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Enhancing Police Efficiency in Detecting Crime in Hong Kong

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Abstract

In this study we examine how the process of crime detection by frontline and investigative police can be modified so that the same level of policing inputs (i.e. police strength) can produce more outcomes (i.e. crime detection rate). A pooled frontier analysis method is used to measure the relative efficiency of 18 police districts in Hong Kong from 2007 to 2015 ($n = 18$ districts $\times$ 9 years $= 162$ decision making units (DMUs)), demonstrating variable returns-to-scale. Findings reveal that 95 of the 162 DMUs were found to be inefficient compared to the benchmark DMUs (those police districts identified by the Free Disposable Hull (FDH) approach as efficient) with an average FDH efficiency score of 95.37 out of a possible score of 100. Efficient districts provide an exemplar on how an inefficient district could achieve an optimal input–output translation for the detection of crime. This evidence can be used to shape police policy at the district level. This study represents the first frontier analysis of police efficiency in the detection of crime in Hong Kong using the most recent efficiency technique. We produce evidence that can inform police policy regarding the deployment of finite resources that improve the efficiency of detection without compromising other institutional targets.

Keywords Police efficiency · Policing policy · Data envelopment analysis · Crime detection · Applied management

Introduction

Little evidence existed before the mid-1990's regarding the relationship between the number of police and crime. The questions posed around this time were: (1) would more police reduce the number of crimes; or (2) will cutbacks in the

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number of officers potentially increase the rate of crime? Reviews of the literature conducted by Cameron (1988), Marvell and Moody (1996) and Eck and Maguire (2000) conclude that there is little evidence to suggest a link between the number of police and the level of crime (i.e. more police leads to more crime – in other words a net widening effect). The apparent lack of solutions to the above questions was complicated by the fact that researchers in this area were primarily using regression-based analytical methods to ascertain these relationships. Such methods, however, do not provide solutions to what resource allocation changes are necessary to improve police efficiency. In the Marvell and Moody (1996) review of 36 studies, they found only ten studies who reported a negative association between police numbers and crimes of any type. They did, however, find 15 studies that reported a positive association between the rate of crime and the number of police. Subsequently, Sherman and Eck (2002) in their study of the association between police numbers and rate of crime concluded that the lack of police (for example during police-strikes) significantly increases crime. In addition, there was evidence to suggest that the association is weak, whereby there is only a marginal effect of increasing police numbers on crime. Previous literature also suggests that police reduce violent crime more so than property crime (see for example, Chalfin & McCrary, 2013; McCrary, 2002; Evans & Owens, 2007). Chalfin and McCrary (2013) found a significant negative association between numbers of police and levels of murder, rape, robbery, assault, burglary, larceny and motor vehicle theft. In their study, the elasticity for violent and property crimes is -0.34 and -0.17, respectively. A comprehensive review of selected studies focusing on the relationship between police numbers and/or arrests and crime is provided in Appendix Table 5.

The studies of estimates of the police elasticity of crime provide evidence regarding the potential deterrence of police deployment (i.e. a 10% increase in the number of police results in an x% decrease in a given crime type). They do not, however, provide evidence of where changes can be made in the deployment of officers and detectives to improve the detection of crime. We argue that the concept of efficiency is particularly important with respect to policing, as it is significantly different to other activities where employees and resources can be laid off or quickly hired (as new police recruits require significant training) in response to changes in demand. We propose that stable police presence is always required to act in response to crime but also in the prevention of crime. In other words, the presence of police deter crime by raising the probability of arrest and, to some degree, lower the demand for offending (Yezer, 2013). In an environment where the growth of police numbers is driven by: (1) the perception that government is being tough on crime and responding to public need; and (2) increases in the population – which directly or indirectly affects the crime rate – the efficiency of the police is of principal concern to both the state and the organisation. In this study, we propose an empirical solution to this concern and argue that relying on intuition and non-empirical methods alone when examining efficiency of crime detection is difficult to defend and unsystematic and vulnerable to bias and error in judgement.

