire and West Midlands in the post-austerity period. Among the 37 forces that reduced personal property crimes from 2011/12 to 2014/15, only 17 forces successfully continued to reduce crime rates during the post-austerity period.

In terms of personal violent crime, 27 police forces reduced their crime rates between 2011/12 and 2014/15, with 15 forces recording elevated crime rates. Nottingham performed worst, with crime rates rising by 178. Dyfed-Powys experienced the greatest change in its rates, with personal violent crime decreasing by 228 per 1000, only to later increase by 82 until 2017/18. The areas in which crime rates decreased by more than 100 per 1000 were: Bedfordshire, Cambridgeshire, Derbyshire, Dorset, Durham, Dyfed-Powys and Kent. Among these areas, crime rates continued to decrease in Bedfordshire and Durham during the post-austerity period. Of those 27 forces where the personal violent crime rates decreased between 2011/12 and 2014/15, only 10 forces successfully continued to reduce crime rates in the post-austerity period.

Table 5.3. Changes in crime rates (motor and household property crime) in police force area during the period of austerity, post-austerity and the whole period, per 1000 population. Notable changes are highlighted in red: the red in “2011/12 -2014/15” means remarkable reductions, and the red in “2014/15-2017/18” means having decreased crime rates during both periods.

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	-74	12	-62
Bedfordshire	-130	13	-117
Cambridgeshire	23	-10	13
Cheshire	37	-121	-84
Cleveland	-81	-62	-143
Cumbria	59	-221	-162
Derbyshire	-1	-191	-192
Devon and Cornwall	-173	81	-92
Dorset	-197	23	-174
Durham	-62	-157	-219
Dyfed-Powys	-181	32	-149
Essex	-42	67	25
Gloucestershire	-274	58	-216
Greater Manchester	46	-42	4
Gwent	-43	-84	-127
Hampshire	-163	124	-39
Hertfordshire	-210	20	-190
Humberside	3	-80	-77
Kent	138	-134	4
Lancashire	46	-155	-109
Leicestershire	-322	76	-246
Lincolnshire	-133	-61	-194
Merseyside	-249	33	-216
Metropolitan Police	-81	-63	-144
Norfolk	186	-309	-123
North Wales	-179	204	25
North Yorkshire	-70	-46	-116
Northamptonshire	-282	-10	-292
Northumbria	-192	-21	-213
Nottinghamshire	-161	-121	-282
South Wales	34	-87	-53
South Yorkshire	-119	66	-53
Staffordshire	-212	14	-198
Suffolk	-262	13	-249
Surrey	-122	42	-80
Sussex	-96	35	-61
Thames Valley	4	-20	-16
Warwickshire	-9	-115	-124
West Mercia	-107	9	-98
West Midlands	-26	-71	-97
West Yorkshire	-126	72	-54
Wiltshire	-177	48	-129

Table 5.4. Changes in crime rates (personal property crime) in police force area during the period of austerity, post-austerity and the whole period. Notable changes are highlighted in red: the red in "2011/12 -2014/15" means remarkable reductions, and the red in "2014/15-2017/18" means having decreased crime rates during both periods.

Police force area	2011/12-2014/14	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	-1	-19	-20
Bedfordshire	-40	-5	-45
Cambridgeshire	-2	1	-1
Cheshire	-38	6	-32
Cleveland	1	-19	-18
Cumbria	-36	-2	-38
Derbyshire	-43	16	-27
Devon and Cornwall	-80	7	-73
Dorset	-24	-9	-33
Durham	-11	-23	-34
Dyfed-Powys	-32	2	-30
Essex	-15	15	0
Gloucestershire	-31	12	-19
Greater Manchester	-9	-24	-33
Gwent	-17	2	-15
Hampshire	-50	22	-28
Hertfordshire	-14	-6	-20
Humberside	-26	5	-21
Kent	-11	-11	-22
Lancashire	-11	-26	-37
Leicestershire	-11	26	15
Lincolnshire	-52	20	-32
Merseyside	-72	23	-49
Metropolitan Police	24	-19	5
Norfolk	-30	13	-17
North Wales	-19	-14	-33
North Yorkshire	-13	-4	-17
Northamptonshire	-19	28	9
Northumbria	-44	-9	-53
Nottinghamshire	-33	-11	-44
South Wales	-37	19	-18
South Yorkshire	-38	2	-36
Staffordshire	-28	-5	-33
Suffolk	9	-34	-25
Surrey	-29	22	-7
Sussex	21	-22	-1
Thames Valley	1	-5	-4
Warwickshire	-55	-2	-57
West Mercia	-32	17	-15
West Midlands	-66	-7	-73
West Yorkshire	-7	-8	-15
Wiltshire	-9	24	15

Table 5.5. Changes in crime rates (personal violence) in police force area during the period of austerity, post-austerity and the whole period. Notable changes are highlighted in red: the red in "2011/12 -2014/15" means remarkable reductions, and the red in "2014/15-2017/18" means having decreased crime rates during both periods.

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	11	-4	7
Bedfordshire	-174	-11	-185
Cambridgeshire	-134	65	-69
Cheshire	48	-30	18
Cleveland	-26	-47	-73
Cumbria	-59	21	-38
Derbyshire	-156	39	-117
Devon and Cornwall	19	-32	-13
Dorset	-123	91	-32
Durham	-101	-49	-150
Dyfed-Powys	-228	82	-146
Essex	-66	39	-27
Gloucestershire	-18	70	52
Greater Manchester	-41	21	-20
Gwent	81	-139	-58
Hampshire	-74	25	-49
Hertfordshire	-60	65	5
Humberside	46	-14	32
Kent	-165	27	-138
Lancashire	-28	-14	-42
Leicestershire	64	-79	-15
Lincolnshire	-53	45	-8
Merseyside	-63	103	40
Metropolitan Police	-81	-35	-116
Norfolk	3	33	36
North Wales	-11	-45	-56
North Yorkshire	-70	-24	-94
Northamptonshire	-24	32	8
Northumbria	-77	-20	-97
Nottinghamshire	178	-237	-59
South Wales	15	-7	8
South Yorkshire	48	126	174
Staffordshire	-86	55	-31
Suffolk	6	86	92
Surrey	46	-54	-8
Sussex	35	4	39
Thames Valley	20	-2	18
Warwickshire	-35	-70	-105
West Mercia	-8	-3	-11
West Midlands	0	27	27
West Yorkshire	36	23	59
Wiltshire	-42	86	44

(3) Clear-up rates: reporting rates, detection rates and charge rates

As set out in section 4.3, the Clear-up Rate is calculated as a multiple of three indicators: reporting rates (from the question "did the police come to know about the matter"), detection rates (from the question "did the police find out or knew who did it"), and charge rates (what action, if any, did the police take against the person who did it"). Actions taken were then translated into charge rates, which refer to the following actions: "charge them", "give them a caution", "give them a fine or Penalty Notice for Disorder", "make them do something to make amends for the matter" and "some other specific action". The DEA assessment framework takes the clear-up rates for violent crime as an output indicator. However, in this chapter, this research tries to investigate the clear-up rates for two categories: property crime (household property and motor crime, as well as personal property crime) and personal violent crime.

Figures 5.13-15 present the reporting, detection, and charge rates for both property crime and personal violent crime at the national level for the 2011/12 to 2017/18 period. At the national level, each year the reporting rates for property crime are less than those for personal violent crime. Also, the detection rates for property crime are far below those for personal violent crime. However, in most years, the charge rates for property crime are slightly higher than those for personal violent crime.

In general, the overall reporting rate fluctuated within a narrow range across the whole period. It is hard to say there have been significant changes in reporting rates in England and Wales. Reporting rates slightly increased in 2014/15 relative to 2011/12. Similar to reporting rates, detection rates in England and Wales also slightly improved during the austerity period, before stabilising during the post-austerity period. Charge rates fluctuated in a wider range than the other two rates, improving from 2011/12 to 2013/14 before deteriorating sharply in 2014/15. After taking the three rates into account, the overall clear-up rate in 2011/12 in England and Wales was 51%, rising to 55% in 2013/14 before sharply falling to 46% in 2014/15. From these results, it can be concluded that overall, although the police performed better prior to 2014, they performed worse during the austerity period as the proportion of crimes cleared up was less than those in 2011.

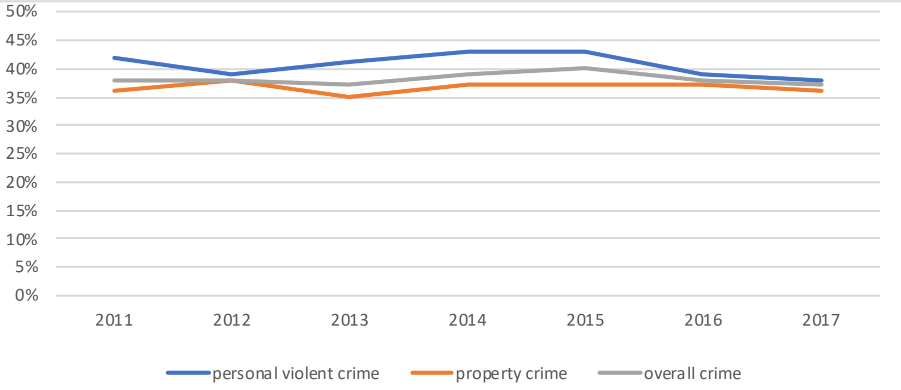

Figure 5.13. Reporting rates at the national level from 2011/12 to 2017/18.

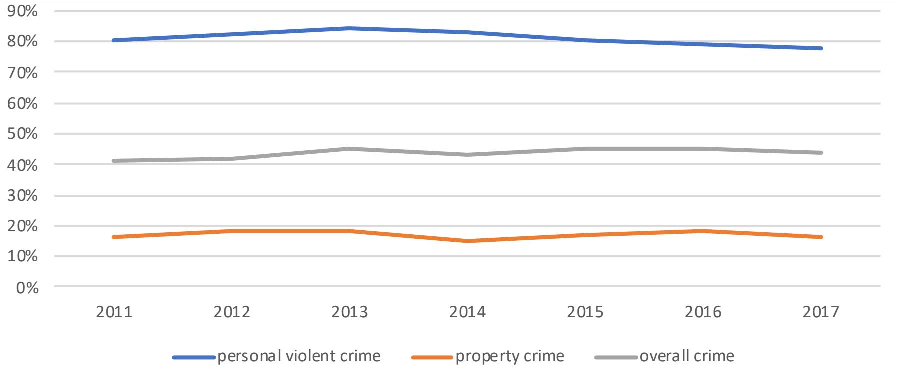

Figure 5.14. Detection rates at the national level from 2011/12 to 2017/18.

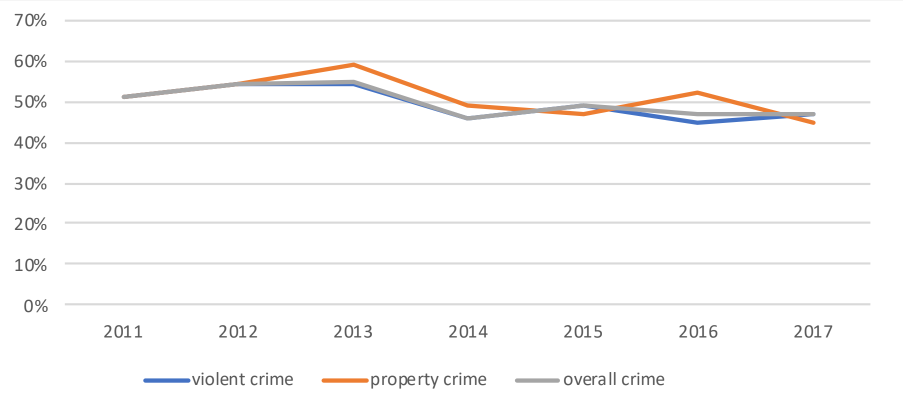

Figure 5.15. Charge rates at the national level from 2011/12 to 2017/18.

It should be pointed out that clear-up rates vary between different types of crime. Taking the year 2015/16 as an example, the reporting rate for “vehicle stolen or driven away without permission” was 94.59%, whilst the rate for “member of household has used force or violence on adult respondent” was just 49.7%. The detection rates of these two crime types were 18.5% and 100% and the charge rates were 61.9% and 75.8%, respectively. Table 5.9 lists the reporting rates, detection rates, charge rates, and overall clear-up rates for each specified crime type at the national level in 2015/16.

Table 5.6. Clear-up rates in England and Wales, 2015/16.

Crime category	Crime type	Reporting	Detection	Charge	Clear-up
Motor	vehicle being stolen or driven away without permission	94.6%	18.5%	61.9%	10.8%
	something being stolen off or out of vehicle	39.8%	8.2%	61.6%	2.0%
	vehicle being tampered with or damaged	29.8%	18.4%	37.9%	2.1%
	Bicycle being stolen	49.1%	12.0%	23.4%	1.4%
Household property	Someone got into current residence to steal/try to steal (movers)	78.5%	17.7%	81.6%	11.3%
	Someone got into current residence and caused damage (non movers)	81.8%	35.9%	24.4%	7.2%
	Someone tried to get into current residence to steal/cause damage	48.3%	15.4%	52.2%	3.9%
	Something was stolen out of current residence	30.0%	40.2%	34.6%	4.2%
	Something was stolen from outside the current residence	27.3%	14.3%	44.4%	1.7%
	Something was damaged outside current residence	43.3%	30.1%	38.8%	5.1%
Personal property	Something was stolen out of hands, pockets or bag	49.8%	9.2%	68.0%	3.1%
	Someone tried to steal anything from hands, pockets or bag	20.1%	37.3%	53.3%	4.0%
	Something has been stolen from a cloakroom, office etc.	21.4%	13.2%	70.3%	2.0%
	Personal items have been deliberately damaged	26.5%	9.1%	68.8%	1.7%
Personal violence	Someone has deliberately used force/violence on adult respondent	52.1%	75.6%	48.7%	19.2%
	Someone has threatened to damage things/use force or violence	39.1%	82.4%	42.9%	13.8%
	Adult respondent has been sexually assaulted or attacked	32.0%	87.9%	37.4%	10.5%
	Member of household has used force or violence on adult respondent	49.7%	100.0%	75.8%	37.7%

It is more accurate to also analyse the clear-up rates for each specific crime type at the police force area level. However, as there were only around 1000 samples in each area per year, it is hard to investigate any specific crime type. Thus, comparisons of clear-up rates at the police force area level can only be separately described in relation to two categories: property crimes and violent crimes.

Firstly, Figure 5.16 shows the distribution of clear-up rates for property crime at the police force area level. Most forces recorded clear-up rates of less than 10% and the medians hovered around 3% across the entire study period. In 2014/15, most police forces exhibited a degree of convergence, though the clear-up rates were lower than those recorded in 2011/12. In Table 5.7, notable changes are highlighted in red. These shed light on which police forces were better able to improve their clear-up rates during the austerity period.

20 of the 42 police forces improved their clear-up rates between 2011/12 and 2014/15, and 21 forces cleared up a smaller proportion of property crimes. Norfolk performed worst, as its clear-up rate decreased by 5.4 percentage points. Lincolnshire improved the most, with the force clearing up 5.6 percentage points more property crimes in 2014/15 than in 2011/12, though this fell by 0.4 percentage points until 2017/18. The following forces improved their clear-up rates by more than three percentage points: Avon and Somerset, Cheshire, Lincolnshire, North Yorkshire, and Staffordshire. Among these areas, only Cheshire continued to improve its rates during the post-austerity period. Among the 20 forces that improved their property crime clear-up rates, only five forces continued to make improvements during the post-austerity period: Cheshire, Cleveland, Cumbria, Dorset, and West Yorkshire.

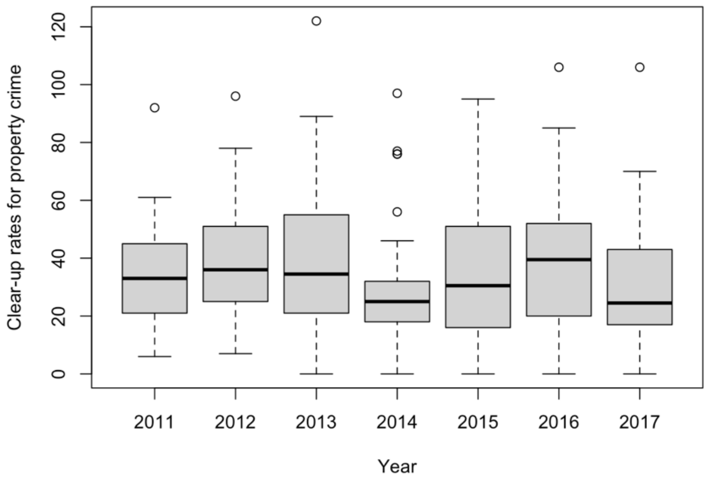

Figure 5.16. Clear-up rates for property crime (‰) at the level of police force area from 2011/12 to 2017/18.

Table 5.7. Changes in clear-up rates (property crime, ‰) in police force area during the period of austerity, post-austerity and the whole period. Notable changes are highlighted in red: the red in "2011/12-2014/15" means remarkable improvements, and the red in "2014/15-2017/18" means having improved clear-up rates during both periods.

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	33	-58	-25
Bedfordshire	3	17	20
Cambridgeshire	-15	-6	-21
Cheshire	33	11	44
Cleveland	23	2	25
Cumbria	13	48	61
Derbyshire	-31	25	-6
Devon and Cornwall	-7	-14	-21
Dorset	20	16	36
Durham	23	-30	-7
Dyfed-Powys	-24	1	-23
Essex	19	-28	-9
Gloucestershire	-11	-18	-29
Greater Manchester	-16	-9	-25
Gwent	14	-28	-14
Hampshire	-7	23	16
Hertfordshire	-4	5	1
Humberside	-50	0	-50
Kent	-14	-9	-23
Lancashire	-17	-11	-28
Leicestershire	-6	20	14
Lincolnshire	56	-4	52
Merseyside	-6	29	23
Metropolitan Police	4	-2	2
Norfolk	-54	63	9
North Wales	35	-51	-16
North Yorkshire	-31	-12	-43
Northamptonshire	-29	-17	-46
Northumbria	23	-55	-32
Nottinghamshire	22	-4	18
South Wales	-4	-33	-37
South Yorkshire	3	21	24
Staffordshire	50	-32	18
Suffolk	0	6	6
Surrey	-16	8	-8
Sussex	-30	21	-9
Thames Valley	5	-3	2
Warwickshire	6	-33	-27
West Mercia	-9	-31	-40
West Midlands	2	-15	-13
West Yorkshire	6	19	25
Wiltshire	21	-8	13

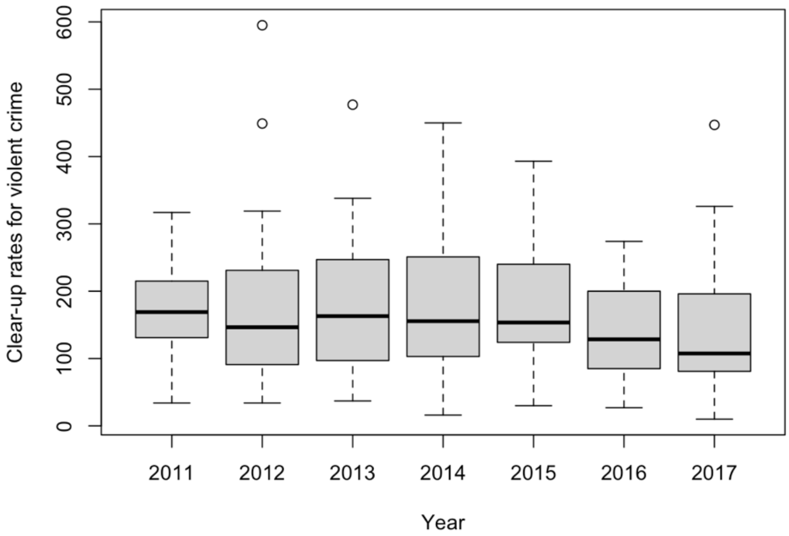

Figure 5.17. Clear-up rates for violent crime (‰) at the level of police force area from 2011/12 to 2017/18.

Table 5.8. Changes in clear-up rates (violent crime, ‰) in police force area during the period of austerity, post-austerity and the whole period. Notable changes are highlighted in red: the red in "2011/12-2014/15" means remarkable improvements, and the red in "2014/15-2017/18" means having improved clear-up rates during both periods.

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	-49	94	45
Bedfordshire	-93	34	-59
Cambridgeshire	-21	-97	-118
Cheshire	134	41	175
Cleveland	-3	92	89
Cumbria	255	-131	124
Derbyshire	107	-56	51
Devon and Cornwall	25	8	33
Dorset	19	215	234
Durham	92	-248	-156
Dyfed-Powys	-40	-152	-192
Essex	21	45	66
Gloucestershire	-13	28	15
Greater Manchester	-2	-191	-193
Gwent	24	-63	-39
Hampshire	-98	-67	-165
Hertfordshire	30	-61	-31
Humberside	42	-206	-164
Kent	96	-105	-9
Lancashire	170	-137	33
Leicestershire	109	-241	-132
Lincolnshire	-25	-28	-53
Merseyside	-18	-45	-63
Metropolitan Police	-39	-47	-86
Norfolk	-97	172	75
North Wales	-210	181	-29
North Yorkshire	-5	-54	-59
Northamptonshire	-43	5	-38
Northumbria	-115	147	32
Nottinghamshire	0	25	25
South Wales	-51	1	-50
South Yorkshire	54	-28	26
Staffordshire	-117	-23	-140
Suffolk	-185	-10	-195
Surrey	17	-76	-59
Sussex	97	-197	-100
Thames Valley	-98	64	-34
Warwickshire	7	-24	-17
West Mercia	113	-185	-72
West Midlands	17	-25	-8
West Yorkshire	-22	93	71
Wiltshire	149	-111	38

Subsequently, violent crime rates are analysed in a similar way. Figure 5.17 shows the distribution of clear-up rates for personal violent crime at the police force area level. Most forces had clear-up rates below 30% in all years and the medians hovered around 15% before 2013 and decreased afterwards. In 2014/15, most police forces exhibited more divergent albeit lower clear-up rates than those recorded in 2011/12. Table 5.8 shows in detail those police forces that were better able to improve their clear-up rates during the austerity period.

Also, 20 of 42 police forces (though not the same 20 noted above that made improvements in Table 5.7) improved their clear-up rates between 2011/12 and 2014/15, whilst 21 forces cleared up a smaller proportion of violent crimes. North Wales performed worst, with its clear-up rate decreasing by 21 percentage points. Cumbria was the most improved area, with the local police clearing up 25.5 percentage points more violent crimes in 2014/15 than in 2011/12, though the clear-up rate later fell by 13.1 percentage points until 2017/18. The following forces improved their clear-up rates by more than 10 percentage points: Cheshire, Cumbria, Derbyshire, Lancashire, Leicestershire, and West Mercia. Among these, only Cheshire continued to improve its rates during the post-austerity period. Of the 21 forces who cleared up more violent crimes during the austerity period, only four forces continued to make improvements during the post-austerity period: Cheshire, Devon and Cornwall, Dorset and Essex.

This section compared effectiveness outcomes between police force areas and over the study period. The following sections aim to discern any relationship between effectiveness outcomes and resource indicators in an effort to determine if and how can a police force improve its effectiveness through the reallocation of resources.

5.2. Workforce, scale efficiency, and fear of crime

In section 4.6, as the scale efficiency scores in the large-size police family (group 6) are extremely low, scale efficiency appears to be negatively related to workforce. In section 5.1, worried about crime values are more similar in the large-scale police family. Here, this research considers the Workforce variable (the sum of the frontline workforce and support workforce; likewise, this variable does not cover the work carried out as part of the national policing function) to represent the size of police forces. This section investigates the relationship between workforce scale and scale efficiency, as well as the relationship between workforce scale and fear of crime.

(1) Workforce and scale efficiency

Firstly, data analysis verifies the correlation between Workforce (*WW*) and Scale Efficiency (*SE*) at $n = 42$ and $T = 7$. The pooling Pearson's correlation test shows that the 95% confidence interval of the correlation coefficient is (-0.67, -0.52) and the p-value is less than 0.001. On this basis, it can be said that the workforce and scale efficiency form a statistically significant negative relationship at the police force level. Figure 5.18 also indicates the broadly negative relationship.

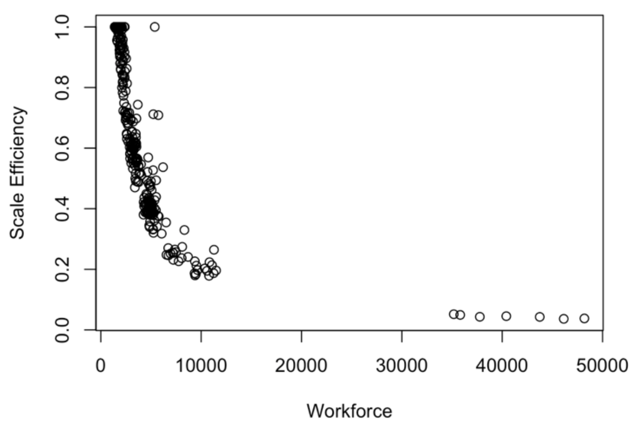

Figure 5.18. Scatterplot for workforce (full-time equivalent) and scale efficiency at the level of police force area in all years.

Before conducting a linear regression model, the Workforce outliers must be dealt with, similar to those in section 5.1. Here, there are 7 outliers (Metropolitan Police in 7 years) that fall far away from other police forces. It is possible to directly remove the outliers; however, the outliers that give rise to this relationship may be more similar to a log function. On this basis, this research also tries to transform Workforce to log(Workforce), rather than removing the outliers directly.

Figure 5.19 more accurately depicts the negative linear relationship between these two variables. Pearson's correlation testing estimates the correlation coefficient to be -0.91 with a p-value below 0.001. These results mean that log(Workforce) has a significantly strong negative relationship with Scale Efficiency at the police force level. The Metropolitan Police force still produces log(Workforce) outliers in each year; therefore, it is excluded from the later analysis.

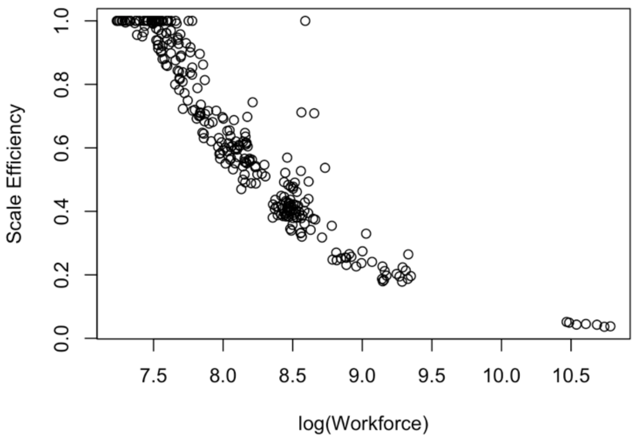

Figure 5.19. Scatterplot for log(Workforce) and Scale Efficiency at the level of police force area in all years.

Similar to the panel regression model series in section 5.1, four panel regression models are conducted here using the "pooling", "individual", "between" and "two-way" methods, respectively. Observations $N = n \times T = 41 \times 7 = 287$.

$$Model\ 5: SE_{it} = \alpha_5 + \beta_5 \log(WW_i) + e_{5it}$$
$$Model\ 6: SE_{it} = \alpha_{6i} + \beta_6 \log(WW_{it}) + e_{6it}$$
$$Model\ 7: \overline{SE_i} = \alpha_7 + \beta_7 \log(\overline{WW_i}) + e_{7i}$$
$$Model\ 8: SE_{it} = \alpha_{8i} + \beta_8 \log(WW_{it}) + \gamma_{8t} + e_{8it}$$

Model 5 ignores the repeated measurement impact and unobserved variables in police force areas. In Models 6 and 7, SE_{it} and WW_{it} represent values of scale efficiency and workforce of individual i at time t; $\overline{SE_i}$, $\overline{WW_i}$ are average values over the years, and α_{6i} is the fixed effect (i.e., it represents intercepts for different individuals). Model 7 estimates the average effect between police forces over the years. It should be noted that it contains the universal intercept α_7, not the fixed effect dummy, α_{7i}. In Model 8, γ_{8t} is a series of dummy variables for each time point. Model 6 seeks to answer the question of how *SE is* related to the log(WW) of a specific police force over the years. Meanwhile, Model 7 asks how a force's average *SE* over the years is related to its average log(*WW*). Finally, Model 8 combines the fixed effects from both individual and time. The results for Models 5 to 8 are presented in Table 5.10.

Table 5.10. Results of panel regression models of Scale Efficiency on Log(Workforce).

	Intercept		Log(Workforce)			
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	RSq	Adj. Rsq
Pooling	4.5053505 (0.0800076)	2.2e-16	-0.4770832 (0.0098592)	2.2e-16	0.89149	0.89111
Within			-0.084025 (0.032140)	0.009493	0.027141	-0.13566
Between	4.631376 (0.144820)	2.2e-16	-0.492644 (0.017847)	2.2e-16	0.95131	0.95006
Two-way			-0.138114 (0.033859)	2.2e-16	0.06509	-0.11876

The standard errors are clustered at the police force area level. As shown in the table of results, the pooled and the between models show that, cross-sectionally, there is a significant negative relationship between workforce size and scale efficiency scores for police force areas (p-values < 0.001, Adj. Rsq = 0.89 and 0.95, respectively). When the fixed unobservable characteristics estimated in the within model are taken into account, the absolute value of the coefficient for log(Workforce) is much smaller than in the between model, though it remains significant (p-value = 0.009, Adj. Rsq = -0.14). Taking into account the time-varying unobservable variables estimated in the two-way model, the negative relationship again remains significant, even though Adj. Rsq is less than 0. Therefore, both the unobservable variables of individuals and time are potentially related to the dependent variable in this regression series.

The coefficient of log(Workforce) in the within model means that for a given area is -0.084. If the total workforce increases by 100%, then the scale efficiency will decrease by 0.084, which is a fair-sized effect. The coefficient -0.493 of log (Workforce) in the between model means that if the total workforce increases by 100%, the average scale efficiency score over the study period is expected to decrease by 0.492, which is a large-sized effect). However, a 100% increase is an unrealistically large increase for in the workforce. The coefficients of the two models imply that if the total workforce increases by 10% (a more realistic rise), the scale efficiency will decrease by 0.0084 and 0.0492, respectively.

Models 5 to 8 indicate that workforce size and scale efficiency are negatively related for a specific force area over the study period; on average over the years, a police force area with a larger workforce size also tends to exhibit low scale efficiency scores. This finding is unsurprising given that the scale efficiency scores are evaluated under the assumption of the "return to scale" variable.

(2) Workforce and Fear of Crime

In section 5.1, the worried about crime scores seem to be sizeable in the large-size force family (group 6). This section investigates this issue using panel regression. Considering the pooling context $N = n \times T = 294$ first, Pearson's correlation testing estimates the 95% confidence interval of the correlation coefficient as (-0.380, -0.169) with a p-value < 0.001. These results indicate that Workforce (WW) and Fear of Crime (FC) (a high value means that respondents are less worried about crime) form a generally negative relationship in police force areas. As noted in the analysis in sections 5.1 and 5.2 above, the Workforce and Fear of Crime data produced outliers: Metropolitan in all years and Dyfed-Powys in four years. Accordingly, when investigating the relationship between the two in later analysis, these two police forces will be removed from the dataset. Figure 5.20 further illustrates the rough negative relationship. When the outliers are removed, the linear correlation coefficient is estimated to be -0.325 with a p-value < 0.001.