Methods employed by criminal justice agencies to enhance the efficiency of crime detection include techniques such as hot spots policing – which focuses on small geographical areas where crime is concentrated and police can highly focus their resources, using traditional law enforcement strategies, to disrupt the crime event (Braga, 2005; Sherman, 1995), risk terrain modelling – that employs GIS techniques to explore the relationship between crime and the spatial features that influence the crime event (Drawve et al., 2016; Valasik, 2018) and community policing – a strategy that attempts to address the causes of crime and reduce fear of social disorder through community partnerships and other third parties (Goldstein, 1990; Mastrofski & Warden, 1995). What differentiates these techniques from the method we employ in this paper (i.e. frontier efficiency modelling techniques such as the data envelopment analysis (DEA)) is that these techniques do not attempt to empirically address the question of efficiency in use of police resources in detecting crime. Rather, the techniques focus on patterns of crime and are employed by police to detect and disrupt the crime event. Our intent is to focus exclusively on the efficient use of policing resources in the detection of crime. Coupled with the use of techniques described above, frontier models provide an opportunity for criminal justice agencies to efficiently target crime using an optimal allocation of finite resources.

In this study we use the frontier efficiency modelling technique to measure the relative efficiency of 18 police districts in Hong Kong between the years 2007 and 2015. The purpose is to empirically examine, using administrative policing data, how the process of detection can be modified so that the same level of inputs (i.e. police strength) can produce more targeted outcomes (i.e. detection rate of selected crimes). These results allow police to make evidence-based decisions on how limited resources can be better used to enhance the efficiency of detection. In short, with this evidence, police are able to strive to meet their district targets (e.g. a rate of detection) within their current budget.

The use of DEA and other frontier methods in examining police efficiency is still in its infancy with only few studies undertaken in Asia or within Chinese communities. Moreover, these studies tend to focus on the count of police (as the input) and number of crimes and/or arrests (as the output). We argue that the use of a count as opposed to the use of a rate (e.g. police-to-crime ratio or arrest/detection rate) is problematic. The use of a count (e.g. crime, arrest or detection) may simply reflect a proxy of other district-specific characteristics such as population size, geographical size or socioeconomic status of the population. Similarly, the use of police strength in the model as a count does not consider the level of crime problem in each district. This study, to the best of our knowledge, represents the first analysis of the efficiency of Hong Kong policing in examining the rate of detection in relation to the deployment of frontline police officers and detectives.

The paper proceeds as follows. First, we provide a review of the economic foundations regarding the efficiency of policing services and provide a non-technical outline of our efficiency modelling technique. Next, we introduce the variables that have been previously employed to measure the efficiency of policing services. Here we highlight key problems associated with the use of some of these variables and present less biased preferable alternatives. This is followed by an outline of the method used in this study. We then present results of the analysis including efficiency scores for the 18 Hong Kong policing districts across the nine years of analysis. Finally, we provide a discussion of our findings and highlight where future research can be undertaken to identify the factors that may influence police efficiency.

Measuring efficiency

Measuring the efficiency consists of two components – technical efficiency and allocative efficiency. *Technical efficiency* refers to the ability of an organisation to achieve maximum output (e.g. rate of crime detection) from a given set of inputs (e.g. police strength – that is, number of police in a given district). In other words, technical efficiency is the effectiveness with which a given set of inputs is used to produce an output. An organisation, such as a police force, is said to be technically efficient if it is producing the maximum output (here, the detection of crime) from the minimum quantity of inputs, such as police strength. *Allocative efficiency* reflects the organisations ability to optimise the use of inputs (such as police strength) given their respective monetary value (e.g. salary) relative to a set of comparable reference organisations (such as other policing districts) (Charnes et al., 1978). In economic terms, allocative efficiency is at an output level where the price equals the marginal cost of production. This is because the price that consumers are willing to pay is equivalent to the marginal utility that they get from a good or service. Therefore the optimal distribution is achieved when the marginal utility of the good or service equals the marginal cost. Since we do not apply any cost data to this experiment, our focus is purly on technical efficiency.

The identification of overall productivity efficiency is often demonstrated through the application of frontier models and illustrated through the use of the production possibilities frontier (PPF). The PPF identifies combinations of outputs that can theoretically be achieved by employing the same or similar amount of inputs or factors of production (e.g. land – natural resources, labour – human inputs or resources, enterprise – entrepreneurial developments, and capital – goods and technology used in the process of production). In the context of policing, this could be the amount of crime detected (outputs) by a combination of factors of production (e.g. police strength) (inputs). To maximise the efficiency of police activity, two models are commonly utilised – input-orientated and output-orientated. The input-oriented model allows us to measure technical efficiency by addressing the question: by how much can inputs be proportionally reduced to produce the same amount of outputs? The output-oriented model addresses the question: by how much can an output be proportionally increased without changing inputs? In summary, frontier analysis allows one to: (1) see if the allocation of resources in an organisation is efficient (through the use of input-/output-oriented models); and (2) identify how efficiency can be improved (by enhancing *technical efficiency*).