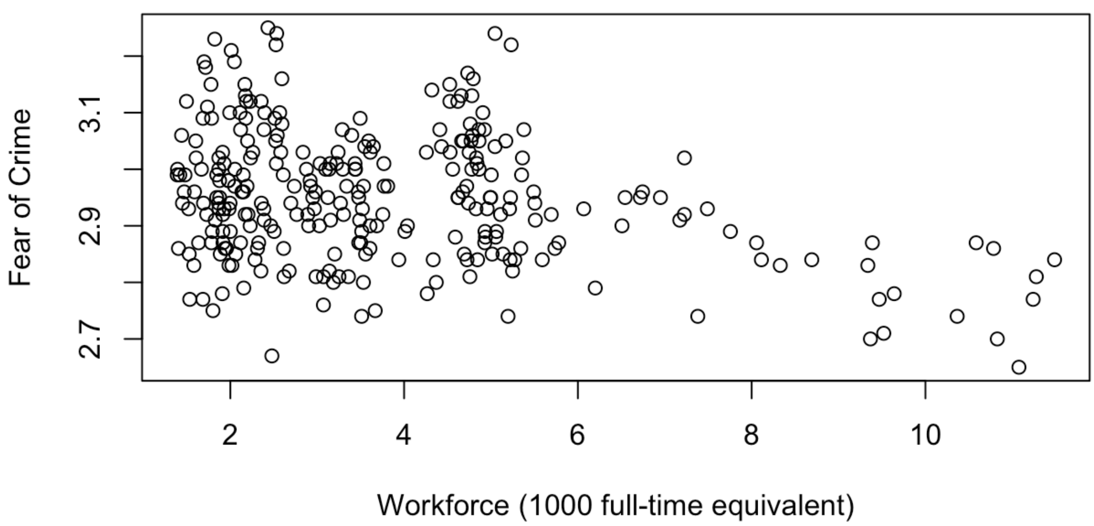

Figure 5.20. Scatterplot for fear of crime and workforce (full-time equivalent), excluding Metropolitan and Dyfed-Powys Police. Fear of Crime: 1 = very worried, 2 = fairly worried, 3 = not very worried, 4 = not at all worried.

Four panel regression models are conducted using the "pooling", "individual", "between" and "two-way" methods to analyse the possible relationship between the explanatory and dependent variables. For present purposes, observations $= n \times T = 40 \times 7 = 280$.

$$Model\ 9: FC_{it} = \alpha_9 + \beta_9 WW_{it} + e_{9it}$$
$$Model\ 10: FC_{it} = \alpha_{10i} + \beta_{10} WW_{it} + e_{10it}$$
$$Model\ 11: \overline{FC_i} = \alpha_{11} + \beta_{11}\ \overline{WW_i} + e_{11i}$$
$$Model\ 12: FC_{it} = \alpha_{12i} + \gamma_{12t} + \beta_{12}\ WW_{it} + e_{12it}$$

Model 9 ignores the repeated measurement impact and unobserved variables in police force areas. In Models 10 and 11, FC_{it} and WW_{it} are values of fear of crime and workforce of individual i at time t; $\overline{FC_i}$, $\overline{WW_i}$ are average values over the course of all years, and α_{10i} is the fixed effect (i.e., the different intercepts of different individuals). Model 11 estimates the average difference between police forces over the study period. It contains the universal intercept α_{11}, not the fixed effect dummy, α_{11i}. In Model 12, γ_{12t} is a series of dummy variables used to stand in for time. Model 10 seeks to answer how *FC* is related to the *WW* of a specific police force over the years, whilst Model 11 probes how a force's average *FC* over the course of all years is related to its average *WW*. Moreover, Model 12 combines the fixed effects from both individuals and time. The results for Models 9-12 are presented in Table 5.11.

Table 5.11. Results of panel regression models of Fear of Crime on Workforce (1000 full-time equivalent).

	Intercept		Workforce			
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	RSq	Adj. Rsq
Pooling	3.0177 (0.013302)	2.2e-16	-0.0173554 (0.0030325)	2.703e-08	0.1054	0.10219
Individual			-0.035594 (0.012166)	0.003767	0.034578	-0.127
Between	3.0151 (0.026086)	2.2e-16	-0.0166948 (0.0059721)	0.008082	0.17057	0.14874
Two-way			0.012773 (0.011071)	0.2498	0.0056805	-0.19062

The pooling and between models reveal that there is a significant cross-sectionally negative relationship (p-values < 0.01) between the values for Fear of Crime (high values mean less worry about crime) and Workforce (when unobservables are ignored in force areas). The coefficient -0.017 in the between model means that where an area has an extra 1000 workers, the worried about crime score averaged over all the years is higher by 0.017. Given that the range of fear is between 2.50 and 3.50, this is not a large-sized workforce effect. When the fixed effect of time-invariant unobserved variables is taken into account, the Workforce coefficient is still significant (p-value < 0.01) and its absolute value becomes larger than it was in the between model, which in turn means that the effect of the explanatory variable increases. However, when the time-varying fixed effect is included in the two-way model, the coefficient becomes positive, albeit insignificant (p-values = 0.250). Accordingly, the time-varying unobservables are potentially related to Fear of Crime, whilst Workforce is not found to be a contributor in the fixed effect models.

Models 9 to 12 indicate that there is not an inevitable relationship between the police force size and worried about crime in a specific area across the study period. Meanwhile, an area with a larger workforce tends to have higher worried about crime scores on average. The latter finding can be explained by another characteristic of the police force areas, namely, crime rates. The mechanism here is that workforce size and fear of crime likely increase in response to rising crime rates.

Section 5.4 will investigate the relationship between fear of crime and crime rates on the basis of survey data in response to this hypothesis. Additionally, the workforce or even policing can influence fear of crime in other ways, e.g. through the media. Two American quantitative studies (Padgett & Gertz, 2000; Romer et al., 2003) suggested that the consumption of television news led to an increase in fear of crime among residents. Elsewhere, another study failed to find a relationship between the media and fear of crime (Chadee & Ditton, 2005). Based on both qualitative and quantitative data in the UK, Ditton et al. (2004) claimed that respondents' perceptions and interpretations influenced their fear of crime, not the frequency of media exposure. According to these links between fear of crime and the media, the finding that residents living in an area with a large-sized workforce are more worried about crime can be explained by the workforce attracting media exposure and this contributing to concerns about crime amongst the public.

In this section, a series of panel regression models with fixed-effect or between-effect terms are used to examine the relationship between workforce, scale efficiency, and worried about crime. There is some evidence to show that a specific police force can improve scale efficiency by cutting down its scale. Further, there is significant evidence that larger-scale police forces tend to attain lower scale efficiency scores and higher worried about crime scores. Consistent with the findings in section 4.6, the relationship between fear of crime and the police workforce also provides evidence against the controversial “merging forces” proposals of 2006.

5.3. Frontline allocation and crime rates

Taking the lead from British research exploring the negative relationship between crime levels and police presence (Machin & Marie, 2005; Draca et al., 2008), this section seeks to identify and verify any relationship between frontline allocation and crime rates at the police force area level based on the CSEW data. In doing so, it will determine whether police visibility impacts crime rates at the police force area level. The hypothesis is that frontline allocation negatively impacts crime rates, whilst the effect size will be different for different categories of crime.

In line with the category definitions detailed in section 5.1, the variables of crime rates measured on the basis of the CSEW data are written as Crime Rate 1 ($CR1$, motor and household property crime, per 1000 population), Crime Rate 2 ($CR2$, personal property crime, per 1000 population), and Crime Rate 3 ($CR3$, personal violence, per 1000 population). Frontline allocation is represented by the ratio of frontline workforce to support workforce ($FS = FW/SW$.) In the seven years the study period spans, FS ranges from 1.896 (2014-Northamptonshire) to 7.152 (2014-Cleveland) with a median of 3.227 (2014-Thames Valley). It should be noted that a reallocation between frontline and support workforce does not necessarily result in a linear change in FS as the variable is determined by a simple ratio, and an increase or decrease in frontline workforce, given that support workforce remains the same, leads to a linear change in FS. It should be noted that in the interpretation, the effect of the coefficient estimator differs for different-sized workforces. One unit of increase in FS is easy to achieve when the workforce size is small and difficult when it is large.

This section answers the following research question: how are Crime Rates 1, 2, and 3 correlated with the frontline allocation ratio? To do so, it starts with the relationship to $CR1$. Resource variables that might be able to explain any policing outcomes are workforce and non-staff cost, which represent two aspects on which the police budget is spent. Besides the workforce allocation variable FS, another explanatory variable, non-staff cost NSC, should also be included in the statistical analysis.

The efficiency analysis in section 4.5 compares input resources between police forces and across the study period. It should be noted that the largest police force, Metropolitan Police, spent 1,283,027 thousand pounds on non-staff costs in 2017/18, whereas the small police force Dyfed-Powys only spent 34,967 thousand pounds in the same year.

With this in mind, when investigating whether non-staff costs impact crime rates as an influential factor, the impact from scale first needs to be eliminated, especially in the analysis of the police forces during the study period. In the present research, the *NSC* variable is divided by the total amount of territory policing workforce *WW* and defined as the new variable: Non-Staff Cost per Workforce Unit (*NW*). After removing outliers, the *NW* values range from 5.193 (North Yorkshire, 2011) to 34.179 (Gwent, 2017) with a median of 13.014 (Hampshire, 2013).

Crime Rate 1 contains four outliers, all of which are 1000. This indicates a 100% chance a resident in the policy area will fall victim to motor or household property crime. As explained in section 5.1, the number is calculated as the sum of all participants' victim experiences divided by the number of participants. If the total number of victim experiences is larger than the number of participants, the crime rate will be over 1000, though for present purposes it is recorded as 1000. This does not indicate extreme crime prevalence in this area, rather it is a possible result of sampling errors. Therefore, in this section, any value of 1000 is seen as an outlier and removed from the regression, along with *NW* outliers. No values in *FS* are considered outliers.

Scatterplots for *CR1* on *FS* and *CR1* on *NW* are presented in Figure 5.21.

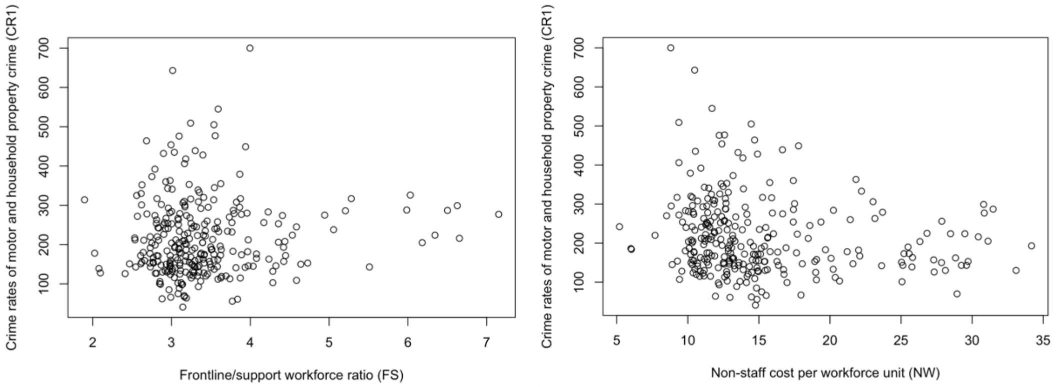

Figure 5.21. Scatterplots for crime rates of motor and household property crime on frontline/support workforce ratio (left) and non-staff cost per workforce unit (right) at the level of police force area.

In the figures, the scatterplots present a very rough linear relationship between *CR1* and the two explanatory predictors. Pearson's correlation tests do not support the linear correlation between *FS* and *CR1* (p-value=0.20), though they do support a weak negative relationship between *NW* and *CR1* (p-value=0.009). Consider these four models in a panel framework:

$$Model\ 13: CR1_{it} = \alpha_{13} + \beta_{13} FS_{it} + \gamma_{13} NW_{it} + e_{13it}$$
$$Model\ 14: CR1_{it} = \alpha_{14i} + \beta_{14} FS_{it} + \gamma_{14} NW_{it} + e_{14it}$$
$$Model\ 15: \overline{CR1}_i = \alpha_{15} + \beta_{15}\, \overline{FS}_i + \gamma_{15} \overline{NW}_i + e_{15i}$$
$$Model\ 16: CR1_{it} = \alpha_{16i} + \delta_{16t} + \beta_{16}\, FS_{it} + \gamma_{16} NW_{it} + e_{16it}$$

where $i = 1, \dots, 42$; $t = 1, \dots, 7$.

Similar to sections 5.1 and 5.2, Models 13-16 use pooling context, fixed-effect within individuals, between individuals, and two-way within both individuals and time methods, respectively. The results of the four models are presented below.

Table 5.12. Results of panel regression models of Crime rate 1 per 1000 on Frontline/Support workforce ratio and Non-Staff Cost per Workforce.

	Intercept		FS		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	205.7188 (28.8081)	2.2e-16	18.2314 (8.2150)	0.02728	-3.4454 (1.0902)	0.00175	0.034618	0.0027572
Individual			-27.5878 (13.6375)	0.0442	-4.6006 (1.1462)	8.011e-05	-0.080595	4.0436e-05
Between	119.5915 (38.6765)	2.2e-16	33.0190 (12.8609)	0.014306	-1.0158 (2.9577)	0.733158	0.15263	0.016224
Two-way			1.5624 (14.0915)	0.9118	-2.7002 (1.9578)	0.1692	-0.19706	0.38707

In terms of Table 5.12, there are cross-sectional relationships between *FS* and *CR1* and between *NW* and *CR1,* respectively. When individual force effects are taken into account, the estimates increase in magnitude and reverse the sign for *FS*. In the within model, increasing frontline allocation and non-staff cost are found to reduce crime rates for a given police force over the years. However, the last two-way model is not consistent with the within model as two explanatory variables are not significant (p-values are 0.9118 and 0.1692 respectively) and the p-value of F-statistics, which indicates the significance of the overall relationship is also greater than 0.05. From this, it can be concluded that although *FS* and *NW* are significant in the within model (both p-values are less than 0.05), the unobserved variables in the police force area are not producing the causal effect, as when time-varying unobserved variables are included, the relationship diminishes.

In the between model, only *FS* has a positive relationship with *CR1*, whereas *NW* is not significant with p-values greater than 0.05. The coefficient estimator 33.019 of *FS* in the between model means that for force areas, a unit increase in the average frontline allocation ratio is associated with, on average, a 33.019 per 1000 increase in motor and household property crime during the study period.

Notably, an *FS* increase does not form a linear relationship with the size of the frontline workforce. For example, improving *FS* from 2 to 3 is different from increasing from 4 to 5. Therefore, on the basis of this dataset, for a specific police force area, an increase in frontline workforce does not significantly reduce crime rates for motor and household property crime during the study period. On average, over this time, an area with more frontline workforce ratio tends to have higher crime rates for motor and household property crime. Although the positive relationship between frontline workforce and crime rates on average during the study period is counterintuitive, it can be explained by how the workforce is increased in response to rising crime rates in the given areas.

Similar panel regression models are conducted for *CR2* and *CR3*. Tables 5.13 and 5.14 presents their results below.

Table 5.13. Results of panel regression models of Crime rate 2 on Frontline/Support workforce ratio and Non-Staff Cost per Workforce.

	Intercept		FS		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	49.74036 (5.61209)	2.2e-16	-1.28755 (1.62269)	0.42818	-0.39590 (0.21018)	0.06065	0.011924	0.068434
Individual			-9.97420 (2.65516)	0.0002161	-0.37135 (0.21219)	0.0813690	-0.090791	0.00013824
Between	41.69981 (8.97502)	3.983e-05	3.33366 (2.94594)	0.2649	-0.89972 (0.65875)	0.1800	0.0003658	0.37474
Two-way			-4.20695 (2.59517)	0.10634	0.71769 (0.34482)	0.03848	-0.17465	0.053679

Table 5.13 reveals that in the individual fixed effect model, the frontline allocation ratio is significant and can explain crime rates with coeff = -9.974 and p-value = 0.0002, which means that a high frontline ratio helps reduce crime rates. This finding is consistent with the initial hypothesis. The magnitude of the effect is small because a one-unit increase in *FS* (e.g. from 3 to 4, which means that a police force is expected to hire an additional one-third of frontline workers) only leads to a reduction of 9.97 cases of crime per 1000 population. The relationship even disappears when the time effect is included in the two-way model. From this, it can be concluded that *FS* is not significant in explaining the variation in crime rates when this research considers common time effects.

Non-staff cost is significant in both the individual fixed effect and two-way models. It is interesting that non-staff cost is negatively related to crime rates in the individual effect model, though this is reversed and forms a positive relationship in the two-way model. Considering the unobserved time effects of each year, for a specific area, a one-pound increase in non-staff cost per workforce is associated with a 0.718 rise in crime per 1000. This is inconsistent with the hypothesis that increasing the provision of resources helps to reduce crime rates. Meanwhile, the F-statistics of the two-way model indicate that the overall relationship between *CR2, FS,* and *NW* is not significant (p-value>0.05).

Table 5.14. Results of panel regression models of Crime rate 3 on Frontline/Support workforce ratio and Non-Staff Cost per Workforce.

	Intercept		FS		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	153.13253 (17.92298)	8.48e-16	-5.70361 (5.11467)	0.2657	-0.75744 (0.68021)	0.2664	0.0048894	0.18588
Individual			-16.02398 (8.55858)	0.06239	-0.90732 (0.72332)	0.21092	-0.14939	0.071067
Between	140.20536 (26.47656)	5.258e-06	-1.58454 (8.84010)	0.8587	-0.81526 (2.01991)	0.6888	-0.039841	0.79272
Two-way			-3.99564 (9.43776)	0.6724	-0.38087 (1.35104)	0.7783	-0.20362	0.86377

As can be seen from Table 5.14, each coefficient for *FS* and *NW* in each model is greater than 0.05. Therefore, the two explanatory variables are not significant in explaining variations in personal violence crime rates, no matter whether time-fixed effects and individual fixed effects are considered.

In conclusion, this research finds that for a given police area, there is no evidence that increasing the frontline workforce allocation ratio reduces the crime rates of any category of crime during the study period. Notably, such findings are inconsistent with those from the existing UK research (Machin and Marie, 2005; Draca, et al., 2008), which observed a negative relationship between crime levels and police presence. Contrastingly, areas with a higher frontline workforce allocation ratio tend to have higher average crime rates for motor and household property crime across the study period, which can be explained by the increasing frontline workforce in response to rising crime rates. In terms of non-staff cost, no coefficients are significant in the four models.

There is an argument about whether the analysis should use time-delayed variables to match movements in the time series. It is reasonable to hypothesise that changes in resources impact crime rates in the following years. The models in this study are carried out as *CR1*~lag(*FS*)+lag(*NW*), *CR2*~lag(*FS*)+lag(*NW*), *CR3*~lag(*FS*)+lag(*NW*). The results are presented in Tables A.2.1-A.2.3 in Appendix II. Due to higher adjusted-R squared and significant coefficient estimators, the models in this section better fit and explain the data than the lag models in the Appendix. On this basis, this research does not consider the lag term in the panel regression.

In addition to the normal distribution assumption in panel regression models, another common distribution of crime rates in criminal statistics can be used (Curiel et al., 2018; Osgood, 2000). Specifically, it assumes that the number of crimes suffered by participant *i* in a fixed period (one year, for example) adheres to a Poisson distribution. Osgood (2000) modelled juvenile arrest rates for robbery at the county level in four U.S. states as a Poisson distribution. This involved introducing seven factors to predict the parameter, namely, the expectation of crime rates: the population at risk, residential instability, ethnic heterogeneity, female-headed households, poverty rate, unemployment, and adjacent to the metropolitan area.

Osgood's research inspired the present analysis. The point of difference here is that the CSEW data cannot be modelled as a Poisson distribution: a Poisson distribution is a distribution with the same mean and variance, whilst the means and variances of *CR1*, *CR2*, and *CR3* are 215, 9868; 39, 360; and 122, 3735, respectively. The distance between the mean and variation of crime rates are far larger than each other; therefore, it cannot be assumed that “mean equals to variance”. The main difference between this research and Osgood’s research is that this study employs victim-based statistics, whilst Osgood (and most research predicting crime rates) used police-recorded crime data. Moreover, Osgood predicts crime rates using reality factors, whilst this research solely investigates the relationship between policing resources and outcomes. For these reasons, this research does not use a Poisson distribution to model crime rates (this will lead to a generalised linear model with a log link function); instead, it continues to use the panel linear regression models used above.

Although most criminal statistical research uses more realistic predictors to explain variations in crime rates, as the main goal of this research is to track if changes in resources impact crime rates for an area, it uses just two variables to represent resource allocation. The fixed effects from individuals and time are controlled by the panel regression models, meaning that the relationship between resources and crime rates is simply released by the differences among the individual, between, and two-way models. There are indeed uncontrollable effects that can be represented by many other realistic predictors, e.g. residents at risk, unemployment, and poverty rate. However, the model would lose degrees of freedom given the sample size and the relationship would become complex. The fixed-effect regressions have captured these other things to the extent that they are time-invariant (or changing very slowly). The current models are not well-suited to predicting crime rates in a given area, though they are capable of capturing the simple relationship between the two resource variables and crime rates.

In this section, workforce is only divided into two categories: frontline and support line. In the following sections, workforce will be observed in relation to detailed functions including responses, neighbourhoods, and intelligence. The relationship between outcome indicators and workforce functions will be investigated using regression methods.

5.4. Neighbourhood workforce, crime rates and fear of crime

According to the ONS (2014), the number of PCSOs, whose main responsibility is to undertake neighbourhood policing, fell from 16,000 in 2010 to 13,400 in 2014 in England and Wales. Their main duties include carrying out foot patrols, interacting with the public, and dealing with low-risk disorder. Additionally, some police officers and police staff also undertake neighbourhood policing work. For example, in Avon and Somerset, there were 268.52 full-time equivalent police officers and 11.5 full-time equivalent police staff working on neighbourhood policing in March 2015. Under the old function framework (ONS, 2012), neighbourhood workforce is defined as the "staff predominantly employed in Neighbourhood Policing Teams, including police community support officers and officers/staff in supporting roles". Under the new function framework (ONS, 2015) introduced in 2015, neighbourhood workforce "(includes non-emergency response and neighbourhood policing), Neighbourhood Policing Teams, and/or Safer Neighbourhood Teams whose primary role is neighbourhood based; includes Planned Response i.e. scheduled or dealt with by appointment". Local Commanders are also included when calculating Neighbourhood policing in this research.

Summing up all of the neighbourhood workforce, Figure 5.22 shows the neighbourhood workforce and neighbourhood allocation ratio relative to the total workforce size (including frontline and support workforce but excluding those undertaking national policing) in England and Wales from March 2012 to March 2018. Although PCSOs' budgets were slashed during the austerity period, the police allocated other staff to undertake the neighbourhood function to ensure the stable provision of policing. In March 2015, both the workforce amount and the allocation ratio increased compared to that in 2012, and since 2015, both progressively decreased.

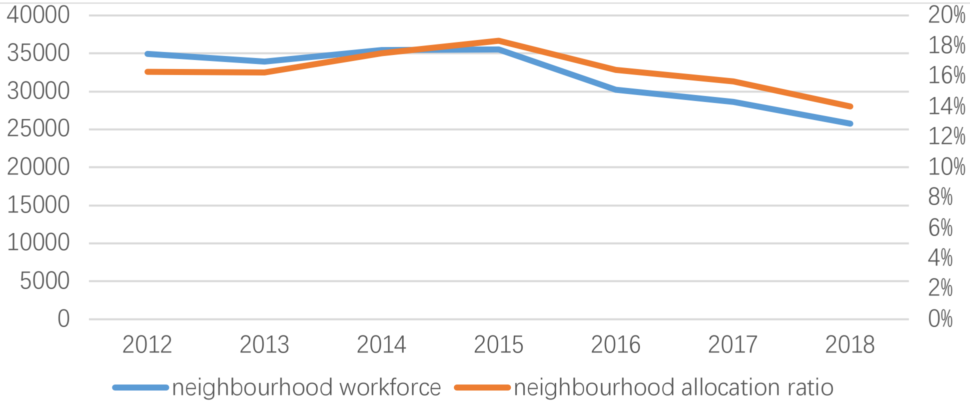

Figure 5.22. Neighbourhood workforce and its ratio over the total workforce in England and Wales from March 2012 to March 2018.

As one of the most visible police activities, foot patrol was found to have an impact on crime and fear of crime. Ratcliffe et al (2011) suggested that foot patrol can be deployed as a strategy to reduce crime and improve community relations. Relying on practical evidence, Karn (2013) pointed out that foot patrol helped to reduce fear of crime and had an impact on dealing with violent crime, though it did not significantly influence crime rates.

The research question is as follows: at the police force area level, is there any relationship between (a) neighbourhood workforce and crime rates and (b) neighbourhood workforce and fear of crime? Police force-level neighbourhood workforce data are listed in Table 5.15.

Similarly to how Non-Staff Cost was dealt with in section 5.3 (dividing it by Workforce), the neighbourhood workforce also contains information about scale. For example, the Metropolitan Police had a neighbourhood workforce of 6019 in 2012, whereas Dyfed-Powys had only 172. This was not a result of any policing strategy of workforce allocation， rather it reflects that the Metropolitan area is far larger than the area policed by the Dyfed-Powys force. Therefore, in the regression models, Neighbourhood Allocation Ratio (*NEIR*= neighbourhood workforce / sum of frontline and support workforce) is more reliable than Neighbourhood (NEI). A descriptive summary of *NEIR* is listed in Table 5.16 below.

Table 5.15. Neighbourhood workforce (full-time equivalent) of 42 police forces from March 2012 to March 2018.

	2012	2013	2014	2015	2016	2017	2018
Avon and Somerset	652	636	596	608	602	595	590
Bedfordshire	420	172	157	122	104	300	315
Cambridgeshire	392	714	675	714	696	667	721
Cheshire	1014	1024	1014	1097	452	378	436
Cleveland	396	375	355	326	304	281	282
Cumbria	507	465	462	567	381	600	137
Derbyshire	353	358	323	395	260	263	274
Devon and Cornwall	899	897	622	593	579	537	472
Dorset	309	280	295	264	269	261	665
Durham	316	304	308	300	275	271	256
Dyfed-Powys	172	221	230	219	201	225	182
Essex	796	652	1044	1430	1304	311	1061
Gloucestershire	712	719	719	640	610	591	505
Greater Manchester	2234	2576	2421	2534	2047	1135	1127
Gwent	735	426	407	742	710	687	793
Hampshire	857	893	854	653	720	720	625
Hertfordshire	456	440	393	396	418	429	388
Humberside	439	446	438	430	276	415	365
Kent	1211	1106	1094	1795	1805	1967	1619
Lancashire	707	664	599	764	604	526	563
Leicestershire	578	715	732	626	490	558	454
Lincolnshire	398	242	239	243	199	207	188
Merseyside	1191	991	894	847	868	916	876
Metropolitan Police	6019	5956	8294	7623	6063	4831	3469
Norfolk	462	456	457	402	250	252	164
North Wales	397	371	275	338	312	296	294
North Yorkshire	1051	886	882	297	288	266	287
Northamptonshire	379	431	371	435	248	238	169
Northumbria	287	236	274	825	733	643	672
Nottinghamshire	572	582	630	578	465	380	409
South Wales	544	653	699	620	591	607	617
South Yorkshire	630	658	651	592	1382	1370	1391
Staffordshire	513	519	479	436	481	392	389
Suffolk	304	294	330	289	237	166	168
Surrey	534	550	489	433	522	655	239
Sussex	638	647	621	573	431	397	356
Thames Valley	1009	979	987	1179	1052	919	804
Warwickshire	207	194	154	186	153	161	123
West Mercia	457	402	391	383	400	393	257
West Midlands	2385	2112	2008	1836	1542	2184	1318
West Yorkshire	2599	2404	2304	1960	696	1008	1087
Wiltshire	245	259	238	234	239	634	649

Table 5.16. Descriptive summary of Neighbourhood Allocation Ratio in police force from 2012 to 2018.

	Value	Police force
Min	0.0580	Bedfordshire-2015
Max	0.4227	Gwent-2017
Median	0.1675	Dorset-2013
Mean	0.1675	
Standard deviation	0.0751	

(1) Neighbourhood workforce and crime rates

This section adopts the same modelling method as used in the last section: the frontline allocation ratio is treated as a linear predictor of crime rates. Scatterplots for crime rates for three categories of crime (*CR1, CR2, CR3*) on Neighbourhood Allocation Ratio (*NEIR*) are presented in Figure 5.22 below. Again, outlier crime rates have been removed from the dataset.

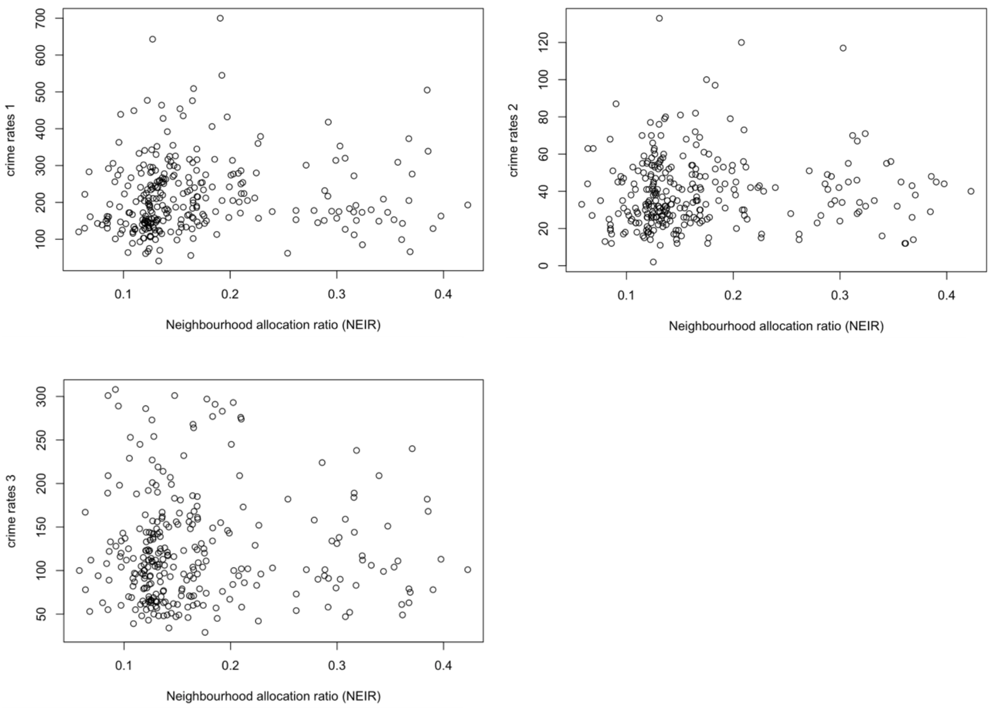

Figure 5.22. Scatterplots for crime rates on Neighbourhood Allocation Ratio at the level of police force area in all years.

No obvious linear relationship can be observed in Figure 5.22. Pearson's correlation testing for *CR1~NEIR*, *CR2~NEIR,* and *CR3~NEIR* also indicates that there is no significant linear relationship in the pooling context (p-values > 0.05). Again, these tests ignore any effect from area or time. This research then models the relationship between policing outcome variables (*CR1, CR2, CR3*) and resource variables (*NEIR,* and *NW* as known as Non-staff Cost per Workforce) using fixed-effect panel regression. The "pooling", "within", "between" and "twoway" methods are all employed for *CR1~NEIR+NW*, *CR2~NEIR+NW*, and *CR3~NEIR+NW.* Accordingly*,* a total of 12 models are carried out, the results of which are presented in Tables A.2.1-A.3.3 in Appendix III.

Among these 12 models, only three regression models estimate significant coefficients for explanatory variables: the pooling regression for *CR1*, the individual fixed effect regression for *CR1,* and the pooling regression for *CR2*. Moreover, in these three regression models, only the *NW* coefficients are significant (p-values < 0.05), not those of *NEIR*. Additionally, there is a negative relationship between non-staff cost and crime rates in property crime. However, when unobserved time-varying effects are included, the relationship is no longer present in the two-way model and no evidence is found to support the presence of any linear relationship between neighbourhood workforce allocation and crime rates.

After defining an aggregate variable Crime Rate (CR) (*CR1+CR2+CR3)* and testing overall Crime Rate models of neighbourhood allocation ratio (NEIR) and non-staff cost per workforce (NW) using the same method as detailed in this section, no new information was identified pertaining to the effect of neighbourhood workforce (see Table A.3.4 in Appendix III). This finding contrasts with that of Ratcliffe et al (2011), who proposed patrol work helped reduce crime, though it agrees with Karn (2013) who argued that patrol work had no significant influence on crime rates. At least, workforce size does not look to have any significant impact on crime rates when the unobserved effects from individual forces and time are controlled.

(2) Neighbourhood workforce, crime rates and fear of crime

As noted in section 5.2, Fear of Crime (*FC*) forms a linear relationship with the workforce variable in panel regression models. In this section, panel linear models are again employed to investigate the relationship between neighbourhood workforce and fear of crime to determine in detail whether the allocation of neighbourhood policing impacts residents' fear of crime. Meanwhile, as the preceding analysis verified that crime rates are not dependent on neighbourhood workforce, both can be used as explanatory variables in the same model.