Data envelopment analysis

A commonly used frontier analytic approach that allows us to achieve the aforementioned points above is DEA. DEA provides a mathematical programming approach to the construction of a production frontier (i.e. PPF) that measures the relative efficiency of similar organisational entities, known as decision-making units (DMUs). Basic DEA models require a choice of input/output orientation (i.e. minimisation of inputs to achieve given levels of outputs or maximisation of outputs given the level of inputs utilised) and an assumption on scale of inputs/outputs conversion (i.e. constant returns-to-scale (CRS) or variable returns-to-scale (VRS)). The original DEA-CCR model (Charnes et al., 1978) assumes a CRS. With an alternative set of assumptions, the DEA-BCC model (Banker et al., 1984) adopts the VRS allowing the generation of DMU-specific scale-efficiency information for each DMU on the PPF. This can be characterised as either increasing returns-to-scale (IRS) (e.g. one unit of input results in more than one unit of output) or decreasing returns-to-scale (DRS) (e.g. one unit of input results in less than one unit of output). In both IRS and DRS, the translation of inputs and outputs could be a relative change as discussed in the results section. The overall technical efficiency (commonly known as the *overall efficiency* measured under the DEA-CCR model) can be decomposed into pure technical efficiency (commonly known as *technical efficiency* measured under the DEA-BCC model) and scale efficiency (i.e. overall efficiency divided by technical efficiency). A DMU is scale efficient (i.e. if a score of 1) if it operates in equal efficiency under CRS and VRS.

Measuring efficiency of policing services

Scholars and policing organisations alike see the benefits of examining the efficiency of police operations with a particular focus on how the same inputs (e.g. number of frontline police) can be transformed into more outcomes (e.g. detections and arrests). A number of studies have been conducted in different jurisdictions including England, Wales, Belgium, Australia, Taiwan, Israel, and India. A list of these studies with information regarding their DEA model and selection of variables is available from: https://drive.google.com/open?id=0B51RyzQHMmUEM2drSklRb1lUbjg (blinded for review). Few studies measuring efficiency of police services have been conducted in Asia, with most undertaken in the late 1990s and early 2000s. Examples include Sun (2002) (14 Taipei municipal police precincts, 1994–96), Verma and Gavirneni (2006) (Indian police forces in 1997), and Wu et al. (2010) (22 police districts in Taiwan, 1994–96). These important studies, albeit old, are typically limited by choice of input variable (e.g. count of police strength as opposed to ratio (e.g. police-crime ratio)), which fails to capture potential heterogeneity. This limitation is discussed in the method section below. DEA as discussed earlier has been used widely, with much success, across a range of disciplines. Only recently, and as highlighted in Appendix Table 5, has it been used in the domain of crime and policing. The method we outline below provides new insights into police efficiency in the Asian context, providing an additional resource for police practitioners and policymakers in the detection and, ultimately, the prevention of crime.

Outputs variables used in DEA of the police production process

Outputs of the police production process can be classified into two broad categories, representing two different dimensions of activity – the control of crime and the maintenance of social order. One of the most commonly used output variables in efficiency analysis of crime prevention activity is the number of offences recorded in the area. Earlier studies (e.g. Carrington et al., 1997; Drake & Simper, 2000; Nyhan & Martin, 1999) have used the total number of offences recorded or the number of offences recorded by crime type or category. This practice, however, is seen as problematic as the choice of crime type/s that the police prevent is/are arbitrary and the inputs or contribution from other interventions from society (e.g. education, occupation and vocational skills training programs) may be neglected. Also, as previously highlighted, findings on the relationship between the number of police officers and crime are mixed – with a positive association found for a net-widening effect and a negative association found in the general deterrence of crime.