The crime rates for the three categories are strongly correlated with each other (p-values of Pearson's correlation test between any two of the three are less than 0.01); therefore, *CR1*, *CR2,* and *CR3* cannot be used in the same model. Three sets of separate models will be conducted respectively in the following analysis. Alternatively, the three categories can be aggregated into one variable, Crime Rate (*CR* = *CR1*+*CR2*+*CR3*). Otherwise, the multivariate regression will lead to collinearity. An American-based research (Rader, 2017) pointed out that even if crime rates decrease, residents' concerns about crime might not change. Using the CSEW data in the UK, this research uses the following models to verify if Rader's view applies in the context of England and Wales.

Scatterplots for the influence of Fear of Crime on *NEIR*, *CR1*, *CR2* and *CR3* are provided below in Figure 5.23.

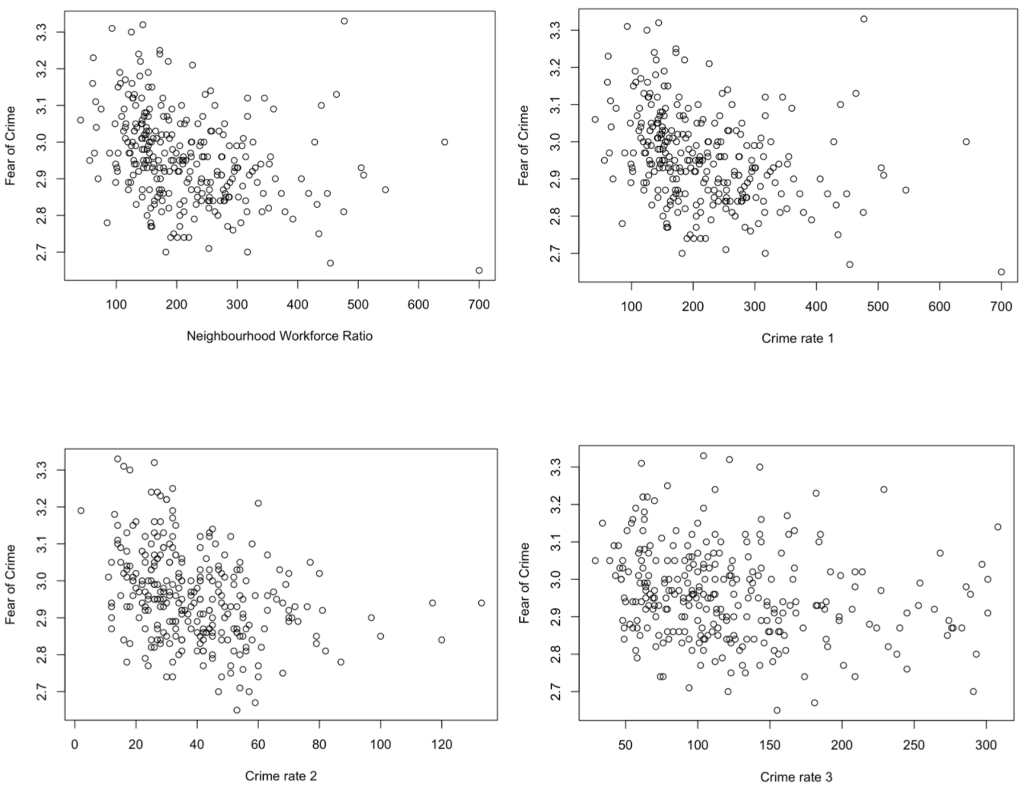

Figure 5.23. Scatterplots for fear of crime on neighbourhood allocation ratio and crime rates of three categories at the level of police force area in all years. Fear of crime: larger values mean less fear.

The four scatterplots reveal the broad negative relationships between the explanatory variables and the dependent variable. Pearson's correlation testing also suggests the presence of significant negative coefficients in these four pairs of relationships (all p-values<0.05). The fixed-effect panel regression model is still used to answer this research question. Each of "pooling", "within", "between" and "twoway" methods is employed for *FC~NEIR+CR1*, *FC~NEIR+CR2*, *FC~NEIR+CR3*, meaning that a total of 12 are conducted. The results from panel regression models are presented in Tables 5.17-5.19.

Table 5.17. Results of panel regression models of Fear of Crime on Neighbourhood Allocation Ratio and Crime Rate 1.

	Intercept		NEIR		CR1		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.0780 (0.02185)	2.2e-16	-0.22010 (0.091935)	0.01732	-3.8379e-04 (6.9631e-05)	8.06e-08	0.11343	1.7673e-08
Individual			-0.10583244 (0.10877171)	0.3315	-0.00030831 (0.00005344)	2.443e-08	-0.026476	9.0642e-08
Between	3.14687357 (0.07677819)	2.2e-16	-0.24968057 (0.23142194)	0.28743	-0.00068250 (0.00032909)	0.04492	0.097223	0.054048
Two-way			-0.096599 (0.092252)	0.29613	-1.1047e-04 (5.1176e-05)	0.03189	-0.17634	0.059108

Table 5.18. Results of panel regression models of Fear of Crime on Neighbourhood Allocation Ratio and Crime Rate 2.

	Intercept		NEIR		CR2		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.07218797 (0.02085314)	2.2e-16	-0.23928035 (0.09056433)	0.008685	-0.00192295 (0.00031915)	5.093e-09	0.12476	1.4013e-09
Individual			-0.09308298 (0.10487256)	0.3756	-0.00135053 (0.00025785)	3.453e-07	-0.050887	1.1983e-06
Between	3.1601792 (0.0665204)	2.2e-16	-0.3404509 (0.2283397)	0.144010	-0.0036809 (0.0012742)	0.006283	0.16819	0.010397
Two-way			-0.11019014 (0.08971291)	0.2205	-0.00039231 (0.00024900)	0.1164	-0.18111	0.1328

Table 5.19. Results of panel regression models of Fear of Crime on Neighbourhood Allocation Ratio and Crime Rate 3.

	Intercept		NEIR		CR3		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.04544783 (0.02205934)	2.2e-16	-0.25174285 (0.09398657)	0.0078158	-0.00039575 (0.00011024)	0.0003882	0.057317	6.8766e-05
Individual			-0.14621 (0.10844)	0.178781	-2.7246e-04 (8.6509e-05)	0.001834	-0.1217	0.0041545
Between	3.10475214 (0.07240811)	2.2e-16	-0.29265852 (0.24340927)	0.2365	-0.00081999 (0.00049147)	0.1032	0.057484	0.11888
Two-way			-0.12269 (0.089921)	0.1737	-1.1490e-04 (7.4005e-05)	0.1218	-0.18145	0.13758

In the previous interpretation, due to how the variable is constructed, a higher value for Fear of Crime (FC) means that the residents in the policing area are less worried about crime. Except for the pooling regression, none of the coefficients for Neighbourhood Allocation Ratio are significant (p values > 0.05) in the other three methods. Accordingly, no linear relationship between neighbourhood workforce allocation and fear of crime is found when unobserved individual effects and common time effects are considered. Moreover, no relationship is found when the variables are measured and averaged over the study period. The difference between fear of crime in the areas is more likely explained by unobserved individual characteristics and time characteristics as opposed to neighbourhood workforce allocation. Therefore, increasing the neighbourhood workforce does not impact fear of crime in this measure.

Regarding crime rates, similar results are returned for all three categories. Negative coefficients are significant in the three within models, indicating that when individual fixed effects are considered, an increase in crime rates (for each category of crime) is associated with a decrease in worried about crime scores over the year in a given area. When considering the time-varying effects on areas, two-way models estimate a significant coefficient for *CR1* (coeff = -1.1047e-04, p-value = 0.031), though the *CR2* and *CR3* (p-values > 0.05) coefficients are insignificant. This means that there is evidence on basis of this dataset to support that the crime rates for motor and household property crime impact residents' worry about crime. For a given police force area, if the crime rates for motor and household property crime increase by 1 per 1000 population, residents are expected to worry 0.0001 more about crime. Equivalently, if an area reduces crimes by 100 per 1000 population, residents are expected to worry 0.01 less about crime in response. It should be stressed that this is not a large magnitude effect given that the range of Fear of Crime is from 2.5 to 3.5.

Additionally, there is no (or only marginal) evidence in this dataset to support the contention that the crime rates of the other two categories impact residents' fear of crime in their area. In the between models, the respective crime rates of motor and household property crime and personal property crime are negatively related to the value of Fear of Crime. Thus, over the study period, residents living in an area with more crime rates tend to have more average worries about crime. For motor and household property crime, an increase in crime rates increased worried about crime by an average of 0.0007 over the study period. Contrastingly, for personal property crime, the magnitude of the impact is 0.0037, although these two relationships do not include the effect of the difference between individual police areas. The personal violence crime rates do not exhibit a similar relationship in the third between model.

Alternatively, using the new Crime Rate variable, which is the aggregate of three categories of crime, panel regression in"pooling", "within", "between" and "twoway" methods were carried out for *FC ~ NEIR + CR*. The results of these four models are presented in Table 5.20.

Table 5.20. Results of panel regression models of Fear of Crime on Neighbourhood Allocation Ratio and the overall Crime Rate.

	Intercept		NEIR		CR		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.1246 (0.024822)	2.2e-16	-0.23377 (0.090333)	0.01017	-3.3477e-04 (5.2019e-05)	5.391e-10	0.14832	8.1322e-11
Individual			-0.11903 (1.0686)	0.2665	-0.00026713 (4.0347e-05)	2.367e-10	0.011921	9.6911e-10
Between	3.21963482 (0.09098605)	2.2e-16	-0.23639830 (0.22582516)	0.3018	-0.00058997 (0.00023613)	0.01692	0.1408	0.021114
Two-way			-0.10416 (0.092405)	0.260823	-1.0697e-04 (4.0577e-05)	0.008955	-0.16701	0.018921

It can be seen from Table 5.20 that the Neighbourhood Allocation Ratio is still not significant in explaining differences in Fear of Crime, regardless of its use in the between model or the within model with both individual and time-fixed effects. Contrastingly, the overall Crime Rate is negatively correlated with Fear of Crime in both the within and between models. Having controlled the unobserved individual characteristics and time-varying effects, this relationship remains still significant: for a given area, if a crime rate rises by 100, residents' worried about crime score is expected to increase by 0.01.

In the models with separate crime rates, only the crime rates for motor and household property crime are found to be significantly related to fear of crime, whilst the other two categories of crime are not significant. There are two possible reasons for this difference: (1) motor and household property crimes are much more prevalent than personal property or violent crimes, indicating there is true bias in the survey data due to the sample size (around 1000 samples in each police); (2) Fear of Crime is a variable that takes the average of worry about six types of crime[27].

Motor and household property crimes are more covered by Fear of Crime but personal property crimes and personal violence are not covered fully, meaning that values of Fear of Crime actually respond to the first category of crime. The model with overall crime rates in Table 5.20 has a higher adjusted R-squared than other models with separate crime rates. Hence, it is reasonable to accept the overall model given that it can explain more of the variance of the dependent variable than the first three models. In the following analysis in Chapters 5 and 6, aggregate crime rates are selected to explain Fear of Crime rather than separate crime rates. It should be noted that crime rates and fear of crime will not be incorporated in the same regression model due to their significant linear correlation.

The conclusion disagrees with Rader's (2017) proposition that where crime rates decrease, residents in the area may still worry about crime to the same degree as before. With the British survey data used in the present research, if crime rates decrease, residents in the area in question will worry about crime less than before. There is still

[27] The calculation of Fear of Crime includes six types of crime: home being broken into, mugging and robbery, car being stolen, things being stolen from car, rape, and being physically attacked by strangers.

an argument that the models above only estimate relationships among variables matched in the same year, which leaves open the possibility of a time-delayed impact. This research also verifies the relationships *FC* ~ lag(*NEIR*)+lag(*CR1*), *FC* ~ lag(*NEIR*)+lag(*CR2*), *FC* ~ lag(*NEIR*)+lag(*CR3*) and *FC* ~ lag(*NEIR*)+lag(*CR*) to investigate whether the residents' worries about crime are associated with crime rates and neighbourhood workforce allocation in the last year. The results are presented in Tables A.4-A.7 in Appendix II. They show that when unobserved time-varying effects and individual fixed effects are both considered, coefficient estimators for crime rates are no longer significant. To be precise, they indicate that, for a given area, residents' worries about crime are more likely dependent on crime rates in the same year than they are in the previous year.

Section 5.4 discusses the relationship between fear of crime, crime rates and neighbourhood workforce. It finds that for a given police force area, changes in neighbourhood workforce allocation do not influence crime rates in a significant way, though changes in crime rates do significantly influence residents' worries about crime. The reasoning here is that the importance of policing does not lie in the size of the frontline workforce or neighbourhood workforce, but rather in how the neighbourhood police work. HMIC (2013) carried out a public survey across all police forces, concluding that the public would feel safer if they had a "face-to-face interaction" with the police in their neighbourhood, as opposed to exclusively seeing them on patrol.

Further research into the relationship between police satisfaction and visibility is discussed in Chapter 6. This section also responds to the argument first posed in Section 5.2 that large urban areas with a large workforce scale tend to have average worried about crime scores and higher average crime rates of property crime over the study period. There is evidence to support the significant correlation between high crime rates and increased worried about crime scores, even when unobserved time-varying effects and individual characteristics are both controlled. Large-scale urban areas tend to have high crime rates, which is one of the reasons the public will be concerned about crime. In the next section, the influence of workforce on response function and its influence is analysed.

5.5. Response workforce, reporting rate and fear of crime

As mentioned in section 5.1, the overall clear-up rate is the multiple of reporting rate (how many crimes are known by the police, per 100), detection rate (given the crime is reported, in how many of them the police find who did them, per 100) and charge rate (given the offenders or criminals are found, in how many of them the police take actions to them, per 100). Hidden crime (i.e., those that are not reported to the police), is one of the main differences between the CSEW data and the police-recorded data.

Early studies (Newburn, 2003) pointed out that historically speaking, an increase in workforce size was accompanied by a higher level of (officially recorded) crime. This was due to the increased capacity of the workforce to record more crimes, which made it look as though the true number of crimes committed was increasing. In current policing, the police allocate a large amount of its workforce to providing frontline responses to a wide range of incidents. This is the first line a resident interacts with then they wish to report anything to the police.

As mentioned in Section 4.3, in CSEW 2015/16, 94.59% of incidents where vehicles are stolen or driven away were reported to the police, whilst only 50% of domestic violence incidents were reported. The questionnaire also asked why the police did not come to know, the five most frequent answers were "too trival/not worth reporting", "police could have done nothing", "police would not bother/not being interested", "dealt with matter myself/ourselves" and "inconvenient/too trouble". Based on the British Crime Survey, Tarling and Morris (2010) found that a crucial factor mediating whether the residents report the crime is its seriousness. Later, a piece of Finnish research (Kääriäinen & Sirén, 2011) studied how public trust affected residents' reporting by incorporating the "generalised trust in citizens" factor, which revealed an inverse effect: high public trust in the police encouraged reporting, though high generalised trust in citizens prevented reporting. A Dutch study (Tolsma et al., 2012) concluded how the reporting system works also impacts whether residents report crimes, including reporting processes, such as duration and methods, anonymity policy, and the police's emphasising on reporting. An American research project (Bosick et al., 2012) went deeper in its investigation of residents' reporting of violent crimes, concluding that reporting rates increase with age.

The studies mentioned above are all based on individual survey data; however, this research is interested in police force area-level data and whether there is an effect from frontline workforce allocation. This begs the question as to whether the allocation ratio of response workforce influences the reporting rate in a police force area. Additionally, consideration needs to be given to how fear of crime relates to response workforce and crime rates. This section aims to investigate the relationship between response allocation ratio (RESR) and reporting rate at the police force area level.

In the old function framework (ONS, 2012), Response Workforce is defined as "includes staff who are predominantly assigned to 24/7 response policing, also includes task force/support group/territorial patrol; includes officers of supervisory rank who perform patrol duties, e.g. shift supervisors." In the new function framework (ONS, 2015) introduced in 2015, it is defined as "Response Teams, this includes officers whose primary role is to respond to emergency and priority incidents which may require attendance."

From 2015 onwards, in some police forces, if the neighbourhood and response workforces cannot be split, two functions will be written in neighbourhood data. Accordingly, in Table 5.21, some police forces had "zero" workforce data for the response function. Another important change in 2015 was that the statistics regard non-emergency response work as a neighbourhood function. As a result, the data is not stable in two different function frameworks. In England and Wales, response workforce and its ratio over the total territorial workforce fluctuated between 2012 to 2015, although the definition of Responses have changed in 2015. Since 2015, Responses significantly increased.

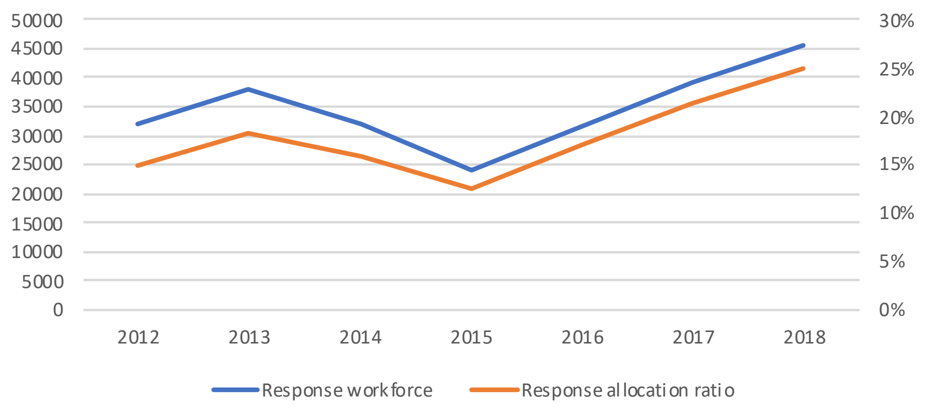

Figure 5.24. Response workforce and its ratio over the total workforce in England and Wales from March 2012 to March 2018.

Table 5.21. Response workforce (full-time equivalent) of 42 police forces from March 2012 to March 2018.							
	2012	2013	2014	2015	2016	2017	2018
Avon and Somerset	1328	1192	1090	1037	1046	1069	986
Bedfordshire	208	358	325	351	233	202	204
Cambridgeshire	413	46	43	32	34	28	45
Cheshire	114	110	121	0	820	839	790
Cleveland	479	464	488	539	445	372	385
Cumbria	233	208	214	184	267	0	445
Derbyshire	766	749	763	780	711	190	127
Devon and Cornwall	1014	977	1082	1052	991	928	958
Dorset	498	482	452	517	488	417	30
Durham	390	375	405	388	382	433	430
Dyfed-Powys	453	454	429	510	451	475	510
Essex	967	1022	647	0	0	952	0
Gloucestershire	31	20	16	29	29	19	2
Greater Manchester	1624	1600	1484	1274	1156	2266	2356
Gwent	178	466	393	0	9	10	0
Hampshire	1049	965	961	916	791	919	880
Hertfordshire	659	676	656	700	727	701	720
Humberside	657	655	659	558	560	543	597
Kent	750	750	707	0	0	0	0
Lancashire	1193	1108	1086	877	991	1056	1190
Leicestershire	733	655	582	611	451	377	394
Lincolnshire	294	448	415	415	437	403	428
Merseyside	1264	1200	1131	1060	856	781	791
Metropolitan Police	8758	7888	7757	5958	6446	6582	7206
Norfolk	542	509	495	581	699	681	734
North Wales	327	321	331	695	676	653	704
North Yorkshire	1624	1547	1459	580	469	510	485
Northamptonshire	561	575	642	28	402	352	395
Northumbria	603	609	602	1484	1444	1374	1243
Nottinghamshire	788	770	763	737	570	587	670
South Wales	1077	1011	861	942	938	980	963
South Yorkshire	965	927	1027	1047	0	0	0
Staffordshire	689	633	608	638	596	660	659
Suffolk	434	411	425	401	409	383	393
Surrey	661	570	532	379	368	515	887
Sussex	1144	1129	1142	1174	1092	720	773
Thames Valley	1437	1454	1468	1401	1401	1251	712
Warwickshire	218	241	344	574	362	397	350
West Mercia	1062	1025	857	846	874	942	873
West Midlands	1936	1462	1412	1308	1360	1317	1643
West Yorkshire	1082	1065	1049	1048	2040	1624	1818
Wiltshire	327	348	329	319	320	0	0

Table 5.21. Descriptive summary of Response Allocation Ratio in police force from 2012 to 2018.		
	Value	Police force
Max	0.3356	Essex-2017
Min	0.0312	Kent-2015
Median	0.2016	Sussex-2012
Mean	0.1890	
Standard deviation	0.0681	

Response Workforce data are listed in Table 5.21 whilst a descriptive summary of its ratio is presented in Table 5.22. The largest ratio is in 2017-Essex and the least is 2015-Kent. In 2012, Sussex had the median response allocation ratio among all police forces across all years. Inspired by the literature mentioned above, this research splits reporting rate into PRR (reporting rate of household and personal property crime) and VRR (reporting rate of personal violent crime). Regression models are employed to investigate the impact on the reporting rate at the police force area level. Besides, regarding the response workforce, crime rates and fear of crime in this area in the same year are also included in the regression.

(1) Property crime reporting rate: PRR

Firstly, it is necessary to verify any linear relationship between Reporting Rate of Property Crime (PRR) and Response Allocation Ratio (RESR), Fear of Crime (FC), Crime Rate 1 (CR1), and Crime Rate 2 (CR2). The Pearson's correlation tests support the presence of a linear correlation between *PRR* and *RESR* (coefficient -0.143, p-value 0.02), and *PRR* and *CR2* (coefficient -0.1469, p-value 0.0117), though they disagree with the finding of a correlation between *FC* (p-value 0.1) and *CR1* (p-value 0.35). Figure 5.25 presents the scatterplots for reporting rates of property crime on response allocation ratio (left) and fear of crime (right).

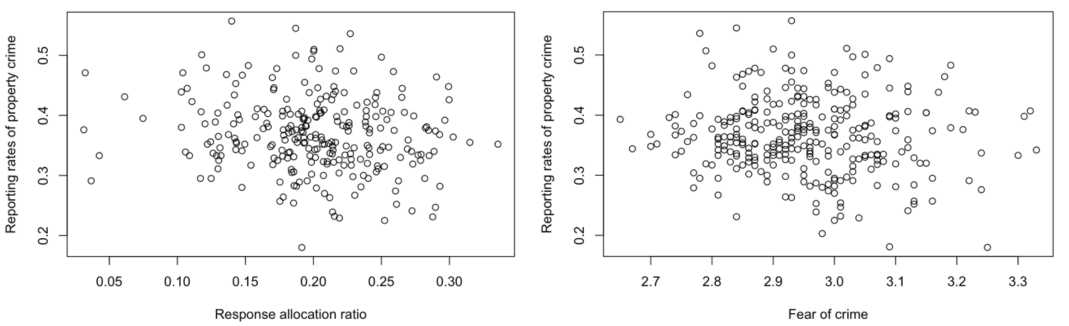

Figure 5.25. Scatterplots for reporting rates of property crime on response allocation ratio and fear of crime at the level of police force area in all years.

This research also incorporates a resource predictor *NW* (non-staff cost per workforce) into the regression. Similar to the aggregated crime rates in the last section, this section employs a new crime rate, Crime Rate Property (CRP) (Crime Rate 1 + Crime Rate 2). Firstly, a set of fixed-effect panel linear regression models is conducted using "pooling", "within", "between" and "twoway" methods: *PRR ~ RESR+ CRP +NW* (without *FC* at present due to the collinearity between crime rates and fear of crime). The results are listed in Table 5.22.

Table 5.22. Results of panel regression models of Reporting Rate of Property Crime on Response Allocation Ratio, Crime Rates of Property Crime, and Non-Staff Cost per Workforce.

	Intercept		RESR		CRP	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	0.40526 (0.022729)	2e-16	-1.5205 (0.075384)	0.04475	-5.6328e-05 (3.6454e-05)	0.12355
Individual			-0.15509 (0.075721)	0.04177	-7.7820e-05 (3.9458e-05)	0.04988
Between	0.36734 (0.067191)	3.063e-06	-0.13357 (0.27072)	0.62458	-7.3712e-05 (9.9941e-05)	0.46532
Two-way			-0.13891 (0.077268)	0.07368	-5.9983e-05 (4.5539-05)	0.18923

	NW		Model	
	coefficient (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	4.6364e-04 (5.9740e-04)	0.43841	0.016125	0.068498
Individual	-5.9519e-04 (6.8591e-04)	0.38652	-0.16816	0.070449
Between	0.0029519 (0.0014269)	0.04542	0.047048	0.18868
Two-way	-8.8698e-04 (0.0012107)	0.46462	-0.21573	0.20932

It can be gathered from Table 5.22 that, when differences between areas are considered, the response workforce allocation ratio and crime rates of a given area significantly impact the reporting rate of property crimes (p-values < 0.05 in the within the model). However, when the common time effects are also included, the two-way models indicates that these two predictors are non-significant (p-values > 0.05). Taking the lead from those police forces that did not split Workforce into Neighbourhood and Responses and instead reported both functions in Neighbourhood, this research aggregates the Neighbourhood Allocation Ratio (NEIR) and Response Allocation Ratio (RESR) variables to avoid bias in the data collection. A new variable is then defined: Neighbourhood and Response Allocation Ratio *NRR = NEIR + RESR*. A set of fixed-effect panel linear regression models are carried out using the "pooling", "within", "between" and "twoway" methods: *PRR ~ NRR+ CRP +NW*. The results are presented in Table 5.23.

Table 5.23. Results of panel regression models of Reporting Rate of Property Crime on Neighbourhood and Response Allocation Ratio, Crime Rates of Property Crime, and Non-Staff Cost per Workforce.

	Intercept		NRR		CRP	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	0.39222 (0.022262)	2e-16	-0.056009 (0.042715)	0.1910	-4.7827e-05 (3.6325e-05)	0.1891
Individual			-0.15351 (0.058410)	0.009215	-7.6402e-05 (3.9015e-05)	0.051509
Between	0.33204 (0.040220)	5.279e-10	0.017501 (0.074179)	0.81475	-7.1553e-05 (1.0009e-04)	0.47905
Two-way			-0.14655 (0.059488)	0.01458	-6.1021e-05 (4.4989e-05)	0.17647

	NW		Model	
	coefficient (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	5.1929e-04 (5.9904e-04)	0.3868	0.0070515	0.18847
Individual	-7.6531e-04 (6.8797e-04)	0.267220	-0.15369	0.021349
Between	0.0030423 (0.0014163)	0.03814	0.042346	0.2044
Two-way	-0.0010267) (0.0012053)	0.39529	-0.19947	0.062517

The model results, when combined with the sum of the neighbourhood and response workforce allocation ratios reveal significant estimators. Cross-sectionally, Neighbourhood and Response Allocation and Crime Rates of Property Crime are not linearly correlated to Reporting Rate of Property Crime. However, when this research adds unobserved fixed effects from individual areas (in the within model) and even unobserved time effects (in the two-way model) into the model, the coefficients for Neighbourhood and Response Allocation are significant (p-value < 0.05).

The negative coefficient means that for a given police force area, an increase in neighbourhood or response workforce ratio is associated with a decrease in the reporting rate of property crime. It seems counterintuitive that a given area allocates more neighbourhood and response workforce (for neighbourhood policing, for example) when residents living there are less willing to report property crime to the police. Drawing on the literature discussed above, there might be several possible interpretations for the negative relationship between the size of neighbourhood, response workforce, and reporting rate: (1) A large neighbourhood-response workforce ratio creates "generalised trust in citizens" (Kääriäinen & Sirén, 2011) in residents' mind, such that residents do not report crimes to the police due to their trust in the local environment; (2) The neighbourhood policing efforts did not include effective face-to-face interaction, leading residents to think they would perform poorly when dealing with other crimes. The latter inference will be discussed in Chapter 6 when public trust is analysed in terms of public-police contact.

The panel regression models on $PRR \sim FC + NRR + NW$ and $CRP \sim NRR + NW$ ruled out linear correlations between Fear of Crime and Reporting Rate of Property Crime and between Crime Rate, Neighbourhood, and Response Allocation Ratio (see results in Table A.3.5-A.3.6 in Appendix III). Therefore, after excluding the collinearity, the impact of Neighbourhood and Response Allocation Ratio on Fear of Crime for a given area through the fixed effect panel regression model $FC \sim NRR + CR + NW$ is investigated. The results are listed in Table 5.24.

Table 5.24 reveals that given the crime rates are related to fear of crime: for a specific area, the Neighbourhood and Response Allocation Ratio coefficients are also significant when the fixed effects from unobserved individuals and time are both controlled (coeff = -0.213 and p-values=0.002), This means that for a specific area, if the neighbourhood and response workforce ratio increases by 0.1 (10 percentage points), residents in this area are expected to worry more about crime by 0.0213 (0.1*coeff), which is not a large magnitude of effect. Further, the two-way model in Table 5.24 has a higher adjusted R-squared (-0.155) than that in Table 5.20 (-0.167), meaning that this is an acceptable relationship for explaining fear of crime. The relationship runs counter to the hypothesis that a visible frontline workforce helps to reduce worries about crime.

Table 5.24. Results of panel regression models of Fear of Crime on Neighbourhood and Response Allocation Ratio, overall Crime Rates of Property Crime and Non-Staff Cost per Workforce.

	Intercept		NRR		CR	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	3.16282917 (0.04204990)	2.2e-16	-0.20349655 (0.07748695	0.009161	-0.00035362 (0.00005358)	2.398e-10
Individual			-0.22883 (0.078478)	0.003929	-2.5835e-04 (4.2254e-05)	4.606e-09
Between	3.26487047 (0.11794800)	2.2e-16	-0.15523473 (0.20170404)	0.446285	-0.00074843 (0.00021699)	0.001391
Two-way			-0.21289 (0.069052)	0.002330	-1.1828e-04 (0.0577939)	0.005633

	NW		Model	
	coefficient (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	0.00021466 (0.00108648)	0.843536	0.16162	2.4991e-10
Individual	2.6189e-04 (9.1556e-04)	0.775119	0.019275	1.3622e-09
Between	0.00201396 (0.00379511)	0.598734	0.19715	0.0098652
Two-way	-2.3690e-04 (1.3969e-03)	0.865495	-0.15527	0.0017597

(2) Personal violent crime reporting rate: VPR

In a similar set of panel regressions (*VRR ~ FC + NRR + CR3 + NW* with “pooling”, “within”, “between” and “twoway” effects), no models or coefficients are sufficiently significant to be accepted. Hence, no variables are found to have a linear relationship with the reporting rate of violent crime. The results are presented in Table A.3.7 in

Appendix III. It is concluded that there is no evidence to support any variable exerting an impact on the reporting of personal violent crimes at the police force area level.

In the next section, the third part of frontline workforce, intelligence, and investigation is discussed in association with the solving rate in police force areas.

5.6. Intelligence and investigation workforce

The final frontline function of interest in this research is the investigation workforce, as it is a key aspect of policing: reactive policing. In this section, Intelligence and Investigation Workforce (INT) is defined as the sum of these functions in the old function framework (ONS, 2012): HOLMES Unit, Intelligence and Surveillance Unit. It includes "staff predominantly employed on duties related to the operational use of HOLMES; staff predominantly employed in criminal intelligence units, including field intelligence officers and local intelligence officers, and staff predominantly employed in coordinating the policing of football matches (football liaison) and collating related intelligence; other staff who maintain indices and records for criminal intelligence purposes are included; includes those officers/staff in support roles. staff predominantly engaged in surveillance duties. includes officers/staff in support roles". Meanwhile, in the new function framework (ONS, 2015), these functions are grouped together: teams assess information and intelligence to identify opportunities at the force level to reduce harm, risk, threats, serious injury, threats to community stability, and victimisation; surveillance teams based locally in a BCU; central surveillance teams providing specialist covert surveillance; and handling major investigations.

The following corresponding outcome indicators are selected: Solving Rate for Property Crime (PSR) and Solving Rate for Violent Crime (VSR). The solving rate is equal to the detection rate multiplied by the charging rate. In general, England and Wales had fewer detectives and investigators in 2015 than in 2012, though the number stabilised between 2012 and 2014. In the post-austerity period, the workforce increased again, exceeding that of 2011. Table 5.25 shows the workforce for each police force in each year.

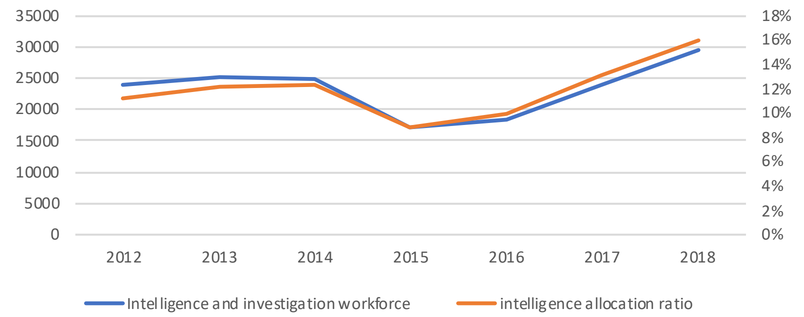

Figure 5.26. Intelligence and investigation workforce and its ratio over the total workforce in England and Wales, March 2012 - March 2018.

Table 5.25. Intelligence and investigation workforce (full-time equivalent) of 42 police forces from March 2012 to March 2018.

	2012	2013	2014	2015	2016	2017	2018
Avon and Somerset	821	932	964	742	717	709	1067
Bedfordshire	330	331	313	310	255	248	427
Cambridgeshire	386	404	411	417	405	357	356
Cheshire	534	520	451	332	235	260	340
Cleveland	351	310	282	228	214	274	255
Cumbria	233	221	203	92	119	123	151
Derbyshire	463	415	443	249	450	471	553
Devon and Cornwall	1125	1023	874	362	337	321	413
Dorset	327	309	299	147	143	257	364
Durham	232	226	210	178	158	157	222
Dyfed-Powys	177	201	187	99	98	96	140
Essex	732	673	678	387	384	355	701
Gloucestershire	220	217	197	133	141	152	175
Greater Manchester	1759	1439	1382	896	916	932	1057
Gwent	312	299	255	170	153	117	148
Hampshire	1082	913	917	301	337	300	661
Hertfordshire	669	661	644	232	203	205	374
Humberside	721	673	641	257	232	203	336
Kent	823	733	702	372	352	351	410
Lancashire	852	830	724	341	310	296	351
Leicestershire	607	552	557	578	420	416	712
Lincolnshire	334	323	292	167	150	166	228
Merseyside	954	921	908	497	431	509	564
Metropolitan Police	6169	5980	6208	3830	3407	3397	3764
Norfolk	345	339	346	142	124	145	229
North Wales	276	260	260	129	131	254	174
North Yorkshire	718	659	643	186	251	185	338
Northamptonshire	242	249	268	301	292	162	242
Northumbria	284	285	304	474	344	360	416
Nottinghamshire	692	701	689	313	275	300	453
South Wales	630	603	807	322	312	302	456
South Yorkshire	807	731	671	285	251	254	353
Staffordshire	443	425	384	213	217	222	327
Suffolk	323	314	302	120	116	144	297
Surrey	748	895	809	284	301	333	459
Sussex	597	595	594	268	259	259	504
Thames Valley	775	679	673	579	580	589	928
Warwickshire	335	351	199	124	94	110	201
West Mercia	557	555	473	247	255	291	304
West Midlands	2035	2405	2211	1166	1133	1147	1189
West Yorkshire	998	942	847	526	552	564	927
Wiltshire	315	367	362	156	144	154	188

Table 5.24. Descriptive summary of intelligence allocation ratio in police force from 2012 to 2018.

	Value	Police force
Max	0.2288	Surrey-2017
Min	0.0483	West Mercia-2012
Median	0.1162	Bedfordshire-2013, Avon and Somerset-2012
Mean	0.1192	
Standard deviation	0.0433	

Table 5.26 presents a descriptive summary of intelligence and investigation allocation ratio at the police force area level. In 2017, Surrey had the largest ratio (22.8%), whilst West Mercia had the least in 2012 (4.8%). Bedfordshire in 2013 and Avon and Somerset in 2012 are the two police forces closest to the median (11.6%). In this section, panel regression models are employed to investigate whether there is a relationship between Intelligence Allocation Ratio and Solving Rate.

(1) Property crime solving rate (PSR)

Scatterplots for *PSR* and *INTR* are presented in Figure 5.27. In terms of property crime, Pearson's correlation tests do not support any linear correlation between solving rate and intelligence allocation ratio, crime rates, and non-staff costs (p-values are all greater than 0.05). Meanwhile, in the panel regression models with "pooling", "within", "between" and "twoway" effects (*PSR* ~ lag(*INTR*)+*CR1*+*CR2*+*NW)*, only the "between" model is significant. However, the coefficient of *INTR* is not significant in the final two-way model, which considers fixed effects from both individual areas and time points. Furthermore, CR2 is the only effective explanatory predictor in the between model. The results are set out in Table 5.25.

(2) Violent crime solving rate (VSR)

No variables are found to form a linear relationship with the solving rate of violent crime. In a similar panel regression (*VSR ~INTR +CR3+NW* with "pooling", "within", "between" and "twoway" effects), no models are sufficiently significant to be accepted. The results are listed in Table A.3.8 in Appendix. This research concludes that there is no evidence to support the conclusions that any variable in this set of regressions influences rates of violent crimes at the police force area level.

This section does not support the hypothesis that the allocation of investigation and intelligent workforce contributes to an increase in solving rates for neither violent crime nor property crime. Accordingly, there does not seem to be a significant linear relationship between the investigation workforce and the solving rate as calculated from the survey data. During the austerity period, police forces tried to maintain the workforce in investigation and intelligence with a limited budget. In the post-austerity period, this workforce function increased with a sharp slope, although the detection rate of personal violence decreased and the property crime rate showed little improvement. This phenomenon reveals a delayed negative impact of austerity: even with the gradual recovery of funds and human resources, the effectiveness of policing has not been enhanced.

Table 5.25. Results of panel regression models of Solving Rates of Property Crime on lag(Intelligence and Investigation allocation ratio), Crime Rate 1, Crime Rate 2, and Non-Staff Cost per Workforce.

	Intercept		lag(INTR)		CR1	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	0.093452 (0.016690)	5.801e-08	0.20850 (0.087974)	0.01857	-3.1034e-05 (4.1363e-05)	0.4586
Individual			0.17692 (0.088799)	0.04767	-3.6925e-05 (4.4692e-05)	0.40966
Between	0.10547 (0.037723)	0.00816	0.28352 (3.1194)	0.36929	-7.2819e-07 (1.1696e-04)	0.99507
Two-way			0.16555 (0.0091090)	0.07067	-3.9086e-05 (4.7381e-05)	0.41040

	CR2		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	-2.0301e-04 (1.9498e-04)	0.29883	-5.2788e-04 (5.6846e-04)	0.35401	0.012675	0.1309
Individual	1.8392e-04 (2.2122e-04)	0.4067	-6.4944e-04 (6.6383e-04)	0.32908	-0.18624	0.1877
Between	-0.0010164 (4.3946e-04)	0.02640	-3.3231e-04 (0.0022765)	0.79606	0.058881	0.18453
Two-way	2.3019e-04 (2.3013e-04)	0.3184	7.0244e-04 (0.0012144)	0.56362	-0.21833	0.22411

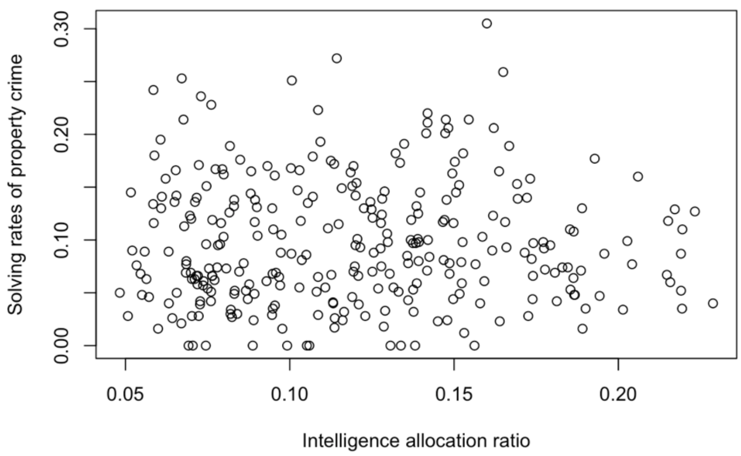

Figure 5.27. Scatterplots for solving rates of property crime on intelligence and investigation allocation ratio at the level of police force area in all years.

5.7. Conclusion

In Chapter 5, effectiveness outcomes and their probable reflection in efficiency assessment and resource allocation are analysed at the level of the police force area. Effectiveness outcomes include fear of crime, rates of vehicle and property crime, rates of violent crime against individuals, rates of clearing up property crime and violent crime, and rates of reporting, detection, and charging of property crime. Meanwhile, resource indicators include total workforce, frontline workforce, support workforce, frontline/support allocation ratio, neighbourhood workforce, response workforce, and intelligent and investigation workforce.

In general, given the reduction of policing budget, the police in England and Wales have generally reduced residents' concerns about crime during the period of austerity. Reduced crime rates, especially in motor and household property crime, but has not improved clear-up rates significantly for all property and violent crimes according to the survey data. It should be emphasised that since police have greater control over clear-up rates than crime rates, a fall in clear-up rates may indicate that austerity measures are having a detrimental effect. Worry about crime decreased in most areas, and the crime rates in the areas have also decreased significantly during the period of austerity, however, only a few of them succeeded in continuing to reduce crime rates during the post-austerity period. The increase in crime rates in the post-period may be due to changes in the criminal and socio-economic environment, or a delayed effect from the austerity. Clear-up rates were divided into three stages of rates: reporting, detection and charge rates. The reporting rate and detection rate improved slightly from 2011/12 to 2014/15, however, the charge rate at a national level in 2014/15 was worse compared to that in 2011/12. The latter indication involves choices made by the criminal justice system and is not entirely under the police's control.

Then, to examine potential connections between effectiveness, efficiency, and resources, this chapter runs several fixed-effect panel linear regression models. For each assumption of linear relationship, four types of effects from the individual (police force) are considered in four models, respectively: (1) pooling context with no time or individual effects, which does not treat the dataset as a panel; (2) within-individual fixed effects, which estimates the relationship over the years and within the same individual; (3) between-individual model, which estimates the relationship on average over the years and ignores the differences in area individuals; (4) two-way fixed effect, which considers unobserved dummy variables from both time points and area individuals. The magnitude and significance of the coefficients of explanatory variables are discussed. Significant results in the two-way models are of particular relevance in this research, which can reveal the relationship between the explanatory and dependent variables within a given area over the years when the unobserved fixed effect from years and individuals are both considered. In conclusion, the panel regression models based on 42 police forces over a seven-year period uncover evidence to support existing research but also highlight some relationships opposing previous proposals.

Two links between efficiency and part of effectiveness are found. (1) Scale efficiency scores are strongly negatively correlated with the scale (represented by the total workforce of local police forces). For a specific police force, there is strong evidence that growing the workforce is linked to lower-scale efficiency scores assessed by DEA models. If the total workforce increases by 10% then the scale efficiency will decrease by around 0.0084, which is a small size of magnitude; and on average over the years, a larger police force probably has a lower score of scale efficiency as if the total workforce increases by 10% then the average scale efficiency over the years is expected to decrease by around 0.0492, which is a fair-sized effect. It can be interpreted that small police forces have more flexibility in organisational management and that large police forces deal with more complicated jobs, including national policing, in addition to more redundancy. Impacted by the austerity, the downsizing of staff in England and Wales had the advantage of increasing scale efficiency. This is also evidence to oppose the rationale for the controversial "merging forces" proposals of 2006. (2) Fear of crime is correlated with the pure efficiency score in the area. In detail, there is no relevance between pure efficiency scores within the same police force over the years, however, an area where crime is more of a concern tends to have lower average pure efficiency scores in the DEA models over the years. Given that locals cannot immediately comprehend how well the police have converted resources to services, it is not unexpected that fear of crime is not connected with the pure efficiency provided by a force area. The relationship revealed by the models can be explained by the relationship between fear of crime and crime rates, as crime rates are the policing outputs in DEA analysis. Frontline to support allocation ratio is also of interest in this research. It cannot, however, address the question of whether the F/S ratio contributes to increased police efficiency because they served as both input indicators in the DEA assessment (in this study, a reduction in either the frontline or support workers is viewed as "fewer resources and more efficiency"). Rather, the frontline workforce ratio is used to explain police effectiveness.

Which factors impact fear of crime in a local area? (1) According to this research, a larger-scale area tends to have more average worries about crime over the years. This may be a result of that the areas have allocated more workforce as a response to high crime rates or because larger forces are likely to have a higher levels of media exposure, which increases concern about crimes due to some negative perceptions of media contact (Padgett & Gertz, 2000; Romer et al., 2003, Ditton et al., 2004). The magnitude of the effect is that if an area has 1000 more police workforce, the average level of concern about crime is predicted to rise by 0.017, which is not a substantial increase. (2) Additionally, for a given police force area, a reduction of motor and household property crimes will indeed help to reduce the fear of crime over the years, but its influence is far less than that in the between model. The magnitude of the effect is that if the crime rates drop by 100 per 1000 people, residents' worries about crime are expected to decrease by 0.01, which is not a significant amount of change given that the fear of crime ranges from 2.5 to 3.5. Consequently, the conclusion based on survey data at the level of the police force area differs from what Rader (2017) advocated, according to which even if crime rates decreased, residents in this area would still be concerned about crime. (3) Surprisingly, when time-varying unobservables and fixed effects from individual areas are taken into account, the neighbourhood and response workforce allocation ratio has the opposite effect on fear of crime for a given police force area; an increase in the ratio is linked to a rise in concern about crime. If the neighbourhood and response workforce ratio increases by 10 percentage points, residents in a given area are expected to worry 0.0213 more about crime, which is a reasonable amount of the effect. Although Karn (2013) and Kelling (1981; 1988) have pointed out that foot patrol helped to reduce fear of crime, this research demonstrates that during the period of austerity and post-austerity, increasing the neighbourhood policing workforce (including the neighbourhood function and response function) does indeed exacerbate residents' fear of crime at the level of police. Three different explanations could be used to interpret it. Foot patrol was not implemented properly, which led to residents associating police visibility with a high level of crime and worrying about crime; second, neighbourhood policing during the austerity period is ineffective; third, there may have been some poor interactions between the police and residents during neighbourhood policing; and finally, residents may have had negative attitudes. Skogan (2006) indicated that bad quality of contact will significantly influence public trust. He also indicates that worry about crime is a dependent variable on public trust in the police (2009). The last interpretation and its hypothesis will be analysed as well in chapter 6.

Which resource factors impact crime rates? No indicators are discovered in this study to have any appreciable impact on lowering crime rates, regardless of the frontline workforce ratio or neighbourhood workforce allocation ratio. This result concurs with Karn (2013) who noted that patrol work had no appreciable impact on crime rates, contrary to Ratcliffe et al. (2011) who suggested that patrol work assisted in reducing crime. At least, the amount of workforce is not as important as the quality of their work. It's probable that due to austerity, most police agencies planned to reduce frontline staff while maintaining support line staff, but the decrease in funding may have nevertheless had an impact on the calibre of their work. Another view is that while the police have a responsibility to deter crime, they are powerless to stop most sorts of crime from happening.

What factors impact clear-up rates? This research does not find any significant relationship between the allocation of intelligent and investigation workforce and solving rates but does find a significant relationship between the allocation of neighbourhood and response workforce and reporting rates. In other words, for a particular police force area, people tend to report 1.47% less property crime to the police, which is a reasonable amount of the effect, if the neighbourhood and response workforce rises by 10%. This research shows that, in the modern period, there is no longer a shortage of workers who can respond to calls for service or record crimes as the primary reason why citizens do not report incidences to the police (Levitt, 1998). There are two different ways to view a negative relationship: (1) A high proportion of neighbourhood and response workers fosters greater "generalized trust in citizens" in residents' minds, preventing them from reporting crimes to the police because they have faith in their community; (2) The neighbourhood policing performed poorly in face-to-face interactions, and the more they did so, the worse residents believed they would perform in dealing with crimes (Skogan, 2006). The latter inference will be investigated in chapter 6 where public trust is analysed in terms of public-police contact.

In chapters 4 and 5, efficiency, effectiveness and reflection are assessed through quantitative models. Then in chapter 6, public trust in policing is to be measured and analysed by similar methods.

6. Public confidence

This chapter moves on to address the third element of police performance: public trust. Section 6.1 reviews the previous surveys of public trust in the police, whilst section 6.2 examines the existing literature on public confidence, visibility, and public-police contact. Section 6.3 measures public trust using the Crime Survey in England and Wales, examines how the measures of sub-concepts in public trust relate to each other and how police forces performed in these measures, and analyses any reflections on police efficiency. Section 6.4 investigates the relationship between policing effectiveness, resources, and public trust. Section 6.5 discusses differences between victims and non-victims, and also between those who have had contact with the police and those who have not. Finally, section 6.6 outlines a novel attempt to measure overall public confidence using social media mining, after which the concluding comments are put forward in section 6.7.

In the report *Improving police performance: A new approach to measuring police efficiency* produced by the Public Services Productivity Panel (Spottiswood, 2000), the policing outcome measures cover three dimensions: reducing disorder, reducing crime, and delivering justice. The present report also uses three report selected three key outcome indicators as measures: level of crime, fear of crime, and feeling of public safety. As the New Public Service model (Denhardt and Denhardt, 2000) advocates, the role of public administration is "serving rather than steering" the public. Similar to this point, it is widely accepted that public attitudes should be taken into account when assessing police performance. The Home Office (2006) emphasised that the assessment of public perceptions of the police is equally as vital as monitoring operational outcomes. Survey questions were held up as an effective means to measure public trust in policing and satisfaction in public-police encounters. There have been various questionnaire surveys commissioned by the government and local police forces to investigate public trust and victim satisfaction. In 2008, a new survey was introduced (Home Office, 2008) to measure public concerns about crime and anti-social behaviour (ASB) in local communities, with a greater focus on ASB concerns that in the survey's previous iterations (Myhill et al., 2010).

6.1. Previous surveys

(1) BCS and CSEW

Since its inception in 1982, the British Crime Survey (BCS) has posed questions on respondents' attitudes and perceptions in its questionnaires, alongside hundreds of questions covering personal information, victim experiences, and police activities. In 1982, the British Crime Survey asked questions about: (a) Fear of crime, including general feelings and fear in different scenes; (b) Quality and satisfaction of public-police contact, covering perceptions from the public and victims; (c) Police engagement with the community; and (d) Overall confidence (see concepts in section 1.7). The details of these questions are listed in Table 6.1.

Table 6.1. Questions about public attitudes and perceptions in BCS 1982. Source: British Crime Survey 1982.	
Type A. Asking about fear of crime	
A1	(ask all)[28] Do you ever worry about the possibility that you or anyone else who lives with you might be the victim of crime? [yes; no][29] If yes, is this [a big worry; a bit of a worry; just an occasional doubt]? Who do you worry about? [self only; other adults; children under 16] What sorts of crime do you worry about most?
A2	(ask all) How safe do (would) you feel walking alone in this area after dark? Would you say: [very safe; fairly safe; a bit unsafe; very unsafe]?
A3	(ask all) Do you ever worry about the possibility that there might be a fire in your home? [yes; no] If yes, is this [a big worry; a bit of a worry; occasional doubt]?
A4	(ask all) Do you ever worry about the possibility of accidents around your home to you or people you live with - falls, cuts, scalding, electric shocks or anything of that sort? [yes; no] If yes, is this [a big worry; a bit of a worry; occasional doubt]?
A5	(ask all) Do you ever avoid going out on foot by yourself in this area because of the risk that you might be a victim of crime? [yes; no] When you are out, do you ever worry about the possibility that your pocket might be picked or your bag snatched? [yes; no] If yes, is this [a big worry; a bit of a worry; occasional doubt]?
A6	(ask if any driving in past 12 month) Do you ever worry about the possibility somebody might steal your car or van or take something from it? [yes; no] If yes, is this [a big worry; a bit of a worry; occasional doubt]?
A7	(ask all) When your home is left empty, do you ever worry at all about the possibility somebody might break in? [yes; no] If yes, is this [a big worry; a bit of a worry; occasional doubt]? And when you are at home, do you ever worry at all about the possibility somebody might break in? [yes; no] If yes, is this [a big worry; a bit of a worry; occasional doubt]?
Type B. Asking about quality and satisfaction of public-police contact	
B1	(ask if ever originated contact with police)[30] When you have wanted help from the police, have you generally found them [very helpful; fairly helpful; mixed experience; a bit unhelpful; very unhelpful]?
B2	(ask if ever originated contact with police) When you have wanted help from the police, have you generally found them [very pleasant; fairly pleasant; mixed experience; a bit unpleasant; very unpleasant]?

[28] "(ask all)" means that all respondents have been asked these questions.
[29] Content in the square brackets are multiple choices for respondents, separated by semicolons.
[30] "(ask if …)" means if the respondent meets this condition, he or she was asked these questions.

B3	(ask if approached by police) When you have been approached by the police, have you found them [very polite; fairly polite; mixed experience; a bit impolite; very impolite]?
B4	(ask all) Have you ever been really annoyed about the way a police officer behaved towards you or someone you know or about the way the police handled the matter in which you were involved? [yes; no] If yes, has this happened at all in the past five years? [yes; no] How often in the past five years? Last time you were really annoyed, what happened that annoyed you?
B5	(ask if annoyed in past five years) On any of these occasions, have you ever felt like making an official complaint to someone about it? [yes; no] If yes, to who did you make the complaint? [police station; senior policeman; other police officer] If no, why not?
B6	(ask all) Have you ever been really pleased about the way a police officer behaved towards you or someone you know or about the way the police handled the matter in which you were involved? [yes; no] If yes, has this happened at all in the past five years? [yes; no] How often in the past five years? Last time you were really pleased, what happened that pleased you?
B7	(ask victims if police know about the matter and the victim talked to uniformed officers/ plain clothes officers) Overall, were you satisfied or dissatisfied with the way the uniformed officers/ plain clothes officers dealt with the matter? [very satisfied; fairly satisfied; a bit dissatisfied; very dissatisfied] If a bit/ very dissatisfied, why were you dissatisfied?
Type C. Asking about public engagement	
C1	(ask all) Do you think the police in this area understand the kinds of problems people here have? [yes; no; don't know]
Type D. Asking about overall confidence	
D1	(ask all) Taking everything into account, would you say the police in this area do a good job or a poor job? [very good; fairly good; fairly poor, very poor; don't know enough to say]

From 2001/02 onwards, the BCS was published annually. Notably, the questionnaires became more organised than before, including the questions set out in the table above (though question D1 was articulated as: How good a job do you think THE POLICE are doing? [excellent; good; fair; poor; very poor]). In 2012, the BCS was renamed the Crime Survey in England and Wales (CSEW), in which questions about perceptions of police activities became more concrete. The Type B questions on the quality and satisfaction of police-public contact were put to all respondents and to those who had come into contact with the police.

In Type D, the questionnaire asked two questions (below) to all respondents about overall opinions of the police.

Table.6.2. Type B Questions in CSEW 2012/13.
Source: Crime Survey for England & Wales, 2012/13.

B1	(ask all) you do not need to have had contact with the police, we are interested your opinion based on what you do know, how much would you agree or disagree that: They (the police in this area) would treat you with respect if you had contact with them for any reason. [Strongly agree; tend to agree, neither agree nor disagree, tend to disagree, strongly disagree]
B2	(ask all) The police in this area treat everyone fairly regardless of who they are [Strongly agree; tend to agree, neither agree nor disagree, tend to disagree, strongly disagree]
B3	(ask if the police come to know=yes) Do you think the police treated you fairly? [Yes; not entirely; Not at all]
B4	(ask if the police come to know=yes) Did the police treat you with respect? [Yes; not entirely; Not at all]
B5	(ask if the police come to know=yes) Overall, were you/(the victim) satisfied or dissatisfied with the way the police handled this matter?[Very satisfied; fairly satisfied; a bit dissatisfied; very satisfied]

Table.6.3. Type D Questions in CSEW 2012/13.
Source: Crime Survey for England & Wales, 2012/13.

D1	(ask all) Taking everything into account, how good a job do you think the police in this area are doing? [Excellent; good; fair; poor; very poor]
D2	(ask all) Taking everything into account I have confidence in the police in this area. [Strongly agree; tend to agree, neither agree nor disagree, tend to disagree, strongly disagree]

(2) Metropolitan Police surveys and other local area surveys

There are two main surveys used by the Metropolitan Police Service to understand the views of Londoners: The Metropolitan Police Public Attitudes Survey (PAS) and the Metropolitan Police Service User Satisfaction Survey (USS). Since 1983, the PAS has been carried out through face-to-face interviews that cover topics including fear of crime, attitudes to policing, and contact with the police. Since 2005, the USS, also known as the Crime Victim Survey, recalibrated its focus to emphasise contact with and treatment by the police. Both surveys ask questions about “overall satisfaction”.

Every other police force area has its own surveys based on residents' experiences in the local area, most of which are victim-based surveys.

(3) HMIC study

Since 2015, Her Majesty’s Inspectorate of Constabulary (HMIC) has conducted an annual survey of public perceptions of policing in England and Wales (Ipsos MORI, 2017). The questionnaire explores public perceptions of local safety, the reputation of policing, public engagement, and contact with the police. The questionnaires are completed online by respondents aged 16 and over. As well as the typical questions pertaining to overall satisfaction and fear of crime, the HMIC surveys also include perceptions of anti-social behaviours, reflecting what has been specifically highlighted as a recent policing priority. Different from most surveys which include perceptions of police effectiveness, the HMIC studies perceptions of police efficiency by asking whether the respondent agrees or disagrees that the police provide good value for money. As the public is not privy to all of the relevant financial information and police costs, their direct perception of value for money is not precise; instead, responses to this question will be informed by perceptions of effectiveness. Moreover, the HMIC asks whether the participants are interested in what the police are doing and links their interest to satisfaction with the police.

6.2. Understanding public trust

As discussed in chapter 1.7, overall confidence in the police encompasses three trust sub-concepts: trust in police effectiveness, legitimacy, and public engagement (Tyler & Huo, 2002; Sunshine & Tyler, 2003). Residents perceive the police as effective when they see them in the local area performing their role as expected; thus, police visibility has a key impact on public confidence (Sindall and Sturgis, 2013; Bradford, 2011). Legitimacy includes treatment in the process and feelings of fairness, while public engagement is perceived when the public believes that the demands of the community are meaningfully understood. In relation to the latter two sub-concepts, contact with the police is also of central importance when studying public attitudes (Fitzgerald et al., 2002; Skogan, 2006; Tyler & Fagan, 2006; Bradford et al., 2009).

(1) Visibility

Several types of research have employed visibility as a factor of public confidence in policing. Although police visibility has always been defined as police presence on the streets (Pfuhl, 1983) and the use of police crackdowns (Sherman 1990), the main components of police visibility are car (or motor) patrolling and foot patrolling (Schnelle et al., 1977; Kelling, 1981). Kelling (1981; 1988) pointed out that foot patrols had a greater positive effect on fear of crime than motor patrols. Accordingly, if foot patrols were removed, fear of crime would increase.

Hawdon and Ryan (2003) studied the relationship between police-resident interactions and satisfaction with the police using survey data derived from 130 respondents living in a small neighbourhood in the US. The questionnaires asked residents about police visibility, fear of several types of crime, trust in police effectiveness, police interactions, and community solidarity. When considering community solidarity, the factor of police-resident interaction did not play a significant role in public trust in police effectiveness. However, the factor of police visibility had an apparent influence on fear of crime: increased visibility was related to a higher public trust in police effectiveness.

Another American study (Skogan, 2009) tested the accountability and reassurance models of fear of crime and public confidence. To be precise, the accountability model employed confidence as a dependent variable, while the reassurance model employed fear of crime as a dependent variable. Participants selected from four communities with significant crime problems were asked questions about confidence in the police from three aspects: preventing crimes, helping victims, and maintaining order. The results supported the reassurance model, in that a reduction of fear of crime would significantly increase confidence in the police.

Bradford et al. (2009a) utilised data from the 2005/06 Metropolitan Police Public Attitudes Survey to illustrate how contact was vital in assessing public confidence. The two main reasons for high public confidence were good contact quality and high visibility. The authors also proposed that visibility could more readily be improved than the contact experience. However, the situation changed during the austerity period in the UK when the police workforce was cut due to reduced funding.

Based on data from the British Crime Survey 2006/07 and 2007/08, Sindall and Sturgis (2013) discussed workforce reductions and austerity policing in the UK and its impact on visibility, and by extension, on public confidence. Police visibility determines: (a) The frequency of patrolling, which has a significant effect on fear of crime; and (b) The ease with which the police can be contacted and the effectiveness of the investigation process, which are vital for the formation of opinions on police effectiveness. The researchers observed that increased visibility exerted a significant positive impact on public confidence. Moreover, although some police forces maintained the same level of visibility, reductions in total their workforce led to lower satisfaction of victims due to increased workload and reduced service quality. These findings are relevant to the austerity period when the absolute number of staff decreased despite efforts by most forces to maintain police visibility.

In addition, a Finnish study (Salmi et al., 2004) proposed a better way of patrolling by examining the differential impact of foot and motorised patrols. To do so, it investigated the relationships between fear of crime and police visibility by constructing a structural equation model with four factors: two visibility factors, including patrol-car-related activities and police-on-foot activities and two fear of crime factors, including crimes against property and crimes against persons. Using survey data drawn from over 400 respondents, the model concluded that residents who frequently saw police on foot patrol had less fear of crime, whilst residents who frequently saw on motor patrol were more fearful of crime. These findings are consistent with an earlier study (Salmi et al., 2000), which used survey data to examine the relationship between police image and visibility, concluding that motorised patrols had a negative effect on police image.

A review study (Hail et al., 2018) on visible policing and public confidence also found that both foot and bicycle patrols help to improve public confidence, though it stressed that patrol techniques also have an important effect on public perception. Wood et al. (2014) posited that patrols should be based on accruing neighbourhood knowledge to integrate into the community and that community engagement is important for building trust. Motor patrols do not allow officers to meet residents or connect with the community, and as such, they do not build public trust. Kochel and Weisburd (2017) found that in experiments, areas using standard police practice performed better in maintaining legitimacy than those using direct patrol and problem-solving techniques.

(2) Contact

Since the 1980s, academic research and policymakers have begun to pay attention to police-public contact. The 1982 British Crime Survey asked about respondents' experiences of personal contact with the police. Smith and Grey (1985) researched the frequency of contact with the police in London and assessed the impact of this contact on public confidence.

Confidence was found to be lower among those who had previously contact come into contact with the police. Skogan (1990) analysed data from the 1998 British Crime Survey and found that people's perceptions of performance were based on their own experience of contact with the police. However, a significant number of respondents were negative about their experiences interacting with the police. The top three sources of dissatisfaction were: concerns about police efforts, doubts about their ability to solve problems, and specific criminal incidents. Later, analysing data from the British Crime Survey 2004/05, Edmonds (2006) observed that those who had no recent contact with the police were more likely to agree that the local police were doing an excellent or good job than those who had recent contact. This phenomenon is contrary to the situation in other aspects of the public sector, where those who had a recent experience were more likely to give positive ratings (see the example of the NHS (MORI, 2017)).

Skogan (2006) outlined an "asymmetric" dilemma faced by police officers: It is harder for an officer to demonstrate their effectiveness through personal contact, they can readily show their personal shortcomings. A set of survey data from Chicago was employed to explore the impact of good and bad-quality contact. The results showed that bad contact had a statistically significant influence on public trust, whereas the impact of good encounters was not as apparent. The author also referenced several sets of survey data for international regions such as St Petersburg, the UK, and Indianapolis with consistent findings.

Bradford et al (2009a) tested Skogan's (2006) findings using data from the Metropolitan Police Public Attitudes Survey 2005/06. In contrast to the earlier research, they found more positive attitudes towards good quality encounters, saying that although it was hard for police officers to show police effectiveness through contact with the public, it was easier for them to demonstrate their fairness and engagement with the public. This led to a symmetric impact on public trust, in contrast to the asymmetric impact mentioned by Skogan (2006). Based on the MPS surveys, Bradford et al. (2009b) suggested that public trust could be increased by improving police-public communication channels. After analysing the British Crime Survey 2007/08, Myhill and Bradford (2012) agreed with asymmetric impacts though made further findings on other positive factors: although encounters were rated as unsatisfactory by participants, other positive aspects were not overlooked. In particular, for victims of crime, the way in which they were treated by the police had a greater impact on satisfaction than criminal justice outcomes. This finding suggests that public confidence could be enhanced by improving the quality of police-public contact.

The review by Hail et al. (2018) posited that policing styles (i.e. enforcement vs. engagement) also impact public perceptions in different ways, i.e., mistrust and barriers to engagement often stem from enforcement policing, whilst positive communication and experience of contact increase public trust. This review highlighted that public trust increase when the police demonstrate regular community engagement with ongoing communication to demonstrate that the police are helpful, familiar, accessible, and listen to and understand the needs of the communities they serve.