Number of arrests and clear-ups/detection are also commonly used as output variables. These numbers and figures can be presented in absolute terms (i.e. the number of arrests/offence cleared) or in relative terms (i.e. the arrest/clear-up rates – number of arrests/clear-ups in relation to the number of recorded crimes). With the aim of reflecting this possible heterogeneity in resolution of different crimes, analysts may also segregate the numbers and figures by crime type or category. With regards to arrests and clear-ups/detection, arrests are considered to be a less preferable option. For example, Diez-Ticio and Mancebon (2002) identify two key limitations—the first limitation concerns over evaluation of efficiency due to the potential scenarios with wrongfully arrested individuals or illegitimate arrests of guilty individuals without the support of evidence for conviction and sanction. The second focuses on the higher possibility of manipulation and misconduct by the police in making a false (single or multiple) arrest opposed to detecting crime.

Based on the potential limitations that are observed among counts of number of crimes and arrests, detection, and specifically the detection rate of crime (as the output variable), is deemed to be a less biased measure of efficiency than the available alternatives. A key strength of using the detection rate, as a relative term, more accurately reflects the efficiency of policing in relation to the level of the crime problem in a given district. The use of a rate would, therefore, ensure that the output (e.g. crime, arrest or detection) is not a proxy of other district-specific characteristics such as population size, geographical size or socioeconomic status of the population. Since the detection rate is dependent on the level of the crime problem (i.e. detection rate equals number of detected crimes divided by the number of recorded crimes), caution should be exercised as the presence of police officers may potentially affect the rate in a number of ways: (1) detecting more crimes; (2) deterring crime – reducing the denominator; or (3) widening the net and recording more crimes – increasing the denominator.

Input variables used in DEA of the police production process

There are two key types of input factors that affect the police production process: (1) resources (e.g. land, labour and capital); and (2) contextual factors (e.g. population size, geographical size of the district). Resources tend to be under the control of the policing agency, while contextual factors lie outside the control of the policing agency.

With regards to resources, labour—as in the strength of police (sworn officers and civilians), and capital equipment (e.g. number of premises, vehicles and information systems etc.) are commonly included in efficiency analysis models. Depending on the type of efficiency model, these resources may be priced as expenses (for cost-efficiency analysis) or quantified as functional inputs such as labour force (for allocative efficiency analysis). In the former, where the analyst attempts to evaluate the relative cost-efficiency of a DMU (e.g. police station) in relation to the benchmark DMUs, the expenditure/s are commonly captured under categories including, total department costs, employment costs, premises-related expenses, transport-related expenses and capital and other costs. In the latter, the unit used for each labour and capital input may vary. Earlier models (e.g. Barros & Alves, 2005; Carrington et al., 1997; Diez-Ticio & Mancebon, 2002; Gorman & Ruggiero, 2008; Hughes & Yaisawarng, 2004; Moore et al., 2005; Sun, 2002; Thanassoulis, 1995) used the total number of police officers to reflect the endowment of the labour force. Some of these studies calculate the ratio of the total number of police officers to total population of the district for the input.

Police strength may be disaggregated according to employment duties and fundamental mission – sworn police (e.g. regular police and detectives) and civilian/non-sworn police officers (e.g. crime analysts). Sworn positions include uniformed police officers that are responsible for general law enforcement duties such as regular patrols and response to calls for service, and detectives who gather facts and collect evidence for criminal cases. There may be other grouping methods for accommodating a range of specialised units, but the simple division between uniformed police officers and detectives allows the analyst to distinguish the labour inputs according to their contribution in identifying potential offences and subsequently employing criminal justice processes as guided by jurisdictional laws. Such a distinction by reference to functions, however, is not widely applied in the existing DEA models of police efficiency. This may be due to data limitations, where detailed information about the police strength in each DMU is not available, and/or assuming that the participation of all police officers in the production process is equal. Civilian or non-sworn positions may include a range of roles from a crime analyst who translates crime data into information (e.g. crime trends and patterns), to forensic technicians that collect and analyse evidence at the crime scene. Since civilian officers, by the nature of their duties, are often considered to be less directly involved in the production process of crime clearance, they are sometimes treated as a separate labour input or omitted from the DEA model.

Capital inputs such as vehicles, evidence-gathering equipment, detection materials and premises represent the technology and non-human resources that are available for the police to generate outputs (e.g. detecting crime or arresting offenders). One of the most commonly used capital inputs in allocative efficiency analysis is the number of vehicles available. Most capital inputs may be captured using policing expenditure budgets.