In addition to micro-level contact, Aston et al. (2021) studied meso-level police-public contact. Based on 161 interviews conducted with young minority groups in nine European countries, the researchers concluded that interactional justice, procedural justice, and distributive justice all contribute to building public trust and fostering information sharing, not only through face-to-face contact but also online. Hence, it can be seen that meso-level interactions such as community policing models, data protection, and security procedures are important in building public trust.

Sections 6.1 and 6.2 review existing surveys and the main literature investigating the relationship between public trust and policing. Section 6.3 will use the CSEW survey data to conduct specific variables to measure public trust in England and Wales and conduct further analysis incorporating the previous variables mentioned in chapters 4 and 5.

6.3. Public trust measurement with CSEW data

This section starts by measuring overall public confidence, after which it looks into how public trust has changed at the national level and how it differs at the police force level based on data from the Crime Survey in England and Wales from 2011/12 to 2017/18. It then examines the relationships between the sub-measures of public trust and considers any police efficiency implications.

The surveys asked all participants about the extent to which they were worried about crime and if they felt safe in their area (this part of the data was analysed as an effectiveness outcome indicator in chapters 4 and 5). The findings support the contention that fear of crime is associated with the effectiveness of policing (crime rates, in detail). All participants were then asked to rate the local police based on their work in general, followed by sub-questions on fairness, respect, and public engagement in policing whether or not the respondents had come into contact with the police. These were then followed by an overall confidence question.

For those whose incidents were known by the police (meaning that they had contact with the police), the victim form included corresponding questions about whether they felt they were treated fairly and respectfully in that instance and the extent to which they were satisfied with the police. This set of questions is also in accordance with the public trust framework employed by Tyler and Huo (2002) and Sunshine and Tyler (2003), in that the overall confidence in the police consists of three sub-concepts of trust: trust in police effectiveness (worried about crime), legitimacy (the police treat you fairly and respectfully) and public engagement (the police understand the matter in this community). Detailed questions for the latter two sub-concepts are listed in Table 6.3 in section 6.1. Differences in trust between victims and non-victims warrant separate analysis as the survey included both victim and non-victim forms. The CSEW also surveyed public opinion on the broader criminal justice system; however, this research ignores these questions and the relevant data because the criminal justice system is beyond the control of the police.

(1) Confidence scores and their reflection in police efficiency

It is unclear whether "taking everything into account, how good a job do you think the police in this area are doing" or "taking everything into account, I have confidence in the police in this area" is better for use as a measure to quantify overall confidence in this study. To test whether the choice of indicator has an impact on further analysis, this research first checks whether the values of one variable are related to another. The Pearson's correlation test results for the individual data[31] show that the answers to the "rating" question are significantly and strongly related to those of the "confidence" question (coefficients = 0.80, p-values < 0.001). Therefore, regardless of which question is selected, the results will not be too dissimilar from the other question.

The first question appears earlier in the questionnaire than the second. Before the first question, the participants have already answered a large number of questions about their perceptions of crime and fear of crime. Immediately before the second question, they were asked questions on legitimacy and public engagement. Therefore, when participants are answering the second question, they are more likely to take into account policing effectiveness, legitimacy and public engagement, as opposed to merely considering policing effectiveness in isolation as when facing the first question about "how good a job". Thus, in this research "taking everything into account, I have confidence in the police in this area" is selected as the measure of confidence. Accordingly, an average is calculated for each police force area in conjunction with the individual weighting factor provided by the CSEW. In addition, since 2015/16 the CSEW incorporated a question asking whether "the police can be trusted" in the part, though it is ignored in this research due to its inconsistency with previous surveys.

The available answers to this question are: 1=strongly agree, 2=tend to agree, 3=neither agree nor disagree, 4=tend to disagree, 5=strongly disagree. In the further analysis, it will be hard to remember and understand that a greater value represents lower confidence. Thus, it is necessary to reverse the scale here, such that 1 means "strongly disagree" and 5 means "strongly agree". Confidence (CON) is defined as the weighted average of confidence scores at the police force area level weighted by individual factors. In this measure, an overall confidence score greater than 3 indicates that residents in this area have confidence in the local police, whereas a score smaller than

[31] Individual data: these are the CSEW data at the level of individual instead of police force area.

3 reveals a lack of confidence. A higher confidence score means there is more public confidence in the police in the area.

Figure 5.1 illustrates how confidence at the national level has changed during the period from 2011/12 to 2017/18. Confidence fluctuated within a range of 3.5 to 4, which means that residents generally had confidence in the police. Other than the years 2011/12 and 2017/18, confidence in England and Wales increased. Notably, confidence in 2014/15 was higher than that in 2011/12 despite police budget cuts due to austerity.

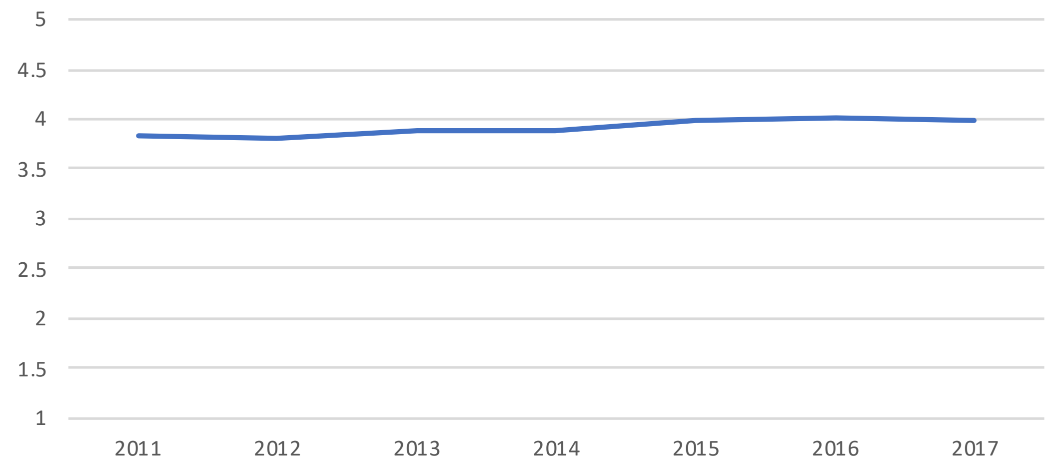

Figure 6.1. Confidence scores in England and Wales from 2011/12 to 2017/18.

In terms of the police force area level, the description and distribution of confidence in each year are summarised in Table 6.4 and Figure 6.2. Unlike the national average, the median for police forces did not change a lot during the austerity period, though it then increased significantly in the post-austerity period. The box plot of 2011 indicates a strong concentration among the police forces, although there was greater divergence in the later years.

Table 6.4. Description summary of confidence scores at the level of police force area from 2011/12 to 2017/18.

	2011	2012	2013	2014	2015	2016	2017
Min	3.72	3.56	3.67	3.67	3.73	3.65	3.69
Max	3.89	3.97	4.05	4.04	4.1	4.7	4.15
Median	3.81	3.8	3.83	3.83	3.95	3.95	3.92
Mean	3.81	3.79	3.83	3.84	3.95	3.95	3.93
St.Dev	0.04	0.10	0.09	0.09	0.08	0.15	0.11

The box plots clearly show the dispersion between police force areas in each year (see Figure 6.2). All values are larger than 3.0, which means that in general, residents living in all police force areas had confidence in policing. There is also an outlier observed in the 2016 box plot: Staffordshire (confidence score = 4.7). As this point is far from the others, it will be removed in the later regression analysis. To help determine which police forces performed better than the national average, the distances to the national level of each police force area in each year are listed below in Table 6.5. Positive values represent confidence in a given policing area is higher than the national level. Only Thames Valley had all positive values in each year, indicating that Thames Valley residents always had more confidence in the police than the average for England and Wales throughout the study period. Referring to the efficiency scores in the DEA models, Thames Valley was not relatively efficient in any year. There were six police forces in which the public had less confidence in the national average each year (followed by the number of years they were efficient or inefficient in brackets): Derbyshire (inefficient in all years), Kent (inefficient in all years), Merseyside (efficient in two years), North Wales (efficient in four years), South Wales(inefficient in all years), and West Midlands (inefficient in all years). It seems that the confidence scores are not reflected in pure efficiency. Regression models will be conducted to verify the extent to which confidence is reflected in efficiency.

Regarding those police forces that saw the greatest improvement in public trust, improvements during the austerity period, post-austerity period, and the study period as a whole are listed in Table 6.6. Here, a positive value represents an improvement in confidence. Most police forces improved public confidence during the austerity period, except for Greater Manchester, Nottinghamshire, and Sussex. Nottinghamshire deteriorated the most (-0.11), whilst Suffolk improved the most, with a 0.32 increase in its confidence score, though this decreased in the post-austerity period. During the post-austerity period, in 2017/18, 21 police forces failed to continue improving their confidence scores. One possible interpretation of this is that the delayed effects of austerity only manifested in the post-austerity period for some police forces. During the whole period from 2011/12 to 2017/18, seven forces saw their public overall confidence decrease to a level lower than in 2011/12: Bedfordshire, Cleveland, Essex, Gwent, Humberside, Nottinghamshire, and South Yorkshire.

Based on the above, this research will investigate whether there is any association between a police force's efficiency score and its public trust score. Pearson’s correlation testing indicates a negative relationship between pure efficiency scores and confidence scores (p-value=0.045, coefficient -0.12), though no significant relationship was found between scale efficiency and confidence (p-value=0.49) or between workforce (scale) and confidence (p-value=0.79).

A scatterplot for confidence on pure efficiency is presented in Figure 6.3, which shows a general negative association. Next, four fixed-effect panel linear regression models are conducted with "pooling", "within", "between" and "twoway" methods, respectively. The results are presented in Table 6.6. In the pooling context, overall public confidence is cross-sectionally positively associated with the pure efficiency of a police force. However, when individual effects and time effects are taken into account, the regressions do not return any significant coefficient for Pure Efficiency; therefore, the differences in the unobserved variables of the areas and time points are potentially related to the variations. This finding suggests that for residents in an area, their overall confidence in the police and their perceptions of police efficiency are not significantly related. It may be that residents in an area may have perceptions of how the police are performing, though it is hard to verify how the local police are utilising their resources to deliver services.

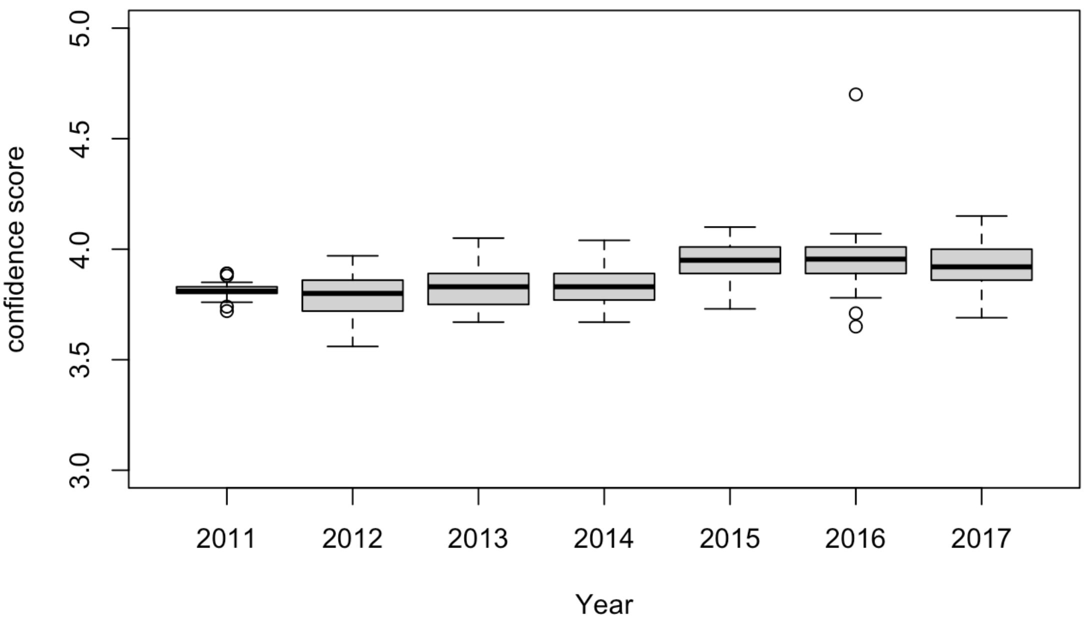

Figure 6.2 Boxplots for confidence scores at the level of police force area from 2011/12 to 2017/18.

Table 6.5. Distance to the average confidence in England and Wales, 2011/12 to 2017/18.

Police force area	2011	2012	2013	2014	2015	2016	2017
Avon and Somerset	-0.03	0.00	0.01	-0.03	-0.07	-0.06	-0.05
Bedfordshire	0.02	-0.02	-0.18	-0.15	0.04	-0.14	-0.17
Cambridgeshire	0.00	0.06	-0.04	-0.13	0.05	0.01	-0.03
Cheshire	-0.03	-0.01	-0.13	0.03	-0.11	0.05	0.07
Cleveland	-0.01	-0.15	-0.19	-0.17	0.06	-0.18	-0.20
Cumbria	-0.02	0.14	-0.04	-0.10	-0.03	-0.04	0.01
Derbyshire	-0.03	-0.04	-0.05	-0.09	0.00	-0.17	-0.13
Devon and Cornwall	-0.02	0.05	0.06	0.05	0.12	0.04	-0.03
Dorset	-0.02	0.10	-0.02	0.07	-0.06	0.07	0.11
Durham	-0.02	-0.08	-0.09	-0.11	-0.08	0.04	0.02
Dyfed-Powys	-0.05	0.12	0.06	-0.06	-0.09	-0.05	-0.09
Essex	0.00	-0.03	-0.19	-0.07	0.02	-0.19	-0.21
Gloucestershire	-0.02	0.00	-0.04	-0.04	-0.04	0.05	-0.02
Greater Manchester	0.00	-0.01	-0.06	-0.14	-0.16	-0.15	-0.14
Gwent	0.02	-0.14	-0.22	-0.21	-0.13	-0.35	-0.27
Hampshire	-0.03	0.11	0.02	0.06	-0.02	0.00	0.04
Hertfordshire	-0.03	0.17	0.11	0.09	-0.10	0.00	0.04
Humberside	0.01	-0.24	-0.17	-0.22	-0.14	-0.29	-0.30
Kent	-0.02	-0.03	-0.14	-0.09	-0.02	-0.09	-0.09
Lancashire	0.06	0.02	0.11	-0.01	0.10	-0.05	-0.09
Leicestershire	-0.11	0.07	0.00	0.06	0.03	-0.03	-0.08
Lincolnshire	-0.06	-0.09	-0.12	-0.06	0.05	-0.02	-0.07
Merseyside	-0.03	-0.10	-0.13	-0.19	-0.07	-0.09	-0.15
Metropolitan Police	0.01	0.03	-0.05	-0.02	-0.03	-0.02	0.01
Norfolk	-0.05	0.08	-0.03	0.15	0.04	0.03	0.06
North Wales	-0.03	-0.18	-0.14	-0.13	-0.03	-0.08	-0.09
North Yorkshire	-0.04	0.05	0.10	0.08	-0.17	0.01	0.00
Northamptonshire	-0.06	0.00	-0.09	-0.04	0.03	-0.09	-0.11
Northumbria	0.06	0.04	0.01	-0.01	-0.08	-0.04	0.05
Nottinghamshire	0.01	-0.15	-0.21	-0.11	-0.25	-0.21	-0.17
South Wales	-0.03	-0.12	-0.14	-0.12	-0.02	-0.04	-0.08
South Yorkshire	0.00	-0.09	-0.15	-0.09	-0.09	-0.22	-0.25
Staffordshire	-0.06	-0.05	-0.06	-0.16	-0.07	0.70	-0.11
Suffolk	-0.09	0.06	-0.04	-0.01	0.08	-0.06	-0.15
Surrey	-0.07	0.16	0.16	0.09	0.03	0.05	0.16
Sussex	0.05	0.05	-0.01	0.00	-0.13	-0.14	0.00
Thames Valley	0.02	0.08	0.06	0.08	0.08	0.04	0.08
Warwickshire	0.00	-0.12	-0.09	-0.04	0.03	-0.05	-0.07
West Mercia	-0.03	-0.05	-0.18	-0.10	0.01	-0.03	-0.09
West Midlands	-0.01	-0.07	-0.09	-0.09	-0.07	-0.09	-0.06
West Yorkshire	-0.07	0.02	-0.08	-0.16	-0.11	-0.11	-0.05
Wiltshire	0.01	0.12	-0.07	-0.04	-0.03	-0.01	0.12

Table 6.6. Changes in confidence scores in police force area during the period of austerity, post-austerity and the whole period. (The forces that did not improved their confidence in the period of austerity and in the whole period are highlighted in red.)

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	0.11	0.03	0.14
Bedfordshire	0.17	-0.20	-0.03
Cambridgeshire	0.20	-0.07	0.13
Cheshire	0.07	0.19	0.26
Cleveland	0.22	-0.25	-0.03
Cumbria	0.14	0.05	0.19
Derbyshire	0.18	-0.12	0.06
Devon and Cornwall	0.29	-0.14	0.15
Dorset	0.11	0.18	0.29
Durham	0.09	0.11	0.20
Dyfed-Powys	0.11	0.01	0.12
Essex	0.17	-0.22	-0.05
Gloucestershire	0.13	0.03	0.16
Greater Manchester	-0.01	0.03	0.02
Gwent	0.00	-0.13	-0.13
Hampshire	0.16	0.07	0.23
Hertfordshire	0.08	0.15	0.23
Humberside	0.00	-0.15	-0.15
Kent	0.15	-0.06	0.09
Lancashire	0.19	-0.18	0.01
Leicestershire	0.29	-0.10	0.19
Lincolnshire	0.26	-0.11	0.15
Merseyside	0.11	-0.07	0.04
Metropolitan Police	0.11	0.05	0.16
Norfolk	0.24	0.03	0.27
North Wales	0.15	-0.05	0.10
North Yorkshire	0.02	0.18	0.20
Northamptonshire	0.24	-0.13	0.11
Northumbria	0.01	0.14	0.15
Nottinghamshire	-0.11	0.09	-0.02
South Wales	0.16	-0.05	0.11
South Yorkshire	0.06	-0.15	-0.09
Staffordshire	0.14	-0.03	0.11
Suffolk	0.32	-0.22	0.10
Surrey	0.25	0.14	0.39
Sussex	-0.03	0.14	0.11
Thames Valley	0.21	0.01	0.22
Warwickshire	0.18	-0.09	0.09
West Mercia	0.19	-0.09	0.10
West Midlands	0.09	0.02	0.11
West Yorkshire	0.11	0.07	0.18
Wiltshire	0.11	0.16	0.27

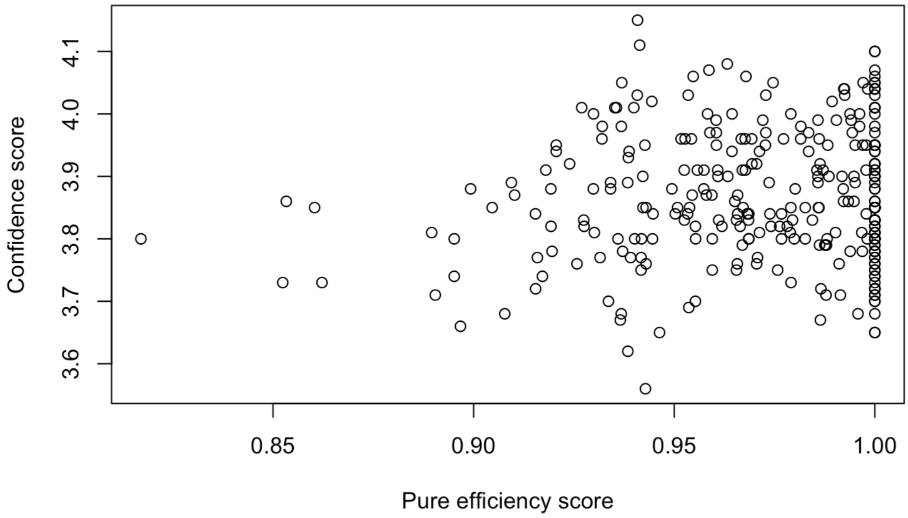

Figure 6.3. Scatterplot for confidence scores on pure efficiency score at the police force area in all years.

Table 6.6. Results of panel regression models of Confidence on Pure Efficiency.						
	Intercept		Pure efficiency			
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	RSq	Adj. Rsq
Pooling	3.49532 (0.18543)	2.2e-16	0.38478 (0.19115)	0.04503	0.013734	0.010345
Individual			0.39263 (0.20049)	0.0513	0.015108	-0.15035
Between	3.51616 (0.52909)	5.858e-08	0.36309 (0.54558)	0.5095	0.010951	-0.013775
Two-way			0.092809 (0.151447)	0.5406	0.0015367	-0.19488

(2) Contact: satisfaction scores and legitimacy scores

In the victim forms, those who reported incidents to the police were asked three questions: “do you think the police treated you fairly”, “did the police treat you with respect” and “overall were you satisfied or dissatisfied with the way the police handled this matter”. The first two questions get to the issue of legitimacy that runs through policing, whilst the last question actually includes other aspects, such as how the police officers communicated with the respondent. Therefore, the contact satisfaction scores and legitimacy scores can be calculated from the responses to the last question and the first two questions, respectively.

This research defines the Satisfaction (SAT) variable as the weighted average of the contact satisfaction scores, where the individual factors (provided by the CSEW) in a police force area are weighted and the variable Legitimacy (LEG) is the average of the fairly-treated scores and respect scores. Similar to how the scale was reversed in the Confidence, the scales of Legitimacy and Satisfaction are also reversed so they can easily be compared. In *SAT*, a higher score means more satisfaction, with a value greater than 2.5 indicating that residents feel that the public-police contact in this area is generally satisfactory. In LEG, a greater value indicates that the public in this area perceives more fairness and respect in the contact. If the value is greater than 2, the police are seen as having treated their residents fairly and respectfully.

Figure 6.4 indicates that in general, the police treated residents fairly and respectfully in their contact with them, as the value in each year was far larger than 2. There has been an improvement since 2012/13, and during the austerity period, the police significantly improved their legitimacy. The level of average legitimacy remained stable in the post-austerity period.

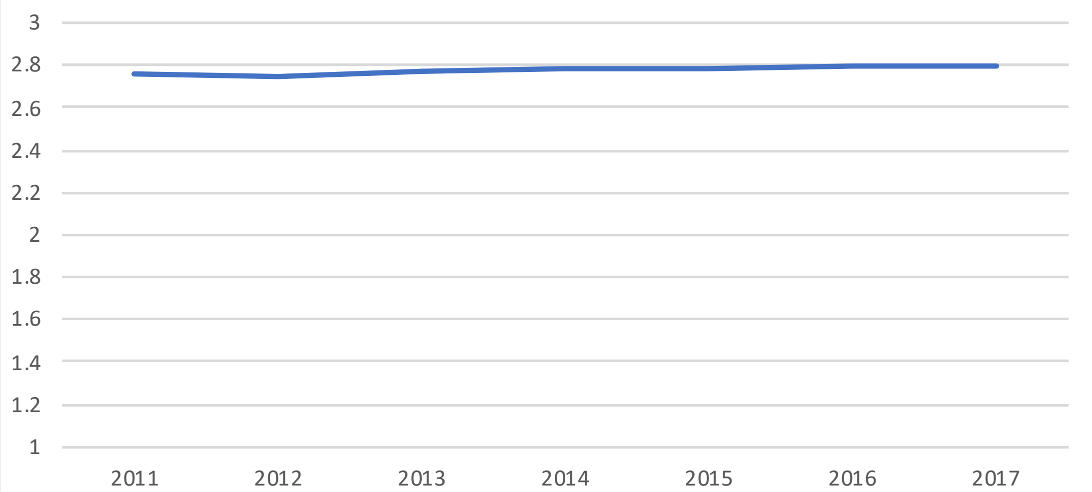

Figure 6.4. Legitimacy scores in England and Wales from 2011/12 to 2017/18.

Figure 6.5 shows that at the police force area level, the median of legitimacy each year fluctuated around 2.8 and that did not perform consistently to the trend of national average. Police force performance in this regard diverged in 2014/15 compared to 2011/12. To determine which police forces performed better in contact than the national average, Table 6.7 lists distance to the national level in each year. The only force that performed better than the national level across all the study years was the Metropolitan

Police. That is to say, during the sampled years, residents in the Metropolitan Police policing area were treated more fairly and respectfully than the national average. However, referring to the pure efficiency scores, it was not an efficient police force in the DEA assessment. There are three police forces whose legitimacy scores were worse than the national level across the six years (the number of years the police force was estimated to be fully efficient is shown in the brackets): Gwent (efficient in three years), Humberside (efficient in one year), and West Mercia (efficient in two years).

It appears that legitimacy in contact is not reflected in pure efficiency, as police forces that perform well in the efficiency measure do not always perform well in the legitimacy measure. To address which police forces improved legitimacy in contact during the austerity period, the changes in legitimacy scores at the police force area level can be found in Table 6.8. 20 police forces improved their legitimacy during the austerity period: Surrey made the greatest improvement (+0.44), whilst Northamptonshire's score decreased the most (-0.34). 20 police forces had improved their legitimacy scores by 2014/15, though only nine of them continued to improve their legitimacy in the post-austerity period. This could be due to a delayed effect from the austerity that only manifested in the post-austerity period. Although most police forces endeavour to optimise their frontline workforce allocation and maintain visibility, legitimacy still decreased, most likely due to budget constraints. A delayed effect may occur if the workforce felt overwhelmed after four years of an increasing workload and decreasing budget support. Throughout the whole period from 2011/12 to 2017/18, residents in 15 police force areas viewed the police as having less legitimacy than they did at the beginning of the study period.

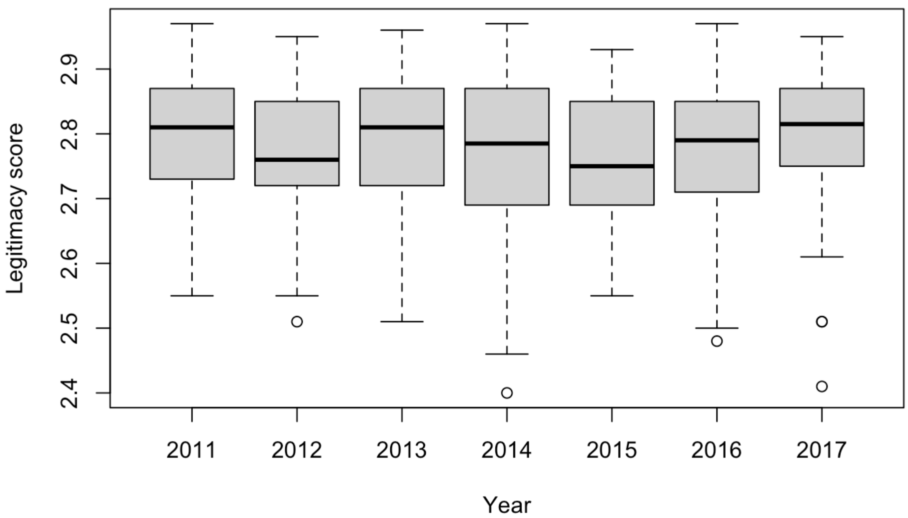

Figure 6.5. Legitimacy scores at the police force level from 2011/12 to 2017/18.

Table 6.7. Distance to the average legitimacy scores in England and Wales, 2011/12 to 2017/18. (The forces that are consistently above the national average in all years and lower in most years are highlighted in red.)

Police force area	2011	2012	2013	2014	2015	2016	2017
Avon and Somerset	-0.07	-0.12	-0.19	0.09	0.03	-0.17	0.12
Bedfordshire	-0.02	-0.04	-0.27	0.03	-0.24	0.04	-0.03
Cambridgeshire	0.17	0.12	0.05	0.06	-0.12	-0.10	-0.15
Cheshire	-0.01	-0.02	-0.25	-0.05	0.15	0.10	0.12
Cleveland	0.06	0.11	0.06	-0.07	-0.11	-0.04	-0.28
Cumbria	-0.07	0.19	-0.01	-0.04	0.01	0.13	0.01
Derbyshire	-0.01	-0.06	-0.03	0.07	0.06	0.07	0.18
Devon and Cornwall	0.01	-0.29	0.19	0.06	0.02	0.10	0.05
Dorset	-0.05	-0.09	0.03	0.06	0.08	-0.05	0.12
Durham	-0.08	0.14	0.12	-0.17	0.17	0.13	-0.03
Dyfed-Powys	0.04	-0.18	0.05	-0.08	-0.10	-0.14	-0.18
Essex	-0.07	0.00	0.13	0.01	-0.23	-0.02	0.07
Gloucestershire	0.04	0.16	0.06	0.10	0.17	0.08	-0.39
Greater Manchester	0.12	0.04	0.08	0.04	0.04	-0.13	-0.20
Gwent	-0.25	-0.04	-0.04	-0.03	0.06	-0.01	-0.11
Hampshire	-0.25	0.01	-0.03	-0.01	0.06	0.18	0.12
Hertfordshire	0.07	0.00	0.15	-0.06	-0.03	0.08	0.06
Humberside	-0.12	0.08	-0.22	-0.05	-0.01	-0.28	-0.01
Kent	0.05	0.14	0.07	0.04	0.09	-0.07	0.09
Lancashire	0.10	-0.05	0.07	0.08	-0.04	-0.10	0.09
Leicestershire	0.11	0.19	0.03	0.15	-0.06	0.06	-0.07
Lincolnshire	0.17	-0.07	-0.22	0.06	0.10	0.10	-0.01
Merseyside	0.00	-0.15	0.10	0.11	-0.07	-0.06	-0.14
Metropolitan Police	0.01	0.02	0.02	0.06	0.06	0.07	0.04
Norfolk	0.06	0.20	-0.07	-0.10	-0.04	0.13	0.18
North Wales	0.06	-0.05	-0.01	-0.05	-0.05	0.10	0.06
North Yorkshire	0.08	0.20	0.17	-0.07	0.04	0.14	0.10
Northamptonshire	-0.01	-0.02	0.08	0.10	-0.37	-0.13	-0.04
Northumbria	-0.19	-0.12	0.10	0.09	0.06	0.06	0.07
Nottinghamshire	-0.02	0.02	0.05	0.03	0.17	-0.12	0.07
South Wales	-0.02	-0.07	0.10	0.00	-0.06	0.11	-0.07
South Yorkshire	0.11	0.12	-0.15	-0.07	-0.03	0.00	-0.05
Staffordshire	0.04	-0.04	0.18	-0.21	-0.02	-0.17	-0.16
Suffolk	0.03	0.11	0.03	-0.21	0.04	0.04	-0.11
Surrey	-0.24	0.17	0.09	0.10	0.17	-0.01	0.06
Sussex	0.05	-0.09	0.14	0.03	0.05	0.03	-0.10
Thames Valley	0.08	-0.03	0.14	-0.02	0.03	-0.07	0.09
Warwickshire	0.09	0.01	0.11	0.08	-0.01	-0.01	0.11
West Mercia	-0.03	0.15	-0.01	-0.14	-0.09	-0.22	-0.01
West Midlands	0.04	-0.16	-0.09	-0.17	-0.13	-0.02	0.02
West Yorkshire	0.03	0.05	-0.29	-0.10	-0.06	0.03	-0.04
Wiltshire	-0.01	0.14	0.13	0.02	0.03	0.18	-0.13

Table 6.6. Changes in legitimacy scores in police force area during the period of austerity, post-austerity and the whole period. (The forces that improved and deteriorated the most in the austerity period, and the forces that lost legitimacy in the whole period are highlighted in red.)

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	0.13	0.09	0.22
Bedfordshire	-0.19	0.22	0.02
Cambridgeshire	-0.26	-0.03	-0.29
Cheshire	0.19	-0.02	0.17
Cleveland	-0.14	-0.17	-0.31
Cumbria	0.11	0.01	0.12
Derbyshire	0.10	0.13	0.23
Devon and Cornwall	0.04	0.04	0.08
Dorset	0.17	0.04	0.21
Durham	0.29	-0.20	0.09
Dyfed-Powys	-0.11	-0.08	-0.19
Essex	-0.13	0.31	0.18
Gloucestershire	0.16	-0.55	-0.40
Greater Manchester	-0.05	-0.24	-0.29
Gwent	0.34	-0.17	0.18
Hampshire	0.34	0.06	0.40
Hertfordshire	-0.07	0.10	0.03
Humberside	0.15	0.01	0.15
Kent	0.06	0.01	0.08
Lancashire	-0.11	0.14	0.03
Leicestershire	-0.14	-0.01	-0.15
Lincolnshire	-0.03	-0.11	-0.14
Merseyside	-0.03	-0.07	-0.10
Metropolitan Police	0.08	-0.01	0.07
Norfolk	-0.08	0.23	0.16
North Wales	-0.08	0.12	0.04
North Yorkshire	-0.01	0.06	0.06
Northamptonshire	-0.34	0.34	0.00
Northumbria	0.28	0.01	0.30
Nottinghamshire	0.22	-0.09	0.13
South Wales	0.00	-0.01	-0.01
South Yorkshire	-0.11	-0.01	-0.12
Staffordshire	-0.03	-0.14	-0.17
Suffolk	0.03	-0.15	-0.11
Surrey	0.44	-0.11	0.34
Sussex	0.03	-0.15	-0.11
Thames Valley	-0.02	0.06	0.05
Warwickshire	-0.07	0.13	0.05
West Mercia	-0.03	0.09	0.06
West Midlands	-0.14	0.16	0.02
West Yorkshire	-0.06	0.02	-0.04
Wiltshire	0.07	-0.16	-0.09

Turning to the influence of satisfaction scores and the contact between the public and police, values greater than 2.5 generally indicate that the public viewed police-public contact in England and Wales between 2011/12 and 2017/18 as satisfactory. In 2013/14, satisfaction improved compared to 2011/12, though it then decreased in most years after 2013. Although contact with the police was viewed as more satisfactory in 2014/15 compared to the beginning of the study period, it became less satisfactory in 2017/18. The police made no progress in contact satisfaction by 2017/18, probably due to a delayed effect of austerity budget cuts.

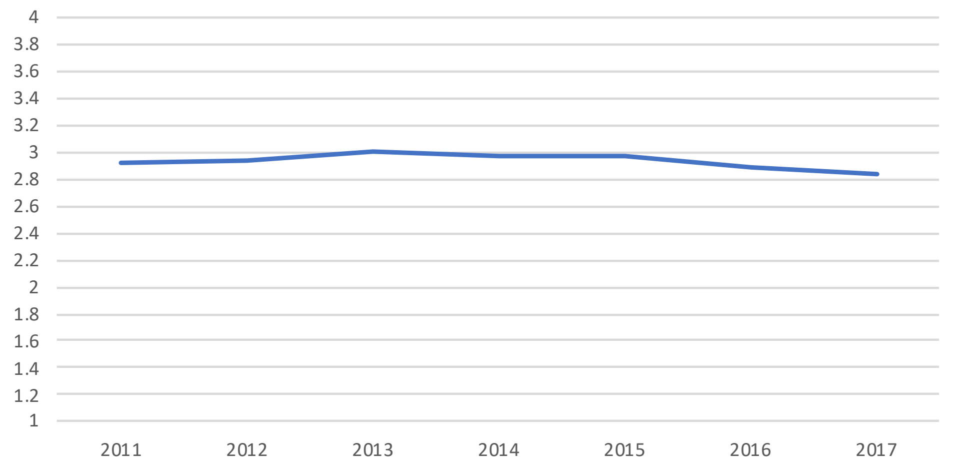

Figure 6.6. Satisfaction scores in England and Wales from 2011/12 to 2017/18.

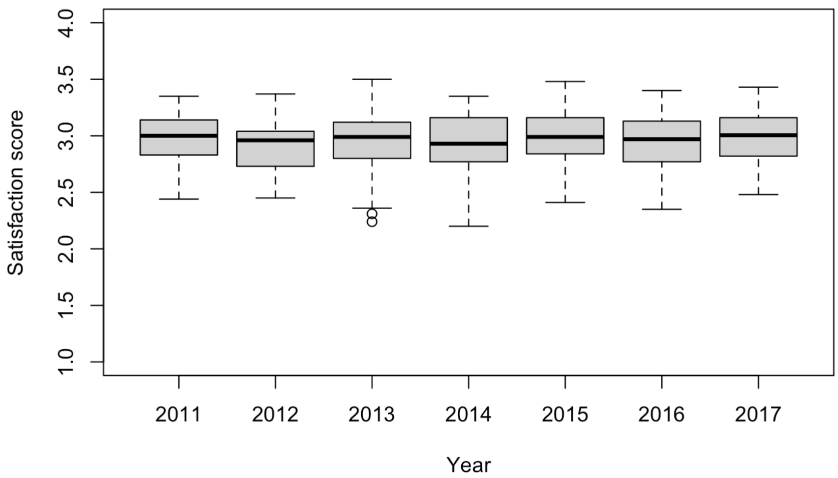

Figure 6.7. Boxplots for satisfaction scores at the level of police force area from 2011/12 to 2017/18.

As shown in Figure 6.7, some values are lower than 2.5, indicating that residents were dissatisfied on average with their contact with the police. These police forces are listed here, followed by the pure efficiency scores for that year in brackets: Bedfordshire-2013 (1); Cheshire-2017 (1); Cleveland-2017 (1); Gloucestershire 2017 (0.959); Humberside-2012 (0.953), 2017 (0.954), Merseyside-2016 (0.961); North Wales 2012 (1); Staffordshire-2017 (1); and Warwickshire-2017 (1). It can be seen that some areas with poor contact scores were recognised as full efficiency at that time. An outlier, Nottinghamshire-2013 (lower than 2.0), will be removed in the further regression analysis.

To determine which police forces improved their contact with the public, Table 6.7 lists changes in satisfaction scores. Surrey improved the most (+0.74) from 2011/12 to 2014/15, though its score later fell by 0.45 during the post-austerity period. Norfolk's contact satisfaction decreased the most when the budget was cut. Half of the police forces improved their contact scores during the austerity period, whilst the other half did not. Among those that improved, only three succeeded in continuing to make progress: Avon and Somerset, Derbyshire, and Thames Valley. Thus, although the overall confidence increased in most police forces, legitimacy and satisfaction with the contact between the public and police were more affected by austerity, not only in the years from 2011/12 to 2014/15, but also throughout the post-austerity period.

Table 6.7. Changes in satisfaction scores in police force area during the period of austerity, post-austerity and the whole period. (The forces that improved and deteriorated the most in the austerity period and the forces that continued to improve satisfaction in the post-austerity period are highlighted in red.)

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	0.27	0.17	0.44
Bedfordshire	-0.16	0.08	-0.08
Cambridgeshire	-0.17	-0.25	-0.42
Cheshire	0.53	-1.14	-0.61
Cleveland	-0.09	-0.60	-0.69
Cumbria	0.51	-0.55	-0.04
Derbyshire	0.20	0.23	0.43
Devon and Cornwall	0.35	-0.05	0.30
Dorset	0.35	0.34	0.69
Durham	0.32	-0.40	-0.08
Dyfed-Powys	-0.08	-0.29	-0.37
Essex	-0.33	0.44	0.11
Gloucestershire	0.23	-1.06	-0.83
Greater Manchester	-0.20	-0.46	-0.66
Gwent	0.61	-0.31	0.30
Hampshire	0.41	-0.39	0.02
Hertfordshire	-0.05	0.09	0.04
Humberside	0.17	-0.52	-0.35
Kent	-0.18	0.34	0.16
Lancashire	-0.14	0.01	-0.13
Leicestershire	-0.24	-0.35	-0.59
Lincolnshire	-0.12	-0.28	-0.40
Merseyside	-0.19	-0.20	-0.39
Metropolitan Police	0.08	-0.03	0.05
Norfolk	-0.73	0.82	0.09
North Wales	-0.22	0.12	-0.10
North Yorkshire	-0.12	0.10	-0.02

Northamptonshire	-0.25	0.04	-0.21
Northumbria	0.63	-0.32	0.31
Nottinghamshire	0.13	-0.69	-0.56
South Wales	0.07	-0.03	0.04
South Yorkshire	-0.25	-0.04	-0.29
Staffordshire	-0.09	-1.37	-1.46
Suffolk	-0.18	-0.02	-0.20
Surrey	0.74	-0.45	0.29
Sussex	0.27	-0.38	-0.11
Thames Valley	0.23	0.06	0.29
Warwickshire	0.33	-0.68	-0.35
West Mercia	-0.09	0.31	0.22
West Midlands	-0.12	0.32	0.20
West Yorkshire	0.21	-0.40	-0.19
Wiltshire	0.32	-0.26	0.06

(3) Public engagement

Turning back to the non-victim forms, two questions cover the concept of public engagement: “the police in this area understand the issues that affect this community”, and “the police in this area are dealing with the things that matter to people in this community.” This research calculated the Engagement (ENG) variable as the average of these two scores within an are weighted by the individual factor. A larger *ENG* value represents that the police force carried out better community engagement in this area, whilst an engagement score greater than 3 means that the residents think the police understand the needs of local residents.

In general, residents in England and Wales agreed that their local police understood their concerns and engaged in the activities that mattered to their communities. Figure 6.8 shows that public engagement fell from 2011/12 to 2012/13, before increasing from 2012/13 to 2015/16 and then falling again in 2017/18. The distributions of public engagement at the police force area level are shown in box plots in Figure 6.9. Looking at the second box plot, there is one outlier that has a significantly higher public engagement than the others, Essex-2012, whose pure efficiency score is 0.984 (inefficient) for that year. In contrast to the average trend, the median trend shows a decrease in public engagement from 2011/12 to 2014/15 followed by stabilisation in the post-austerity period. Additionally, the forces are more convergent in 2014/15 than in 2011/12. In general, police’s public engagement declined during the study period.

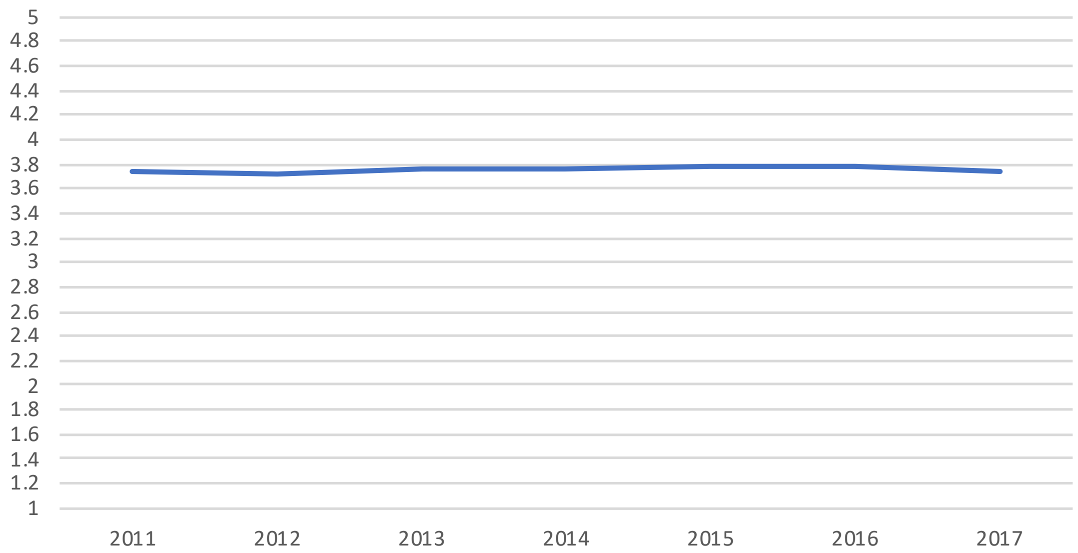

Figure 6.8. Engagement scores in England and Wales from 2011/12 to 2017/18.

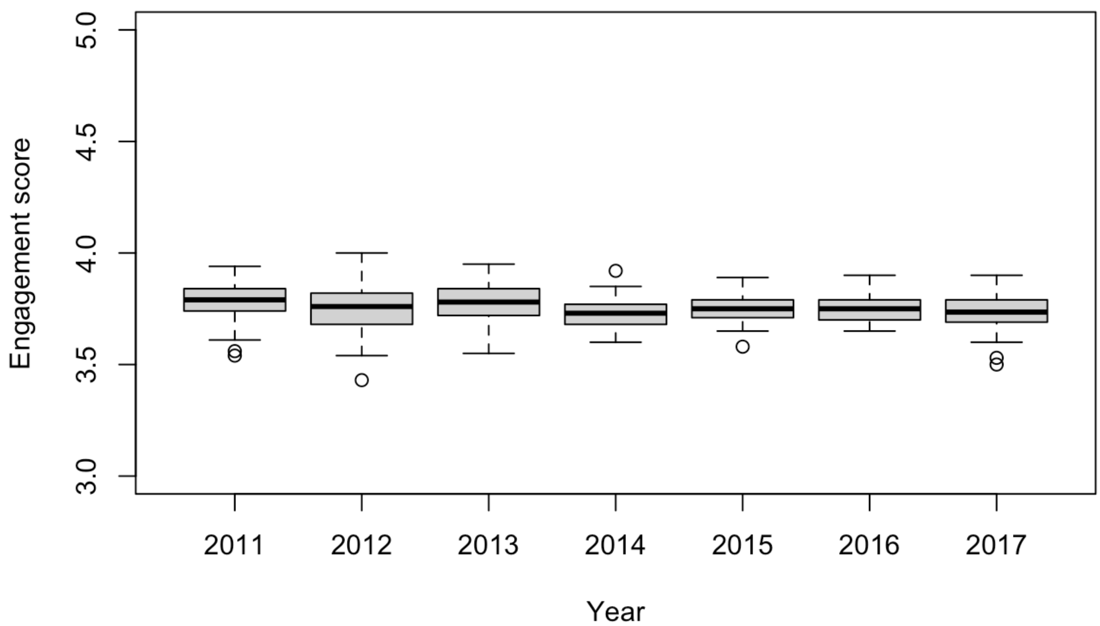

Figure 6.9. Boxplots for engagement scores at the level of police force area from 2011/12 to 2017/18.

Six police forces that performed better than the national average in terms of public engagement in 6 of the 7 years included in the sample (the number of the years they performed efficiently in DEA models in brackets): Cumbria (6); Devon and Cornwall (2); Dorset (3); Dyfed-Powys (7); Hampshire (0); Lancashire (0); and Lincolnshire (6). Meanwhile, two forces consistently performed worse than the national average (the number of years they performed efficiently is in brackets): Merseyside (2) and South Yorkshire (1).

Overall, residents in most police force areas (29 areas) thought that their local police improved their understanding of issues in communities and dealt with more matters in their community. Suffolk was the most improved in this regard (+0.25), whilst Greater Manchester saw the largest decrease (-0.13). Among those who only performed better in public engagement during the austerity period, nine continued to improve public engagement in the post-austerity period. Again, this may be attributable to the delayed effect of austerity. Overall, for 19 police forces, their 2017/2018 engagement scores were lower than their 2011/12 scores.

Table 6.8. Changes in engagement scores in police force area during the period of austerity, post-austerity and the whole period. (the forces that improved and deteriorated the most during the period of austerity, and the forces that continued to make progress in the post period are highlighted in red.

Police force area	2011/12-2014/15	2014/15-2017/18	2011/12-2017/18
Avon and Somerset	-0.08	0.08	0.00
Bedfordshire	0.10	-0.23	-0.13
Cambridgeshire	0.06	-0.15	-0.09
Cheshire	0.03	0.02	0.05
Cleveland	0.12	-0.24	-0.12
Cumbria	0.09	0.02	0.11
Derbyshire	0.05	-0.13	-0.07
Devon and Cornwall	0.16	-0.07	0.08
Dorset	0.01	0.09	0.10
Durham	0.01	0.00	0.02
Dyfed-Powys	0.13	0.00	0.13
Essex	0.06	-0.27	-0.21
Gloucestershire	-0.02	-0.04	-0.06
Greater Manchester	-0.13	0.05	-0.08
Gwent	0.09	-0.29	-0.19
Hampshire	0.10	0.00	0.11
Hertfordshire	-0.03	0.09	0.06
Humberside	-0.06	-0.14	-0.20
Kent	0.11	-0.11	0.00
Lancashire	0.09	-0.20	-0.11
Leicestershire	0.15	-0.20	-0.04
Lincolnshire	0.11	-0.09	0.02
Merseyside	-0.08	-0.04	-0.12
Metropolitan Police	0.04	0.02	0.05
Norfolk	0.09	0.01	0.10
North Wales	0.10	-0.04	0.05
North Yorkshire	-0.02	0.14	0.12
Northamptonshire	0.09	-0.15	-0.07
Northumbria	-0.02	0.00	-0.02
Nottinghamshire	-0.18	-0.06	-0.24
South Wales	0.06	0.01	0.08
South Yorkshire	0.02	-0.33	-0.31
Staffordshire	-0.02	0.03	0.02
Suffolk	0.25	-0.30	-0.05
Surrey	0.13	0.09	0.22
Sussex	-0.15	0.05	-0.09

Thames Valley	-0.01	0.09	0.07
Warwickshire	0.00	-0.08	-0.08
West Mercia	0.09	0.09	0.19
West Midlands	0.03	0.00	0.03
West Yorkshire	-0.02	0.10	0.08
Wiltshire	0.15	0.16	0.30

To investigate how overall Confidence (CON), Legitimacy (LEG) in contact, Satisfaction (SAT) with contact, and Engagement (ENG) in communities are correlated, it is first necessary to verify if there are correlations between victims' perceptions of legitimacy in contact, their satisfaction with the contacts, and the police's community engagement. Panel regression models with fixed effects (i = 42, t = 7) are conducted for $SAT \sim LEG + ENG$. It should be noted that *LEG* and *SAT* are both variables derived from questions in victim forms, whereas *ENG* corresponds to the questions asked to all participants, not just victims. *ENG* should also be included in this relationship as it represents a policing style wherein the local police force focuses on the demands and issues that really matter to the community. This model probes whether community engagement style also impacts victims' satisfaction with police contact. The results are presented in Table 6.9.

Table 6.9. Results of panel regression models of Satisfaction on Legitimacy and Engagement.

	Intercept		LEG		ENG		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	-2.231672 (0.500494)	1.18e-05	1.430241 (0.094281)	2.2e-16	0.326429 (0.124799)	0.009374	0.46512	2.22e-16
Individual			1.44930 (0.10020)	2.2e-16	0.42354 (0.13067)	0.001353	0.40059	2.22e-16
Between	1.03495 (1.48000)	0.4885	1.36569 (0.26569)	8.042e-06	-0.49633 (0.39380)	0.2150	0.37329	4.1623e-05
Two-way			1.474534 (0.099953)	2.2e-16	0.456722 (0.131409)	0.000604	0.40587	2.22e-16

It is unsurprising that in Table 6.9 all the coefficient estimates for Legitimacy in the four models are significant, as the Legitimacy and Satisfaction questions are all in the same block, which asks about perceptions of how the police handled the incidents. Satisfaction measures overall perceptions of police-public contact. These are broader than Legitimacy because they include not only being treated respectfully and fairly, but also satisfaction with other elements of the experience, such as communication with and the professionalism of the police. In the pooling context model, Legitimacy is cross-sectionally positively associated with Satisfaction: if residents in an area perceive more fairness and respectfulness in the contact then they tend to be more satisfied with the contact. Considering the fixed effects from individual forces, the relationship becomes stronger (the coefficient rises from 1.430 to 1.449); contrastingly, when unobserved time-varying variables are also taken into account, the positive relationship becomes even stronger (the coefficient rises to 1.475). On this basis, for a given force area, increasing the legitimacy at contact helped to improve victims' satisfaction with the police during the study period. If legitimacy increases by one unit, then satisfaction is expected to rise by 1.475, which is a large magnitude of effect, given that the scale is between 1 and 3.

The significant coefficient estimates in the between model indicate that on average over the years, a police force which delivers more fairness and respectfulness when it is in contact with the public is also expected to attain more average satisfaction from victims (though it should be noted that this relationship does not consider unobserved differences in force areas).

In terms of community engagement, significant coefficient estimates in the pooling, individual and two-way models indicate that Engagement also contributes to victims' satisfaction. When unobserved dummy variables for police areas and time points are taken into account, the positive coefficient for Engagement (coeff = 0.457, p-value < 0.001) is even greater than those in the pooling and within-individual models. The coefficient estimate in the two-way model indicates that for a given police force area, if residents feel that the police are dealing with more issues and demands that matter in the community, then the police were more likely to satisfy victims in terms of police-public contact across the study period. This implication highlights the importance of policing style, in that the police should pay attention to communities' demands and the issues that really matter in local areas. A coefficient of 0.457 means that when Engagement rises by one unit (scale from 1 to 5), satisfaction is expected to increase by 0.457 (scale from 1 to 3). The magnitude of the effect of Engagement is only one-third of that of Legitimacy. Referring to the adjusted R-squared, the two-way model accounts for 40.6% of the variance in victims' satisfaction.

Therefore, for a given police force, increasing community engagement in policing and being more fair and respectful when coming into contact with the public help satisfy victims. This implication provides evidence at the police force area level to support the importance of public engagement in policing.

Secondly, the way in which legitimacy in contact (LEG), victim's satisfaction (SAT) and engagement community (ENG) relate to the overall confidence scores (CON) warrants further consideration. The present research verifies the relationship $CON \sim LEG + SAT + ENG$ with fixed effect regression models, the results of which can be checked in Table A.3.9 in Appendix III. In the two-way model, when fixed effects from individual areas and time points are both considered, none of the coefficients are significant. Thus, there is no evidence to suggest that for a given area, the overall confidence scores form a linear relationship with community engagement in policing, victims' perceptions of legitimacy, or satisfaction. Accordingly, at the police force area level, residents' overall confidence in the police is not significantly correlated with their perceptions of police-public engagement or contact between victims and the police. More factors that impact overall public confidence will be discussed in the next section.

This section describes the measurement of public confidence and compare it between police forces and across the study period. The relationships between confidence variables and between confidence and pure efficiency of police forces are also investigated here. In section 6.4, police effectiveness, resources, and public confidence are discussed further.

6.4. Effectiveness, resources and public confidence

This section aims to investigate whether there is any relationship between public trust and effectiveness or resources using panel regression methods.

(1) Confidence scores

To answer the question posed in chapter 5 pertaining to whether the significant negative relationship between *NRR* (Neighbourhood and Response Workforce Allocation Ratio) and *PRR* (Reporting Rate of Property Crime) is driven by the intermediate variable Fear of Crime, the relationship between overall confidence scores and fear of crime is estimated using a series of a fixed-effect regression model with “pooling”, “individual”, “between” and “twoway” methods. The results are presented in Table 6.10.

Note that Fear of Crime is coded as higher values representing fewer worries about crime, whilst Confidence is coded such that higher values represent greater confidence in the police. The results indicate that for a given police force area, a lower level of worried about crime among residents is associated with higher public confidence during the study period once unobserved dummy variables from both time points and individual areas are accounted for. If worried about crime decreases by 1 unit (e.g. from “fairly worried” to “not very worried”) then the overall confidence scores are expected to improve by 0.14. This is a large magnitude of effect since Fear of Crime of police forces ranges from 2.5 to 3.5 and Confidence at the area level ranges from 3.72 to 2.89. The between model also reveals a significant relationship between Fear of Crime and Confidence, with the magnitude of the effect almost double (coeff = 0.253, p-value < 0.05) of that in the two-way model.

This research accepts the hypothesis that fear of crime in an area is significantly associated with public confidence.

For the confidence scores, further work is needed to discern which resource and effectiveness indicators are associated with public trust. Inspired by the existing literature reviewed in section 6.2, visibility and good contact both build confidence. This section investigates the CON ~ *FC*+*NRR*+*NW* (*NRR*: neighbourhood and response workforce allocation ratio, *NW*: non-staff costs per workforce) relationship using fixed-effect regression models. The results are set out in Table A.3.10 in Appendix III.

The results do not support any linear correlation between the neighbourhood frontline workforce and public confidence. This finding contrasts with existing literature (Bradford et al., 2009a; Sindall & Sturgis, 2013) which suggested that visibility helps to build public confidence in the police, as well as posting that policing style and carrying out foot patrols are of greater importance than frequency (Salmi et al., 2000, 2004; Hail et al., 2018).

Table 6.10. Results of panel regression models of Confidence on Fear of crime.

	Intercept		Fear of crime			
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	RSq	Adj. Rsq
Pooling	2.971818 (0.139970)	2.2e-16	0.303472 (0.047336)	5.819e-10	0.12376	0.12075
Individual			0.378734 (0.064672)	1.484e-08	0.12063	-0.027101
Between	3.119689 (0.287922)	1.817e-13	0.253370 (0.097411)	0.01296	0.14467	0.12329
Two-way			0.140334 (0.061751)	0.02392	-0.17192	0.023923

(2) Reporting crime and public trust

The next stage is to determine whether there is any relationship between public trust and reporting rate at the police force area level. The Pearson's correlation testing results suggest there is no linear correlation (p-value=0.82) between reporting rates of property crimes (PRR, calculated from the survey data) and confidence scores (CON). Moreover, the panel regression reveals that confidence is not significantly associated with a reporting rate of property crime for either the within or the between models (see Table A. in Appendix III). The reporting rate of violent crime (VRR, calculated from the survey data) is not significantly correlated (p=0.54) with public confidence in the pooling context; contrastingly, in the between model, scores are positively correlated with reporting rates (p-value=0.0194) and the Adjusted R-Squared is 10.74% (see Table 6.11 below). That is to say, for a specific police force area, improvement or erosion of public trust does not lead to any change in reporting rate over the years. However, on average over the years, in the areas covered by those police forces that gained more trust from the public, less violent crime was reported. This result does not take into account any differences in individual areas and merely describes the relationship between the averaged variables over the study period. This result differs from the findings of studies on individual data – Rader (2017) and Tarling and Morris (2010) have shown that, at the individual level, if a resident has more trust in the police, they are more likely to report crimes.

Table 6.11. Results of panel regression models of Reporting Rate of Violent Crime on Confidence.

	Intercept		Confidence			
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	RSq	Adj. Rsq
Pooling	0.570771 (0.268085)	0.03409	-0.041798 (0.069275)	0.54674	0.0012494	-0.0021827
Individual			0.076335 (0.086709)	0.3795	0.0030906	-0.16439
Between	1.40493 (0.40878)	0.001386	-0.25741 (0.10566)	0.019390	0.1292	0.10743
Two-way			0.063425 (0.121951)	0.6035	0.0011073	-0.1954

This section provides evidence at the police force area level that public confidence in the police is significantly associated with residents' fear of crime. As all respondents have been analysed together up until now, the next section examines the differences between victims and non-victims.

6.5. Difference between victims and non-victims

In this section, the research goal is to verify whether victims and non-victims exhibit different degrees of trust in the police at the level of police force area.

(1) Confidence scores

Figure 6.10 separately maps the confidence scores of victims, non-victims, and all responders from 2011/12 to 2017/18 in England and Wales. In general, all three groups were more confident in the police in 2014/15 than they were in 2011/12, whilst non-victims expressed more confidence in their answers than victims in each year. Tested by paired T-test at the individual level, victims were 0.24 less confident than non-victims on average (p-value < 0.001).

Drilling down into the data at the police force area level, Table 6.12 lists the differences between these two groups for each police area. Positive values indicate that non-victims had more confidence in the local police and vice versa. It should be noted that in Derbyshire-2015, Lincolnshire-2015, Staffordshire-2015, South Wales-2017, and Warwickshire-2017, victims had more confidence in the police than non-victims. The greatest difference between the groups can be seen in Cumbria, where non-victims had 0.68 more confidence in the police than victims. It is worth investigating why in some specific areas non-victims recorded higher confidence scores. Possible reasons for this include that the police treat the victims very well, which may offset the negative attitudes that stem from their status as victims of crime. However, as underscored previously, if the victim did not report the incident, they may not have had contact with the police. Using the framework of public trust proposed by Kääriäinen and Sirén (2011), residents living in the areas covered by these five forces might have a generalised positive trust in the citizens, compounded by a positive trust in the police. Consequently, although not all victims reported crimes, this group still exhibited more confidence in the police than non-victims.

Table 6.12. Confidence difference between victims and non-victims at the police force area, 2011/12 to 2017/18. (The force with the largest difference and forces with negative differences are highlighted in red).

Police force area	2011	2012	2013	2014	2015	2016	2017
Avon and Somerset	0.15	0.29	0.26	0.41	0.16	0.09	0.06
Bedfordshire	0.23	0.4	0.2	0.26	0.1	0.22	0.37
Cambridgeshire	0.32	0.11	0.13	0.34	0.09	0.01	0.21
Cheshire	0.27	0.38	0.33	0.36	0.15	0.19	0.07
Cleveland	0.36	0.43	0.44	0.37	0.12	0.16	0.35
Cumbria	0.35	0.27	0.68	0.4	0.29	0.31	0.17
Derbyshire	0.37	0.1	0.11	0.14	-0.01	0.15	0.11
Devon and Cornwall	0.14	0.2	0.16	0.13	0.1	0.06	0.15
Dorset	0.38	0.26	0.21	0.14	0.16	0.15	0.02
Durham	0.35	0.23	0.26	0.27	0.3	0.15	0.22
Dyfed-Powys	0.21	0.38	0.21	0.28	0.29	0.17	0.26
Essex	0.22	0.43	0.31	0.33	0.19	0.17	0.21
Gloucestershire	0.3	0.25	0.12	0.2	0.24	0.02	0.52
Greater Manchester	0.27	0.28	0.23	0.28	0.32	0.18	0.25
Gwent	0.19	0.47	0.37	0.47	0.16	0.54	0.21
Hampshire	0.23	0.13	0.26	0.12	0.13	0.03	0.14
Hertfordshire	0.36	0.27	0.12	0.04	0.29	0.29	0.13
Humberside	0.19	0.45	0.44	0.28	0.1	0.35	0.49
Kent	0.2	0.37	0.22	0.23	0.27	0.25	0.32
Lancashire	0.13	0.18	0.16	0.3	0.17	0.05	0.02
Leicestershire	0.16	0.2	0.23	0.21	0.05	0.2	0.34
Lincolnshire	0.39	0.26	0.3	0.16	-0.04	0.35	0.51
Merseyside	0.16	0.46	0.52	0.29	0.09	0.27	0.23
Metropolitan Police	0.3	0.26	0.15	0.19	0.23	0.07	0.26
Norfolk	0.32	0.15	0.56	0.17	0.19	0.1	0.17
North Wales	0.38	0.45	0.5	0.29	0.3	0.25	0.28
North Yorkshire	0.2	0.23	0.27	0.38	0.37	0	0.26
Northamptonshire	0.38	0.17	0.07	0.31	0.17	0.28	0.29
Northumbria	0.27	0.26	0.12	0.04	0.32	0.27	0.16
Nottinghamshire	0.09	0.17	0.27	0.28	0.05	0.38	0.23
South Wales	0.28	0.49	0.34	0.31	0.23	0.08	-0.06
South Yorkshire	0.36	0.49	0.4	0.23	0.24	0.48	0.22
Staffordshire	0.39	0.18	0.21	0.33	-0.02	0.64	0.18
Suffolk	0.33	0.22	0.2	0.31	0.09	0.32	0.33
Surrey	0.27	0.09	0.35	0.26	0.25	0.28	0.05
Sussex	0.3	0.37	0.22	0.43	0.3	0.31	0.07
Thames Valley	0.26	0.17	0.33	0.1	0.2	0.19	0.14
Warwickshire	0.13	0.23	0.1	0.44	0.09	0.28	-0.07
West Mercia	0.21	0.19	0.27	0.47	0.22	0.23	0.13
West Midlands	0.54	0.11	0.33	0.46	0.22	0.23	0.19
West Yorkshire	0.36	0.34	0.14	0.3	0.22	0.11	0.29
Wiltshire	0.26	0.42	0.21	0.18	0.18	0.17	0.1

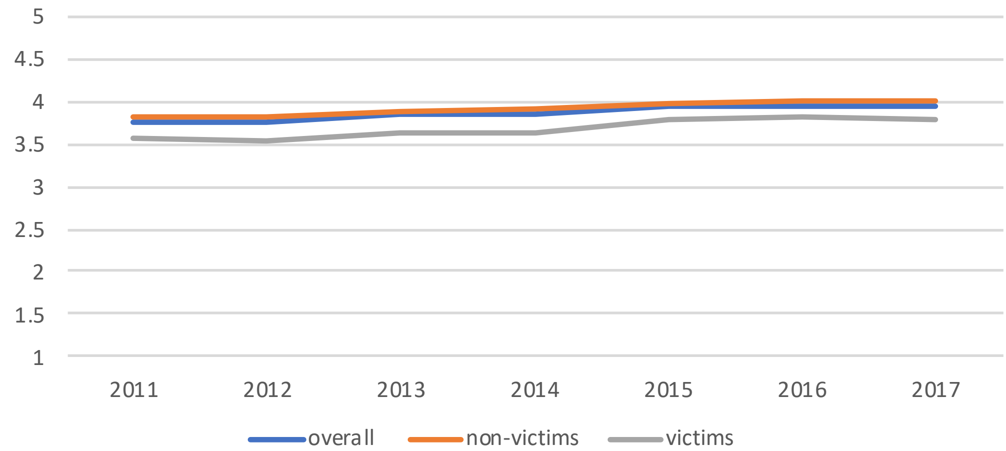

Figure 6.10. Confidence scores in England and Wales from 2011/12 to 2017/18, grouped by overall, non-victims and victims.

(2) Contact

Skogan (2006) and Bradford (2009a) offered opposing views on how contact influences public trust. Skogan proposed that English and Welsh residents who had recently been in contact with the police expressed less confidence in the police than those who had no contact. Contrastingly, based on an analysis of London data, Bradford adopted the view that public-police contact helps to improve confidence. Bradford (2009b) also proposed that the police can improve satisfaction with contact by treating the public fairly and respectfully (this point was verified in section 6.3, namely, that legitimacy indeed contributes to contact satisfaction).

This section will investigate whether legitimacy scores differ between contact and all-responder groups based on police force data. This research has analysed the legitimacy scores recorded in the victim forms. The non-victim forms[32] also pose two questions about legitimacy to all participants: "the police in this area would treat you with respect if you had contact with them for any reason" and "the police in this area treat everyone fairly regardless of who they are". An answer of 1 means the responders strongly agree with these statements, whilst a score of 5 means they strongly disagree. Again, the scale

[32] Non-victim forms is designed for all responders, not only the responders haven't suffered any crimes in the past 12 months. If a responder tell any crimes he or she suffered, a victim form will be provided following that.

is reversed for present purposes to render the results more readable: high scores represent more perceptions of legitimacy.

The present research defines the legitimacy perceived by all respondents no matter whether they had contact with the police or not (LEG1) as the average values of these two answers in an area. The weighting for the individual factor is taken from the CSEW. It should be pointed out that the legitimacy scores calculated from all respondents (LEG1) range from 1 to 5, whilst the legitimacy scores calculated from the contact cases (LEG) range from 1 to 3. In order to be comparable, *LEG1* and *LEG* should be standardised. The *LEG* scale can be stretched due to the symmetrical coding of both variables; as such, the new scale of standardised *LEG* is set from 1 to 5[33], meaning the standardised *LEG* is comparable to *LEG1*. Figure 6.11 charts the standardised legitimacy scores for these two groups in England and Wales from 2011/12 to 2017/18.

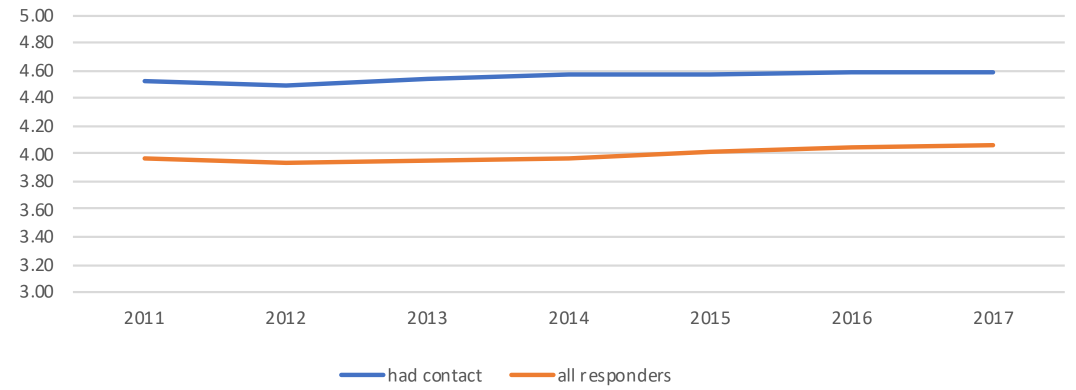

Figure 6.11. Standardised legitimacy scores from all responders and those who had contact with the police in England and Wales from 2011/12 to 2017/18.

It can be seen from Figure 6.11 that those victims who have had contact with the police perceived higher legitimacy than the imagined legitimacy of all residents. At the police force level, paired t-tests indicate that there is a significant difference in trust between the contact and all-response groups because the contact group have been treated respectfully and fairly by the police. The estimated mean difference is 0.58 and the p-value is less than 0.001. As a result, the perceived respectfulness and fairness of those

[33] Standardised *LEG* = (*LEG* -1)*2+1 and the scale is stretch to from 1 to 5.

who have had contact with the police are expected to be 0.58 higher than the imagined legitimacy of all residents. This suggests that the police in England and Wales generally perform well in public-police contact and that residents tend to imagine their contact with the police will engender diminished feelings of legitimacy than what they actually experience. This gap is likely to be driven by the fact that specific examples of negative police action tend to be amplified in the media or in social communication, causing residents' perceptions of legitimacy to be lower than their assessment of legitimacy based on actual contact.

To examine whether there are any police force areas in which the contact group has a lower mark than all residents' imagination, the differences between all responders and those who had contact are presented in Table 6.13. In this table, the positive values represent how contact groups experienced better legitimacy than general imagination. Hampshire-2013, Stafford-2014, Surrey-2014, Merseyside-2017 and Nottinghamshire-2017 are the police forces that performed poorly in terms of contact, with the victims perceiving less legitimacy than the general imagination. Additionally, this section also rejects the hypothesis set out in chapter 5: poor performance in contact drives the negative relationships between neighbourhood policing workforce allocation and reporting rates of property crime. A possible interpretation of the negative relationship could be that the visibility (e.g. patrolling work) of neighbourhood policing can negatively impact public confidence to such an extent that residents are unwilling to report crimes to the police.

In the next section, a new type of data is employed to measure public confidence in the police.

Table 6.13. Standardised Legitimacy differences between responders who had contact with the police and all responders at the police force area, 2011/12 to 2017/18. (Negative values are highlighted in red.)

Police force area	2011	2012	2013	2014	2015	2016	2017
Avon and Somerset	0.64	0.48	0.62	0.53	0.51	0.24	0.6
Bedfordshire	0.72	0.87	0.26	0.56	0.59	0.6	0.65
Cambridgeshire	0.72	0.62	0.69	1.09	0.45	0.56	0.44
Cheshire	0.39	0.86	0.57	0.82	0.34	0.63	0.47
Cleveland	0.82	0.94	0.84	0.82	0.42	0.57	1.04
Cumbria	0.68	0.16	0.83	0.5	0.4	0.22	0.57
Derbyshire	0.52	0.21	0.26	0.63	0.27	0.6	0.81
Devon and Cornwall	0.96	0.35	0.44	0.76	0.46	0.65	0.98
Dorset	0.6	0.49	0.51	0.86	0.63	0.48	0.63
Durham	0.48	0.71	0.83	0.76	0.66	0.66	0.63
Dyfed-Powys	0.49	0.51	0.22	0.72	0.53	0.31	0.65
Essex	0.74	0.49	0.45	0.77	0.53	0.69	0.7
Gloucestershire	0.46	0.8	0.59	0.41	0.75	0.7	0.76
Greater Manchester	0.98	0.02	0.62	0.9	0.51	0.79	0.41
Gwent	0.76	0.64	0.78	0.38	0.73	0.69	0.85
Hampshire	0.53	0.78	-0.03	0.37	0.55	0.56	0.63
Hertfordshire	0.65	0.61	0.74	0.44	0.75	0.64	0.82
Humberside	0.22	0.39	0.6	0.36	0.47	0.84	0.8
Kent	0.69	0.62	0.78	0.86	1	0.72	0.76
Lancashire	0.76	0.6	0.75	0.62	0.47	0.55	0.24
Leicestershire	0.85	0.18	0.85	0.68	0.4	0.48	0.89
Lincolnshire	0.44	0.61	0.74	0.33	0.72	0.73	0.63
Merseyside	0.29	0.6	0.58	0.82	0.63	0.5	-0.09
Metropolitan Police	0.38	0.88	0.94	0.66	0.82	0.21	0.31
Norfolk	0.69	0.7	0.52	0.81	0.18	0.69	0.13
North Wales	0.59	0.52	0.13	0.8	0.91	0.85	0.93
North Yorkshire	1	0.44	0.47	0.83	0.7	0.14	0.75
Northamptonshire	0.73	0.73	0.52	0.16	0.61	0.64	0.8
Northumbria	0.81	0.18	0.87	0.51	0.6	0.66	0.82
Nottinghamshire	0.64	0.58	0.26	0.92	0.45	0.87	-0.19
South Wales	0.34	0.56	0.67	0.75	0.4	0.99	0.64
South Yorkshire	0.35	0.58	1.02	0.38	0.32	0.26	0.14
Staffordshire	0.71	0.59	0.71	-0.14	0.83	0.5	0.7
Suffolk	0.87	0.56	0.75	0.41	0.41	0.04	0.62
Surrey	0.36	0.67	0.25	-0.04	0.77	0.07	0.61
Sussex	0.88	0.6	0.74	0.8	0.69	0.79	0.99
Thames Valley	0.69	0.53	0.67	0.7	0.36	0.75	0.4
Warwickshire	0.01	0.41	0.94	0.21	0.72	0.8	0.98
West Mercia	0.91	0.32	0.72	0.47	1.01	0.57	0.64
West Midlands	0.36	0.68	0.34	0.6	0.13	0.01	0.75
West Yorkshire	0.61	0.76	0.83	0.1	0.77	0.13	0.05
Wiltshire	0.62	0.64	0.55	0.79	0.27	0.4	0.81

6.6. Social text mining for London 2011-2017

The analysis conducted to this point exclusively uses survey data gathered in England and Wales. However, a new type of data, social media data, can be introduced into the research. This section assesses whether social media mining is a viable alternative or supplementary measure of public trust in policing. An overwhelming amount of data is produced on social media platforms every day. This data is easily accessible through application programming interfaces (APIs). At present, social media data are widely used in finance (Bollen et al., 2011) where the stock market has been predicted by tweets, and in business marketing (Linoff & Berry, 2011) where customer opinions about branches have been measured by their comments, and in public affairs (Boussalis & Coan, 2016) where tweets have been used to measure public attitudes towards climate change.

Social media data has also been applied to study policing issues in the UK. Williams et al. (2013) and Burnap et al. (2015) analysed cyber communities using Twitter data. They analysed data generated on the social network, detected tensions between 'neighbourhood' users, and discussed how police interactions with users on the platform affected the monitoring of tensions. Adopting a novel approach such as this extends policing from the real world to the virtual world. Elsewhere, Dencik et al. (2015) analysed how police can detect threats of domestic extremism and disorder through tweets. Notably, social media data has yet to be used to measure public trust in general.

This section only analyses public attitudes towards the police in the London area (the City of London and the Metropolitan Police) as expressed on Twitter. To simplify the research, only one large area is selected as an example, as this helps to verify whether social media data can be used in any way to study public trust in the police. There are two reasons why London is chosen as the example rather than other police force areas: (1) London is an area with a high population density, such that a large number of residents live are covered by the same police force; (2) It is an area with a large youth population; as this group are avid social media users, it is expected that the required data will be readily accessible.

Text mining is a catch-all term that encompasses several approaches to extracting information from textual data and deriving a representative quantitative result. A measure of public confidence is expected to provide a perspective that can at least identify whether a tweet indicates a positive or negative attitude towards the police.

Sentiment analysis, which quantifies the sentiment orientation in the text, is one text-mining approach that meets the requirement of a confidence measure. It first marks those words that indicate emotional tendencies or intensity before classifying them as positive or negative with polarity scores of 1 and -1. Any meaningless words such as prepositions and neutral words (usually nouns) in a piece of text are ignored in the polarity classification process. The overall sentiment score of a piece of text is then calculated according to the polarity scores of all the words that indicate emotional tendencies or intensity.

The calculation is not a simple average or aggregate. For example, the words containing a sentimental orientation are averaged, whilst adverbs such as "not" and "very" act as multipliers in the calculation. The intensity of the overall sentiment represents the degree of positive or negative sentiment (e.g., 0.7 is considered more positive than 0.5). This method requires a pre-prepared opinion lexicon dictionary that defines the sentiments of words. The Python package "TextBlob" provides such an opinion lexicon dictionary and can be used to process natural language text (Bonzanini, 2016; Chatterjee & Krystyanczuk, 2017). In this section, the confidence measure is defined as the average sentiment score of all sample tweets. To ensure its comparability with the survey data, public confidence is measured separately for each year.

(1) Extracting and pre-processing data

Before connecting to the Twitter API, an application for data use is required that describes the purpose of the data use and highlights any potential ethical implications of such use. This research does not extract any personal information from Twitter accounts and has made a privacy commitment that it will not use, extract, or share any of the private information contained in the textual data.

To collect data that are uniformly distributed over the year, 1000 tweets are collected each month from April 2011 to March 2018. Although public confidence does not need to be assessed on a monthly basis required, this approach is better than collecting 12000 tweets per year, as it avoids the effects of excessive discussion of the same public events. To restrict the samples to opinions on London policing, precise keywords are used, such as “met police” or “met feds”. “Feds” is a common slang term amongst African Americans, borrowed from the Federal Bureau of Investigation. According to the 2011 census, 13.8% of the population of London is Black (though not all black Londoners refer to the police as “Feds”). Thus, the search keywords are set as “london police”, “met police”, “london feds” or “met feds” with the parameter = “popular”, which prioritises those tweets with more interactions.

The following two types of tweets do not represent public opinion and are therefore not included in the samples: (1) Tweets from news accounts, e.g. in 2016 @BBC Breaking News: “Met Police investigation into allegations of abuse at UK charity Kids Company finds no evidence of criminality”; and (2) Tweets from police accounts. If a user has forwarded a tweet from either of the above, the text is included in the sample because it represents public opinion on the news or police action. Carrying out the data collection in this way cannot identify whether a user is an academic or a police officer; it is important to note that the opinions often expressed by these two professions do not reflect public trust. There is also bias in tweets such as “Met Police to decide how many tickets #saintsfc get for brentford away” because this was not an issue the Metropolitan Police were actually involved with. Note that R does not support extracting historical tweets (available in Twitter premium services), so this research uses the “pandas”, “twipy” and “TextBlob” packages in Python. The extraction process only stops when the required number of acceptable tweets is collected or there are no more samples available. After removing any URLs, punctuation, numbers, spaces and characteristics that do not contain sentiment information, the mutual data is ready for analysis. To evaluate the model following the sentiment analysis, this research retained 200 randomly selected tweets as test data.

(2) Sentiment analysis

For each tweet, each word that includes sentiment information is paired with a polarity score according to opinion, from which the total sentiment score is calculated. Public confidence in London policing over a given year is measured by calculating the average of the sentiment scores of all tweets in that year. Scores between 0 and 1 indicate the public has confidence in the police, whilst scores between -1 and 0 indicate a lack of confidence. The main content in texts about the police in London falls into three categories: (1) Reporting or mentioning an illegal activity/disorder that users have experienced; (2) Recording an experience of contact with the police or witnessing police visibility (some of which are complaints); (3) Commenting generally on policing, the future, and the crime environment that users have not experienced in a specific event. Examples are as follows: “So any chance of the Met police noticing that the McCanns are guilty of child neglect? That is about the only certain fact in this case”; “As if they now have undercover met Feds on trams now”; “Met Police continuing to fund for the search of Madeleine McCann for another six months even though her mother still refuses to answer the 48 simple questions she was asked in 2008 to HELP find her daughter. Backwards country”.

Two problems arise when using sentiment as a measure of confidence. In the prepared opinion lexicon dictionary, words such as “crime”, “robbery” and “burglary” are classified as negative. However, in the context of policing, most topics focus on illegal activities, disorder, and the criminal environment; this is an issue as, for present purposes, these words do not necessarily indicate a negative opinion of the police. Another problem is that text mining only extracts information from the text and in some tweets, the sentiment is hidden behind the images whilst the text is actually more neutral.

(3) Model evaluation

The 200 retained pieces of test data are used to evaluate the models after implementing sentiment analysis. By hand, each tweet is given a positive score of 1 or a negative score of -1, depending on the overall meaning and sentiment lexicon orientation behind the text. Those tweets that receive a positive score are treated as “true positives” and vice versa. Examples of actual positives and negatives are as follows:

Positive:

“@CityPolice I need to find details of an accident I was involved in a couple of years ago near bishops gate. I was knocked off my bike and it was attended by the City of London Police. What's the best way to do this? I have since moved and no longer have the letter you sent”

“As if they now have undercover met Feds on trams now.”

Negative:

“Met Police has spent almost a-third of a million pounds on buying, upgrading and maintaining three water cannon that will never be used...”

“#London police will not follow up on minor crimes due to lack of resources giving criminals free reign. The spike in crime is inevitable, it will get worse with the warmth of summer. More terrorism likely too. Get out of London. Avoid London.”

After hand-labelling the test data with the actual classification, 200 tweets are then used to carry out the sentiment analysis. The results of the sentiment scores are then compared to the actual sentiment orientation.

Classification accuracy = (TP+TN)/(TP+TN+FP+FN), where TP is the possibility of actual positives receiving positive scores, TN is the possibility of actual negatives receiving negative scores, FP is the possibility of actual negatives receiving positive scores, and FN is the possibility of actual positives receiving negative scores. In the test dataset, although 71 tweets are labelled as actual positives, only 46 tweets received positive scores in the sentiment analysis, whilst 129 tweets are actual negatives, of which 110 received negative scores. The false negative probability is 35.2%, which indicates that approximately 1 in every 3 positive tweets was misclassified as negative. The false positive probability is 14.7%, indicating that approximately 1 in 7 negative tweets was misclassified as positive. The general classification accuracy is 75%. This indicates that sentiment analysis based on the sentiment lexicon provided in TextBlob tends to give more negative results in the policing context. An accuracy of 75% is not unacceptable, although there must be some bias in the classification.

The results of estimated confidence in London from 2011/12 to 2017/18 are shown in Figure 6.12. The values are all below zero, indicating that the public generally adopted a negative attitude towards the police. With the exception of 2012/13 and 2016/17, the overall trend is that the public has generally expressed less negative attitudes towards the police, i.e., confidence in the police has increased over both the austerity period and the study period as a whole compared to the initial data. Although there were some methodological problems and sample bias, confidence measured by tweet sentiment follows a similar trend to that charted by the survey data: there was a significant increase in confidence over the study period.

Figure 6.13 separately plots confidence as measured by survey data in London from 2011/12 to 2017/18, by young group (aged under 35) and all respondents. In the survey data, there were significant differences between the young and total samples, with young people tending to have less confidence in the police during the austerity period. As Twitter users are concentrated in young groups, the results are compared with the confidence of the young group in the survey measure. With the exception of 2017/18, the trends in the two approaches were similar.

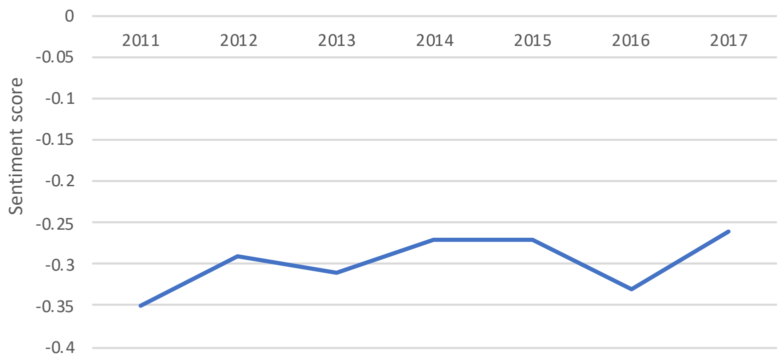

Figure 6.12. Confidence in London from 2011/12 to 2017/18 measured by tweets sentiment.

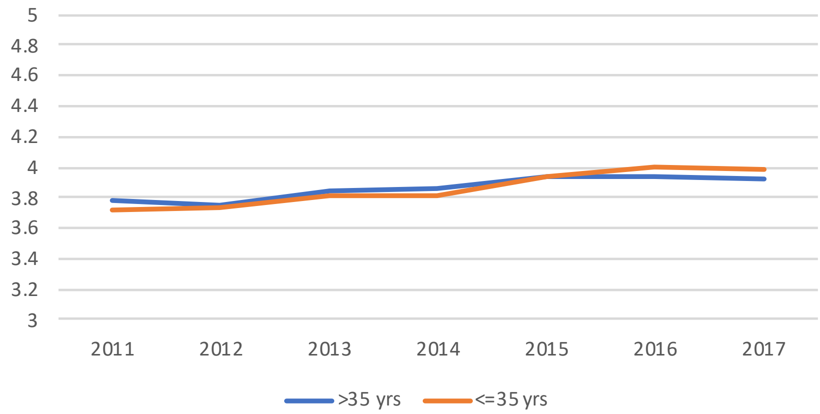

Figure 6.13. Confidence scores in all responders and those aged under 35 in Metropolitan Area from 2011/12 to 2017/18.

An important factor influencing the confidence measure could be if Twitter users became more likely to express dissatisfaction or less likely to post it during the years sampled. If the police became more involved in social media interactions with the public, this would also be a factor in improving cyber confidence. To answer this question, research into police-public interaction on the platform, not just general attitudes, is essential.

There are two options for further research to improve classification accuracy and ensure that the negative emotions in tweets are no longer magnified: (1) Define a special opinion lexicon for policing, correct those words that have been underestimated in the general context, and then reload the sentiment analysis; (2) Introduce a machine learning technique. In the second approach, a training set of samples is manually classified as positive or negative.

An example of a similar approach is as follows: in a piece of American research (Cohen and Zhukov, 2018) investigating whether there is a relationship between rape culture in newspapers and the actual crime rates of rape at the state level, the study sample consisted of 310,000 pieces of news. Of these, 20,000 pieces of news were set as the training data to be classified by hand. Cohen and Zhukov employed a Support Vector Machine (SVM) method, which is a commonly-used technique to train and construct the model to self-learn text meaning, thus allowing it to identify any rape culture content in the newspapers samples. Similarly, in this research, if a larger sample set is available and hand labelling work is undertaken for a large dataset, the tweets can be classified by SVM according to training data from a self-learning model of text meaning. From this, their sentiment orientation towards the police can then be identified.

This section presents another optional method for measuring overall public confidence based on social media data and compares its results with the traditional measures from the survey data. The feasibility, shortcomings and further analysis of this approach are also discussed.

6.7. Conclusion

In this chapter, public trust in policing and their probable reflection in efficiency assessment and resource allocation is analysed at the level of the police force area. Overall public trust is measured by the confidence score calculated from the CSEW data. Legitimacy and satisfaction in police-public interactions, as well as public engagement in policing, are also measured in the survey data. Fear of crime, a frequently used sub-concept of public trust, has been included as part of the effectiveness measurement since it represents how people feel safe.

In general, given the reduction in the police budget, the police in England and Wales have still improved the overall confidence and legitimacy in contact during the period of austerity but did not achieve a significant improvement in contact satisfaction and public engagement. This is not surprising because legitimacy in the contact is simple to see as long as the police perform well. On the other hand, public involvement is difficult for the public to notice. Moreover, contact satisfaction is sensitive to the way the police handle the cases, so it is probably that this variable had been influenced by the reduction in the police budget. From 2011/12 to 2014/15, public trust improved for most police forces, but only a few of them succeeded in continuing to gain more trust from the public. The public may not notice changes in police performance until after they have changed for several years, suggesting that this is the result of a delayed effect of austerity. Performance may alter only after budget cuts have been in place for several years. There is a significant difference in the level of trust experienced by victims and non-victims at an individual level, and a significant difference in perceptions of legitimacy between those who have had contact with the police in the past 12 months and all residents. The victim group shows less confidence in the police due to their experiences of victimisation and the decrease in trust with regard to how the police carry out their duties to prevent crimes and maintain community order. The contact group has more perceptions of legitimacy in the contact compared to general residents. This indicates that the police did better in terms of contact than the public imagined, which may be a result of the spreading of information on media.

This chapter also uses a series of fixed effect panel linear regression models to determine a relationship between effectiveness, public trust and resources. Based on the panel data with 42 police forces over seven years, evidence has been found to support existing research, but also highlights a relationship opposing previous proposals.

In the case of pooling, overall confidence is unrelated to scale efficiency and only weakly positively associated with pure efficiency. It is not surprising that satisfaction and legitimacy in contact, and public engagement reflect no relationship on the efficiency measurement.

At the level of the police force area, contact satisfaction is strongly correlated with the legitimacy of contact and public participation. For example, an increase in legitimacy is predicted to increase contact satisfaction by 1.475 units, while an increase in public participation is predicted to increase contact satisfaction by 0.457 units. Therefore, it suggests that policing practices that involve the community more will likewise increase victim satisfaction. Fear of crime is the only indicator that has been found to significantly correlate with overall confidence; if the fear reduces by 1 unit (the value of Fear of Crime increases by 1), overall confidence scores are projected to rise by 0.14. This also supports the studies of Skogan (2009) on the relationship between fear of crime and public trust.

In contrast to previous research that suggests that visibility and good contact aid to build trust, this research has not found any significant resource factors or effectiveness indicators that contribute to overall confidence at the level of the police force area. However, it is perhaps best understood in terms of the significance of how the neighbourhood workforce operates. Although police forces have attempted to keep the frontline manpower as a result of austerity, their job is nonetheless affected by the rising workload and steadily declining well-being caused by the scarce resources. In this austerity, the forces have not demonstrated effective visibility (e.g. foot patrolling is proven to be more effective in building confidence than motor patrolling, Wood et al., 2014) or have not built strong relationships, both at the micro and meso levels, such as in the areas of data security and social media interaction (Aston et al., 2021).

In addition to employing survey data, text mining techniques were used to implement a supplement measurement based on social media data. From April 2011 to March 2018, more than 80,000 historical tweets containing the terms “london feds”, “london police”, “met feds” and “met police” were retrieved from Twitter. After the data was cleaned, sentiment analysis creates a score for the polarity of each word in the text and determines the sentiment score on average for tweets from the same year by using the pre-made opinion lexicon dictionary that the software provides. That represents confidence among Londoners. Although the results of this measurement of public trust in London were unfavourable, trends during the time of austerity also suggested that the level of public trust had increased. The shortcomings of this strategy as they relate to police issues are also explored, and ultimately, a second optional machine learning strategy with a particular opinion lexical dictionary is suggested.

7. Conclusion

7.1. Contributions of this research

(1) Innovations in methods and its applications

This research is the first study after 2006 that reintroduces DEA models to police efficiency. It develops a systematic efficiency measurement model with resource indicators as inputs and policing outcomes as output. The proposed approach evaluates the relative efficiency of 43 police forces in 2011-2017, providing evidence for assessing police performance during the period of austerity. Moreover, this research offers data support for police force efficiency assessment during the period of austerity and subsequent improvement schemes. Based on the feasibility and validity of the presented approach, the models and indicators this research has developed could greatly enhance the future annual assessments of police force efficiency by improving reliability and reducing technical barriers.

To overcome the issue of incomparability between areas due to their diverse socio-economic and demographic situations, this research groups 42 police force areas into seven police families according to their characteristics of deprivation and ethnic diversity. In this way, DEA scores are comparable within the force family, and the inefficient forces can be contrasted with their efficient peers to determine where they may have the potential for improvement. The inefficient force can learn which areas, such as crime rates across all categories, rates of personal violence cleared up, or resource allocation, it needs to improve to achieve full efficiency by comparing itself to the efficient force within its own family. This work contributes to the application of DEA models combined with environmental factors.

Because hidden crime is considered in this study, constructing variables relies heavily on the use of CSEW data. Crimes that are not reported to the police are disclosed in the construction of crime rates, and the reporting rates can be computed using victimisation-based survey data. This adds another perspective on the fact that some conclusions drawn from police recorded data are still uncertain when compared to survey data.

Although it has been extensively used in other fields of research, the use of textual data on the social media platform, Twitter, is an early attempt to measure public trust in the police. This research collects and examines historical tweets that were uniformly distributed over seven years and that mention the Metropolitan Police. An analysis of the author's attitude toward the police was then measured using the method of sentiment analysis. Based on the survey data, the overall sentiment score and the overall confidence score are comparable. The study also suggests using machine learning techniques on a large dataset to enhance the measurement.

(2) Findings and their responses to the existing literature

In general, it can be said that most forces performed better in the efficiency assessment during the austerity period; at the national level, the improved outputs and reduced policing resources suggest that police forces in England and Wales became more efficient, which is consistent with the Coalition government's expectations. However, the general decline in clear-up rates especially in the first three years implies that austerity negatively impacted the tasks that the police have to deal with after a crime has been committed.

Scale efficiency scores are strongly negatively correlated with the scale (represented by the total workforce of local police forces). For a specific police force, there is strong evidence that growing the workforce is linked to lower-scale efficiency scores assessed by DEA models. It can be interpreted that small police forces have more flexibility in organisational management and that large police forces deal with more complicated jobs, including national policing, in addition to more redundancy. Impacted by the austerity, the downsizing of staff in England and Wales had the advantage of increasing scale efficiency. This is also evidence to oppose the rationale for the controversial "merging forces" proposals of 2006.

A larger-scale area tends to have more average worries about crime over the years. This may be a result of that the areas have allocated more workforce as a response to high crime rates or because a larger forces are likely to have a higher levels of media exposure, which increases concern about crimes due to some negative perceptions of media contact (Padgett & Gertz, 2000; Romer et al., 2003, Ditton et al., 2004). Additionally, for a given police force area, a reduction of motor and household property crimes will indeed help to reduce the fear of crime over the years, but its influence is far less than that in the between model. The conclusion based on survey data at the level of the police force area differs from what Rader (2017) advocated, according to which even if crime rates decreased, residents in this area would still be concerned about crime.

Surprisingly, when time-varying unobservables and fixed effects from individual areas are taken into account, the neighbourhood and response workforce allocation ratio has the opposite effect on fear of crime for a given police force area: an increase in the ratio is linked to a rise in concern about crime. Although Karn (2013) and Kelling (1981; 1988) have pointed out that foot patrol helped to reduce fear of crime, this research demonstrates that during the period of austerity and post-austerity, increasing the neighbourhood policing workforce (including the neighbourhood function and response function) is associated to residents' fear of crime at the level of police. Three different explanations could be used to interpret it. Foot patrol was not implemented properly, which led to residents associating police visibility with a high level of crime and worrying about crime; second, neighbourhood policing during the austerity period is ineffective; third, there may have been some poor interactions between the police and residents during neighbourhood policing; and finally, residents may have had negative attitudes. However, the third hypothesis is rejected by the fact that in most police forces the residents who have had contact with the police perceived far higher legitimacy than the imagined legitimacy of all residents.

No indicator was found to have a significant influence on reducing crime rates, regardless of the ratio of frontline staff to neighbourhood staff. This finding disagrees with Ratcliffe et al. (2011) who suggested that patrols helped to reduce crime, but agrees with Karn (2013) who suggested that patrols had no significant impact on crime rates. It can probably be interpreted by (a) using survey data in the present research; (b) although the police have a duty to prevent crime, the incidence of most types of crime is beyond the control of the police; (c) the number of officers is not as important as the quality of their work.

There is a significant difference in the level of trust experienced by victims and non-victims at an individual level, and a significant difference in perceptions of legitimacy between those who have had contact with the police in the past 12 months and all residents. The victim group shows less confidence in the police due to their experiences of victimisation and the decrease in trust with regard to how the police carry out their duties to prevent crimes and maintain community order. The contact group has more perceptions of legitimacy in the contact compared to general residents. This indicates that the police did better in terms of contact than the public imagined, which may be a result of the spreading of information on media.

Contact satisfaction is strongly correlated with the legitimacy of contact and public participation. It suggests that policing practices that involve the community more will likewise increase victim satisfaction. Fear of crime is the only indicator that has been found to significantly correlate with overall confidence, which also supports the studies of Skogan (2009) on the relationship between fear of crime and public trust.

In contrast to previous research that suggests that visibility and good contact aid to build trust, this research has not found any significant resource factors or effectiveness indicators that contribute to overall confidence at the level of the police force area. However, it is perhaps best understood in terms of the significance of how the neighbourhood workforce operates. Although police forces have attempted to keep the frontline manpower as a result of austerity, their job is nonetheless affected by the rising workload and steadily declining well-being caused by the scarce resources (Charman, 2017; 2022).

(3) Implications of the austerity

Regarding the period of austerity, budget reduction may trigger the decrease of frontline workforce and reshape the resource allocation of neighborhood policing. Although assumptions can be made that police efficiency have been strengthened (fewer resources, more outputs) there are still some more controllable outputs, such as clear-up rates, are weakened. Subsequently, more awareness should be turned to this fact. Referring to the post austerity period, funding is no longer tightened while some indicators of effectiveness are still declined, possible delayed effects from the austerity need to be considered. The analysis in this thesis reveals that quantity of workforce is not the most significant factor in the resource allocation, and more concerns should be turned to the stress of austerity on policing quality.

(4) implications for police funding

Although cost control has its positive impact, it should not weaken efficiency or performance. In summary, police funding affects police performance in two aspects: (a) staff wellbeing and human resource reserves; (b) The cost of performing tasks, collaboration, and technology. Additionally, since service declining for vulnerable populations may appear when police force only tends to meet easy targets, dedicated budgets should be allocated for critical missions that are unmeasurable and costly, i.e., for important work with vulnerable populations that is less easy to measure.

(5) implications for policy

To establish a comprehensive quantification and evaluation system for police efficiency, efforts should include: (a) considering indicators that are unmeasurable; (b) noticing the difference of environmental factors between police force areas; (c) reasonable employment of data mining in various areas.

Regarding tradeoff of resource allocation, policies that support quality may be more effective than decisions only refer to quantity.

On the one hand, the emphasis of constructing neighborhood policing teams and strengthening the quality of contact would significantly contributes to building in public trust. On the other hand, the focus on public trust at the meso level is necessary as well. It is also suggested that efforts on media outreach and police image maintenance should be engaged.

7.2. Discussion and further work

Problems with this research and any subsequent research that was motivated by it are discussed in this final section.

The relative efficiency scores generated by the DEA models were comparable within a single year but not really across years. This study pre-categorized 42 police forces into seven groups based on immigrant and deprivation indices to address this issue. Police forces in Wales were not pre-classified using this method but were grouped directly into an independent group according to spatial proximity, as the index of multiple deprivation in Wales is in a different statistical system and cannot be compared with that of England. This assumes that environmental factors are constant, which is not the case.

Due to the limited dimension of DEA models, efficiency is evaluated without consideration of environmental factors. When examining any relationships between variables, the fixed-effect regressions have captured these factors to the extent that they are assumed to be time-invariant (or changing very slowly). Regression will be more reliable when environmental factors like the population at risk and unemployment are considered. However, this has not been completed in the present study because most economic and employment data are not available at the level of low-layer areas so they are unable to be aggregated for the level of police force area (please note: the boundary of police force area is not equal to that of the administrative divisions).

Only three general indicators of effectiveness—crime rates for household crimes, crime rates for individual crimes, and violent clearance rates—were chosen as outputs to the DEA due to the DEA analysis's dimension restrictions. These addressed customary fundamental duties but did not consider contemporary difficulties or policing's evolving needs. Anti-social behaviours, fraud and cybercrimes were questioned in recent surveys rather from 2011/12 onwards. As such, it was not appropriate to include them in an assessment framework from 2011 to 2017. Cybercrime and police dealing with anti-social activity may be covered in additional research when more annual surveys are available.

CSEW is feasible for research on each distinct type of crime, such as domestic violence and theft from cars, however, it is difficult for research at the police force level because there were only 1000 samples on average in each police force. Due to sample bias, solving rates for particular kinds were calculated as zero in some years. To account for those who were not reported to the police, survey data was still used in this study rather than police-recorded data to determine effectiveness. One possibility for additional investigation is to compute the reporting rate using survey data while computing the clear-up rate using police-recorded data. Questions about crimes against children were asked in the questionnaire, but the samples were small so they cannot be combined with the adult data.

This research divides police resources into three aspects: frontline staff, support staff and non-staff costs. Although non-staff costs were not divided into variables corresponding to different functions, it strives to recognise more explicit roles in the frontline workforce.

The quantitative measurement of efficiency only examined optimising the allocation of resources, but cannot address how best to use resources, therefore suggestions on how to increase police efficiency have solely focused on modifying the number of resources available rather than their usage. In future studies, more precise police work needs to be quantified.

For social media data, the basis of feasibility is how samples on the social media platform match traditional survey samples and how well they reflect the characteristic population. As the provided opinion lexicon dictionary magnified negative sentiment toward policing or crime issues, a special opinion lexicon or machine learning with prepared hand-labelled training samples is required in further research.

This research analyses how police efficiency, effectiveness and public trust in policing have changed and how they were related to changes in resources during the period of austerity. The main contribution of this research is that it proposes a feasible quantitative measurement of police efficiency using survey data, and overcomes the barriers of incomparability due to environmental factors and hidden crime. This research responds to a policy concern: how the police force performance has been affected by the era of austerity in the UK. It implies that although the efficiency has generally improved, some other elements of performance have been weakened. This research also proposed the following suggestions：(1) The tasks that are unmeasurable but important to the vulnerable are also vital in the assessment of police performance;

(2) To improve police performance, policies that support the quality of policing might be more effective than tradeoff in resource allocation; (3) Other than police-public contact and police visibility, media exposure is also worth considering in building public confidence in policing.

Appendix I. Grouping map of police force areas in England and Wales

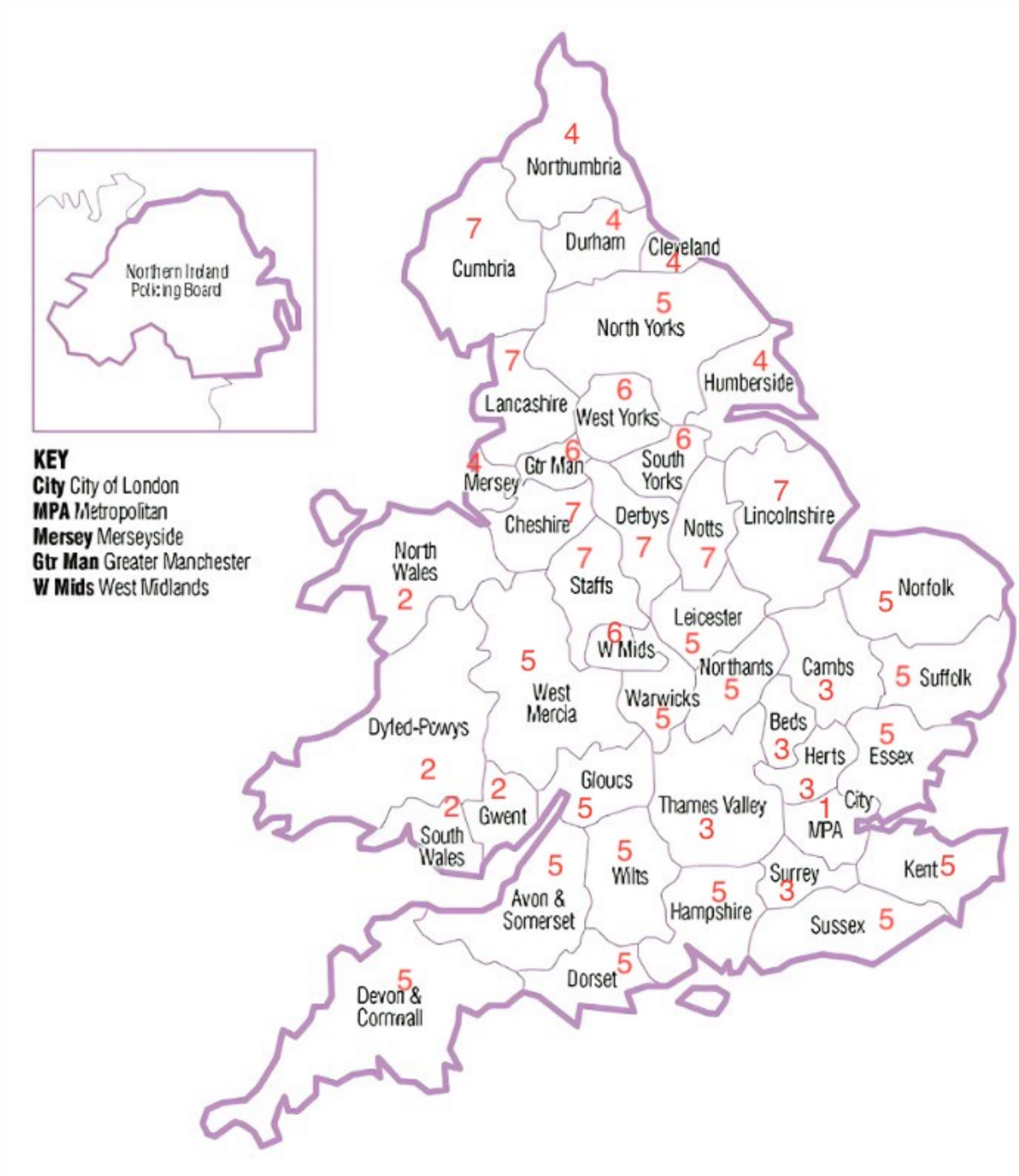

Figure A.1.1 Grouping map of police force areas in England and Wales, according to the clustering model. The group numbers are labelled on the police force area.

Appendix II. Alternative models with lagged terms.

Table A.2.1. Results of panel regression models of Crime Rate 1 on lag(Frontline/Support workforce ratio) and lag(Non-Staff Cost per Workforce).

	Intercept		lag(FS)		lag(NW)		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	177.51117 (29.89552)	1.012e-08	9.24704 (9.51543)	0.3321	-0.37939 (1.79542)	0.8328	-0.0039855	0.59421
Individual			-39.31144 (14.88015)	0.0089	0.43175 (2.30933)	0.8519	-0.16898	0.029654
Between	120.7199 (40.0048)	0.00453	39.7679 (14.8290)	0.01078	-3.8749 (3.1166)	0.22137	0.12344	0.030876
Two-way			-3.1591 (15.4927)	0.8386	1.6308 (2.3042)	0.4800	-0.23899	0.7741

Table A.2.2. Results of panel regression models of Crime Rate 2 on lag(Frontline/Support workforce ratio) and lag(Non-Staff Cost per Workforce).

	Intercept		lag(FS)		lag(NW)		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	47.50149 (5.20738)	2e-16	-0.98121 (1.65766)	0.55445	-0.58330 (0.31273)	0.06336	0.018236	0.039841
Individual			-5.77134 (2.40756)	0.01743	-0.67515 (0.37315)	0.07188	-0.14238	0.0035728
Between	41.07645 (8.94883)	4.73e-05	1.43276 (3.32457)	0.6689	-0.71610 (0.69843)	0.3117	-0.021701	0.56742
Two-way			-0.67102 (2.56015)	0.7935	-0.43863 (0.38223)	0.2525	-0.2293	0.47693

Table A.2.3. Results of panel regression models of Crime Rate 3 on lag(Frontline/Support workforce ratio) and lag(Non-Staff Cost per Workforce).

	Intercept		lag(FS)		lag(NW)		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	145.02412 (18.91994)	4.36e-13	-4.33096 (6.01356)	0.4721	-0.80271 (1.13242)	0.4791	0.000109	0.36458
Individual			-9.40096 (9.46942)	0.3220	-0.50728 (1.46837)	0.7301	-0.20105	0.51701
Between	140.75591 (27.83100)	1.11e-05	-0.70472 (10.32506)	0.9459	-1.39745 (2.16130)	0.5218	-0.030003	0.66173
Two-way			2.55428 (10.28926)	0.8042	-0.17751 (1.53711)	0.9082	-0.23936	0.96619

Table A.2.4. Results of panel regression models of Fear of Crime on lag(Neighbourhood Workforce Ratio) and lag(Crime Rate 1).

	Intercept		lag(NEIR)		lag(CR1)		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.0702 (0.025157)	2.2e-16	-0.26074 (0.10537)	0.014034	-2.2710e-04 (7.4841e-05)	0.002677	0.055031	0.00042651
Individual			-0.019050 (0.10622)	0.85784	-9.8158e-05 4.6739e-05	0.03698	-0.18456	0.11069
Between	3.16853879 (0.08265409)	2.2e-16	-0.33024147 (0.26293413)	0.2168	-0.00061605 (0.00032608)	0.0665	0.086932	0.067036
Two-way			0.0029396 (0.094513)	0.9752	-6.6918e-06 (4.6254e-05)	0.8851	-0.24213	0.98907

Table A.2.5. Results of panel regression models of Fear of Crime on lag(Neighbourhood Workforce Ratio) and lag(Crime Rate 2).

	Intercept		lag(NEIR)		lag(CR2)		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.08405031 (0.02475581)	2.2e-16	-0.27345194 (0.10326671)	0.008629	-0.00156109 (0.00039142)	8.822e-05	0.079467	1.6454e-05
Individual			0.01708650 (0.10008268)	0.8646118	-0.00086821 (0.00024599)	0.0005156	-0.13775	0.0023701
Between	3.1954037 (0.0826393)	2.2e-16	-0.4145776 (0.2628339)	0.12301	-0.0037233 (0.0016369)	0.02866	0.1201	0.033161
Two-way			0.034310 (0.090661)	0.7055	-8.0008e-05 (2.6641e-04)	0.7643	-0.23714	0.89218

Table A.2.6. Results of panel regression models of Fear of Crime on lag(Neighbourhood Workforce Ratio) and lag(Crime Rate 3).

	Intercept		lag(NEIR)		lag(CR3)		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.05976174 (0.02475742)	2.2e-16	-0.29822273 (0.10492657)	0.004864	-0.00027277 (0.00012070)	0.024726	0.042804	0.0018971
Individual			-0.018498 (0.10250)	0.85696	-0.00013407 (7.4818e-05)	0.07464	-0.18993	0.2031
Between	3.13318400 (0.08294126)	2.2e-16	-0.40443454 (0.27094304)	0.1438	-0.00072577 (0.00054808)	0.1934	0.048755	0.14598
Two-way			0.015508 (0.090031)	0.8634	-8.2517e-05 (6.8088e-05)	0.2270	-0.23018	0.46626

Table A.2.7. Results of panel regression models of Fear of Crime on lag(Neighbourhood Allocation Ratio) and lag(Crime Rate).

	Intercept		lag(NEIR)		lag(CR)		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	3.1057 (0.028849)	2.2e-16	-0.28447 (0.10455)	0.0069980	-2.0983e-04 (5.6748e-05)	0.0002708	0.08404	3.1729e-05
Individual			-0.028791 (0.10513)	0.784479	-1.0202e-04 (3.5584e-05)	0.004597	-0.1651	0.017389
Between	3.23759319 (0.09986520)	2.2e-16	-0.33779554 (0.25791793)	0.19816	-0.00053247 (0.00024078)	0.03309	0.11722	0.035311

Two-way			-0.0013551 (0.093843	0.9885	-2.3874e-05 (3.6705e-05)	0.5162	-0.24332	0.80952

Appendix III. Omitted results of panel regression models

Table A.3.1. Results of panel regression models of Crime Rate 1 on Neighbourhood Allocation Ratio and Non-Staff Cost per Workforce.

	Intercept		NEIR		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	242.6624 (21.4396)	2.2e-16	88.7217 (77.9925)	0.256281	-2.7927 (1.0581)	0.008773	0.022067	0.016605
Individual			8.7890 (128.2647)	0.9454	-4.7131 (1.1629)	6.856e-05	-0.099154	0.00030677
Between	148.7016 (40.3400)	0.0007077	93.7120 (112.7987)	0.4112819	3.4479 (2.5017)	0.176189	0.023379	0.24074
Two-way			-21.2501 (117.9893)	0.8572	-2.6898 (1.9446)	0.1679	-0.19696	0.38319

Table A.3.2. Results of panel regression models of Crime Rate 2 on Neighbourhood Allocation Ratio and Non-Staff Cost per Workforce.

	Intercept		NEIR		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	44.07838 (4.09283)	2.2e-16	11.83628 (14.87547)	0.42688	-0.44018 (0.20203)	0.03018	0.011937	0.068313
Individual			17.93904 (23.31648)	0.44243	-0.42267 (0.21840)	0.05412	-0.15183	0.097764
Between	45.18520 (8.83406)	9.268e-06	7.83042 (25.32426)	0.7589	-0.46781 (0.53668)	0.3889	-0.030727	0.67062
Two-way			12.37049 (19.87876)	0.5343	0.62182 (0.34075)	0.0693	-0.18583	0.1634

Table A.3.3. Results of panel regression models of Crime Rate 3 on Neighbourhood Allocation Ratio and Non-Staff Cost per Workforce.

	Intercept		NEIR		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	135.50533 (13.25536)	2.2e-16	8.08014 (48.22802)	0.8671	-0.95892 (0.65705)	0.1456	0.00057002	0.34086
Individual			-87.97719 (77.66814)	0.2585	-1.06012 (0.72901)	0.1472	-0.15998	0.21354
Between	130.6524 (25.6529)	9.923e-06	58.4451 (73.3993)	0.4308	-1.1916 (1.5772)	0.4546	-0.023641	0.58823
Two-way			-74.59957 (76.39253)	0.3298	-0.47098 (1.33840)	0.7252	-0.19965	0.58702

Table A.3.4. Results of panel regression models of Crime Rate on Neighbourhood Allocation Ratio and Non-Staff Cost per Workforce.

	Intercept		NEIR		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	417.2667 (28.1861)	2.2e-16	117.2751 (102.4731)	0.253433	-4.1297 (1.3910)	0.003253	0.028654	0.0067792
Individual			-42.1287 (167.6336)	0.801	-6.3302 (1.5355)	5.195e-05	-0.098973	0.00026612
Between	314.1345 (53.6808)	9.089e-07	165.3011 (152.5696)	0.2854	2.2786 (3.3029)	0.4945	-0.0031048	0.40025
Two-way			-66.1952 (149.9209)	0.6592	-3.0304 (2.5817)	0.2417	-0.20157	0.46603

Table A.3.5. Results of panel regression models of Reporting Rate of Property Crime on Fear of Crime, Neighbourhood and Response Allocation Ratio, and Non-Staff Cost per Workforce.

	Intercept		FC		NRR	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	0.47994206 (0.09892009)	2.123e-06	-0.03216091 (0.03232818)	0.3208	-0.06883082 (0.04298481)	0.1105
Individual			0.00853921 (0.04738002)	0.857142	-0.16211381 (0.05706992)	0.004933
Between	0.4863057 (0.1624539)	0.004829	-0.0572696 (0.0526458)	0.283523	0.0190633 (0.0771831)	0.806247
Two-way			-0.0244920 (0.0589543)	0.678243	-0.1654020 (0.0577939)	0.004637

	NW		Model	
	coefficient (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	0.00058230 (0.00059695)	0.3302	0.004216	0.25334
Individual	-0.00048656 (0.00066077)	0.462316	-0.15758	0.037436
Between	0.0028286 (0.0014058)	0.051340	0.052718	0.17113
Two-way	-0.0010411 (0.0011961)	0.385060	-0.18859	0.035289

Table A.3.6. Results of panel regression models of Crime Rates of Property Crime on Neighbourhood and Response Allocation Ratio, and Non-Staff Cost per Workforce.

	Intercept		NRR		NW		Model	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	316.2170 (32.9404)	2.2e-16	-23.7725 (73.7686)	0.747522	-2.9463 (1.0181)	0.004136	0.024382	0.016068
Individual			-141.6685 (102.1213)	0.1668	-5.4663 (1.1487)	3.595e-06	-0.083811	1.6497e-05
Between	208.1035 (55.044)	0.0005244	40.2602 (118.4982)	0.7358654	2.4998 (2.2302)	0.2691884	-0.014661	0.50088
Two-way			-177.4666 (91.0726)	0.05269	-3.2389 (1.8484)	0.08121	-0.19946	0.04219

Table A.3.7. Results of panel regression models of Reporting Rates of Violent Crime on Fear of Crime, Response Allocation Ratio, Crime Rate 3, and Non-Staff Cost per Workforce.

	Intercept		FC		NRR	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	0.32000004 (0.20276910)	0.1158	0.01828133 (0.06597166)	0.7819	0.11051469 (0.14888745)	0.4586
Individual			-0.02232483 (0.10682163)	0.8347	0.07406898 (0.16291477)	0.6498
Between	0.18897427 (0.26222732)	0.4757	0.04823525 (0.08099803)	0.5551	0.24790323 (0.39953494)	0.5387
Two-way			-0.11955203 (0.12978702)	0.3580	0.09882805 (0.16488731)	0.5496
	CR3		**NW**		**Model**	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	0.00015857 (0.00013248)	0.2324	-0.00012574 (0.00120698)	0.9171	-0.0077996	0.73799
Individual	0.00016807 (0.00015113)	0.2673	-0.00028081 (0.00146288)	0.8480	-0.19957	0.7825
Between	0.00012571 (0.00027917)	0.6551	0.00099526 (0.00213798)	0.6443	-0.079322	0.90983
Two-way	0.00025587 (0.00015593)	0.1023	0.00073377 (0.00264602)	0.7818	-0.2188	0.36691

Table A.3.8. Results of panel regression models of Solving Rates of Violent Crime on lag(Intelligence and Investigation Allocation Ratio), Crime Rate 3, and Non-Staff Cost per Workforce.

	Intercept		Lag(INTR)		CR3	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	0.39610452 (0.05059520)	1.43e-13	-0.07509712 (0.27363888)	0.78398	0.00031818 (0.00018773)	0.09135
Individual			0.07966170 (0.28911111)	0.7832	0.00018241 (0.00021148)	0.3894
Between	0.43693369 (0.12585496)	0.4757	-0.79868963 (0.83702203)	0.346011	0.00064160 (0.00043161)	0.145392
Two-way			-0.06174616 (0.30102876)	0.8377	0.00011156 (0.00022058)	0.6136

	NW		Model	
	coefficient (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	-0.00137274 (0.00179042)	0.44398	0.0030355	0.29053
Individual	-0.00111378 (0.00211901)	0.5997	-0.20565	0.75632
Between	-0.00090052 (0.00368944)	0.808482	0.025981	0.26824
Two-way	-0.00134045 (0.00398769)	0.7371	-0.24003	0.93696

Table A.3.9. Results of panel regression models of Confidence on Legitimacy, Satisfaction and Engagement.

	Intercept		FC		NRR	
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	coefficent (Std.Error)	p-value
Pooling	0.47994206 (0.09892009)	2.123e-06	-0.03216091 (0.03232818)	0.3208	-0.06883082 (0.04298481)	0.1105
Individual			0.00853921 (0.04738002)	0.857142	-0.16211381 (0.05706992)	0.004933
Between	0.4863057 (0.1624539)	0.004829	-0.0572696 (0.0526458)	0.283523	0.0190633 (0.0771831)	0.806247
Two-way			-0.0244920 (0.0589543)	0.678243	-0.1654020 (0.0577939)	0.004637

	NW		Model	
	coefficient (Std.Error)	p-value	Adj.Rsq	F-stats p-value
Pooling	0.00058230 (0.00059695)	0.3302	0.004216	0.25334
Individual	-0.00048656 (0.00066077)	0.462316	-0.15758	0.037436
Between	0.0028286 (0.0014058)	0.051340	0.052718	0.17113
Two-way	-0.0010411 (0.0011961)	0.385060	-0.18859	0.035289

Table A.3.10. Results of panel regression models of Reporting Rate of Property Crime on Confidence.

	Intercept		Fear of crime			
	coefficient (Std.Error)	p-value	coefficent (Std.Error)	p-value	RSq	Adj. Rsq
Pooling	0.3952051 (0.1355004)	0.003814	-0.0076952 (0.0350143)	0.826201	0.00016595	-0.003269
Individual			0.074925 (0.039950)	0.06189	0.013874	-0.15179
Between	0.968559 (0.303210)	0.002733	-0.155944 (0.078375)	0.053488	0.090061	0.067313
Two-way			0.082467 (0.056138)	0.1431	0.0087668	-0.18623

Appendix V. Highlighted characteristics of performance in each force.

This section highlights main characteristics, instead of all details, of performance in each police force under the performance measurement. Firstly, recall the police force families:

Group 1: Metropolitan;

Group 2: Dyfed-Powys, Gwent, North Wales, South Wales;

Group 3: Bedfordshire, Surrey, Cambridgeshire, Thames Valley, Hertfordshire;

Group 4: Cleveland, Merseyside; Durham, Northumbria, Humberside;

Group 5: Avon and Somerset, Norfolk, Devon & Cornwall, North Yorkshire, Dorset, Northamptonshire, Essex, Suffolk, Gloucestershire, Sussex, Hampshire, Warwickshire, Kent; West Mercia, Leicestershire, Wiltshire;

Group 6: Greater Manchester, West Midlands, South Yorkshire, West Yorkshire;

Group 7: Cheshire, Cumbria, Derbyshire, Lancashire

Here characteristics in performance measurement of 42 police force areas are listed as follows. Aspects that police forces did well and worse are recorded.

(1) Avon and Somerset:

Large improvement in clear-up rates for property crimes;

Improved contact satisfaction during both the period of austerity and post austerity.

(2) Bedfordshire:

Outstanding pure efficiency in force family;

More worries in force family in six years;

Large reduction of violent crimes during the period of austerity, and it continued to reduce during the post period;

(3) Cambridgeshire:

Worse pure efficiency in force family;

Large reduction of violent crimes during the period of austerity.

(4) Cheshire:

Worse pure efficiency in force family;

Fear of crime increased during the period of austerity;

Large improvement in clear-up rates for property crimes, and it continued to improve during the post period;

Large improvement in clear-up rates for violent crimes, and it continued to improve during the post period;

Dissatisfied contact in 2017.

(5) Cleveland:

Outstanding efficiency in force family;

Less fear of crime than the national average in all years;

Least fear of crime in family;

Improved clear-up rates for property crimes in both the period of austerity and post period.

Dissatisfied police-public contact in 2017.

(6) Cumbria:

Outstanding pure efficiency in force family;

Less fear of crime than the national average in all years;

Least fear of crime in family;

Improved clear-up rates for property crimes during both the period of austerity and post period;

Improved most clear-up rates for violent crimes during the period of austerity;

Public engagement was better than the national level in six years;

(7) Derbyshire:

Outstanding pure efficiency in force family;

Less fear of crime than the national average in all years;

Reduced crime rates of motor and household crime during both the period of austerity and post period.

Large reduction of crime rates of property violent during the period of austerity.

Large improvement in clear-up rates;

Public confidence less than the national average;

Improved contact satisfaction during both the period of austerity and post period;

Confidence from victims was more than that from non-victims in 2015.

(8) Devon and Cornwall:

Outstanding pure efficiency in force family;

Less fear of crime than the national average in all years;

Most reduction of crime rates of personal property crime among all police forces;

Improved clear-up rates for property and violent crimes in both the period of austerity and post period;

Public engagement was better than the national level in six years;

(9) Dorset:

Outstanding pure efficiency in force family;

Less fear of crime than the national average in all years;

Most reduction of crime rates of personal violent crimes;

Improved clear-up rates for violent crimes largely in both the period of austerity and post period;

Worse legitimacy experience in the public-police contact in six years.

(10) Durham:

Outstanding pure efficiency in force family;

Less fear of crime than the national average in all years;

Least fear of crime in force family;

Reduced crime rates of motor and household crime during both the period of austerity and post period;

Improved clear-up rates for violent crimes largely in both the period of austerity and post period;

Lower legitimacy experience in contact in the public-police contact in six years.

(11) Dyfed-Powys:

Outstanding pure efficiency in force family;

Less fear of crime than the national average in all years;

Largest reduction of fear of crime during the period of austerity;

Largest reduction of crime rates of personal violent crime but it rose during the post period.

(12) Essex:

Fear of crime increased during the period of austerity;

Improved clear-up rates for property and violent crimes in both periods of austerity and post-austerity.

(13) Gloucestershire:

Large reduction crime rates of motor and household property crime;

Public-police contact was dissatisfied in 2017;

(14) Greater Manchester:

Low scale efficiency;

More worried than the national level in all years;

Public confidence deprived during the period of austerity;

The most deprived engagement during the period of austerity.

(15) Gwent

Less fear of crime than the national average in most years;

Reduced crime rates of motor and household crime during both the period of austerity and post period;

Less legitimacy in contact than the national average in six years;

(16) Hampshire

Outstanding pure efficiency in force family;

Large reduction in crime rates of personal property crime during the period of austerity;

More public engagement than the national average in six years;

(17) Hertfordshire

Large reduction in crime rates of motor and household property crime during the period of austerity.

(18) Humberside

Worse pure efficiency in force family;

Less legitimacy in contact than the national average in six years;

Dissatisfied public-police contact in 2017.

(19) Kent

Worse pure efficiency in force family;

Large reduction in crime rates of personal violent property crime during the period of austerity;

Confidence less than the national level in all years;

(20) Lancashire

Large improvement in clear-up rates of violent crime during the period of austerity;

More public engagement than the national average in six years;

(21) Leicestershire

Outstanding pure efficiency in force family;

Increased fear of crime during the period of austerity;

Most reduction of crime rates of motor and household property crime but it rose during the post period.

Large improvement in clear-up rates of violent crime during the period of austerity;

(22) Lincolnshire

Outstanding pure efficiency in force family;
Reduced crime rates of motor and household property crime during both the period of austerity and post period;
Large reduction in crime rates of personal property crime during the period of austerity;
Most improvement in clear-up rates for property crime during the period of austerity;
More public engagement than the national average in six years;
Victims had more confidence in the police than non-victims in 2015;

(23) Merseyside

Most fear of crime in police family;
Increasing fear of crime during both periods of austerity and post-austerity;
Large reduction in crime rates of motor and household property crime during the period of austerity;
Large reduction in crime rates of personal property crime during the period of austerity;
Confidence less than the national average in all years;
Dissatisfied contact in 2017;
Less engagement than the national average in all years;
Better legitimacy experienced in contact than general imagination in all years;

(24) Metropolitan Police

Low scale efficiency;
Increasing fear of crime during the period of austerity;
Reduction in crime rates of motor and household property crime during both periods of austerity and post-austerity;
More legitimacy in contact than the national level in all years;

(25) Norfolk

Worse pure efficiency;
Most rose crime rates of motor and household crime;
Most deprived clear-up rates for property crime；
Most deprived contact satisfaction;

(26) North Wales

More fear of crime than the national level in six years;
Most decreased clear-up rates for violent crime;

Confidence less than the national level in all years;
Dissatisfied contact in 2012

(27) North Yorkshire

Low scale efficiency;
Less fear of crime than the national level in all years;
Least fear of crime in police family in 6 years;
Reduced crime rates of motor and household property crime during both periods of the austerity and post austerity;
Large improvement in clear-up rates for property crime;

(28) Northamptonshire

Large reduction in crime rates of motor and household property crime during the period of austerity and it continued to be reduced during the post period;
Most deprived legitimacy in contact during the period of austerity;

(29) Northumbria

Outstanding pure efficiency in force family;
Reduced crime rates of motor and household property crime during both periods of the austerity and post austerity.

(30) Nottinghamshire

Reduced crime rates of motor and household property crime during both periods of the austerity and post austerity;
Most increased crime rates of violent crime;
Most deprived confidence from the public during the post period.

(31) South Wales

Worse pure efficiency in force family;
Increasing fear of crime during the period of austerity;
Confidence less than the national level in all years;
Public engagement less than the national level in all years;
Victims had more confidence than non-victims in 2017.

(32) South Yorkshire

Low scale efficiency;
Worse pure efficiency in force family;
More fear of crime than the national level in six years;
Increasing Fear of crime during the period of austerity;

(33) Staffordshire

Large reduction in crime rates of motor and household property crime during the period of austerity;

Large improvement in clear-up rates for property crime during the period of austerity;

Dissatisfied contact in 2017;

Victims had more confidence than non-victims in 2015.

(34) Suffolk

Worse pure efficiency in force family;

More fear of crime than the national level in all years;

Large improvement in clear-up rates for property crime during the period of austerity;

Most improved public confidence during the period of austerity, but it fell during the post period;

Most improved public engagement during the period of austerity.

(35) Surrey

Less fear of crime than the national level in all years;

Most improved legitimacy in contact during the period of austerity;

Most improved contact satisfaction, and it fell during the post period;

(36) Sussex

Deprived public confidence during the period of austerity;

(37) Thames Valley

More public confidence than the national average in all years;

Improved contact satisfaction during the both periods of austerity and post austerity;

(38) Warwickshire

Outstanding pure efficiency in police family;

Large reduction in crime rates of personal property crime during the austerity of period, and it continued to reduce during the post period;

Dissatisfied contact in 2017;

Victims had more confidence than non-victims in 2017;

(39) West Mercia

Large improvement in clear-up rates of violent crime during the period of austerity;

Less legitimacy experienced in the public-police contact than the national level in six years;

(40) West Midlands

Low scale efficiency;

Outstanding pure efficiency in police family;

More fear of crime than the national average in all years;

More fear of crime in police force in six years;

Increased fear of crime during the period of austerity;

Reduced crime rates of motor and household property crime during both periods of the austerity and post austerity;

Large reduction in crime rates of personal property crime during the period of austerity and it continued to reduce during the post period.

(41) West Yorkshire

More fear of crime than the national average in all years;

Improved clear-up rates for property crimes during the post period;

(42) Wiltshire

No characteristics identified.

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