Contextual or external factors provide a picture of the underlying context in which the production process takes place. The inclusion of these variables provides an explanation on why similar DMUs (that use a similar volume of resources) may have different relative efficiency scores. The general public can influence the production process, thus efficiency, in various ways. First, the population size is expected to be positively correlated with the demand on police services. That is, a larger population size reflects a larger group of potential and eligible users of police services. These services may or may not be crime-related. Therefore, police stations located in a highly populated district are more likely to spend additional resources dealing with other police tasks that are not directly related to combating crime. Second, a larger population makes the identification and detection of suspected offenders more difficult. Theoretically, the probability of arrest falls when the population in an area increases (Braithwaite, 1975; Yezer, 2013). Finally, apart from the adverse effects that a large population may have on the resolution of crime, the general public may contribute to the production process by working in collaboration with the police. Morris and Heal (1981) suggest that the public's report of crimes to the police is crucial to the detection and clearance of crime. With an implicit assumption that the public's willingness and ability to report crimes do not differ across districts, the population size of the district may serve as an approximation of the public's contribution to the police production process.

Another contextual factor that highlights fundamental variations across districts is the prevalence of crime in each district. This input may be included in output-orientated DEA models for the allocative efficiency of resources. Production models (e.g. Barros, 2006; Barros & Alves, 2005; Drake & Simper, 2005a, 2005b; García-Sánchez et al., 2013; Hadad et al., 2013; Sun, 2002) that consist of the number of various criminal activities recorded allow the analyst to evaluate the DMUs clear-up efficiency with regards to the given level of crime problem and volume of inputs used. This variable, when included as a direct input for the assessment of police efficiency, however, may violate the assumption of perfect substitutability and produce an inaccurate estimation of efficiency (Diez-Ticio & Mancebon, 2002). Specifically, the number of offences recorded often has a complementary relationship with the number of police – more police in a district may or may not lead to higher propensity for public citizens to report crime. The influence of the prevalence of crime/level of crime in the district is, therefore, suggested to be captured under the crime clear-up rate/detection rate as the output in an efficiency model.

Method

Current efficiency model

Administrative data (from 2007 to 2015) from the Hong Kong Police Force (Force from hereon) (2008; 2009; 2010; 2011; 2012; 2013; 2014; 2015; 2016) were used in this study. Our output-oriented model includes two inputs and three outputs. Inputs include two police-crime ratios – detective-crime ratio (i.e. the number of detectives in a district divided by the number of crimes reported in a given district (D)) and uniformed police-crime ratio (i.e. number of uniformed police in a district divided by the number of crimes reported (UPO)). Previous studies have used a count as an input (e.g. number of police officers) when measuring efficiency. We argue that the use of a count as opposed to a ratio (e.g. police-crime ratio) fails to capture potential heterogeneity (e.g. prevalence of crime and population size). In addition, some studies have used a ratio (i.e. a relative value) on one side of the equation and a count (an absolute value) on the other side. This may lead to an error of estimation if the DMUs are not of a comparable context – a police district with 100 officers detecting eight out of ten crimes (i.e. 80 percent) is not more efficient than a district with 100 officers detecting 70 out of 100 crimes (i.e. 70 percent). To the best of our knowledge, this is the only study of police efficiency that accounts for heterogeneity and potential error of estimation.

Some efficiency studies incorporate regional factors (e.g. population size, geographical size of a given area), however, such factors are not appropriate in this context as they do not contribute directly to the input–output translation. That is, the size of the population and geographical size of an area may moderate the efficiency of crime detection but do not generate such efficiency. In addition, the influence of population size will likely be captured in the case/workload of officers in a district. A strong positive correlation is found between population size and the number of reported crimes. As such the further inclusion of population size in our models is inappropriate as: (1) its effect is likely to have been captured through the two police-crime ratios mentioned above; and (2) it does not represent a modifiable input (such as police inputs). It is important to note that the method we employ is not to be confused with regression modelling. Rather DEA or other frontier modelling focuses on translation of inputs to outputs. In regression population may be a predictor of the rate of crime detection, but in efficiency analysis it is not considered to be an input that can be modified to improve the detection of crime.

Outputs in this model include detection rate of violent crimes, property crimes and other crimes (i.e. any crime not classified as a violent or property crime). Other potentially relevant variables such as information on number of civilian officers, capital equipment employed and cost data (e.g. program or operation costs) were not included in this efficiency analysis due to lack of data at the district level.

Similar to Sun (2002) we perform a window analysis (i.e. pooled frontier) to examine efficiencies of the 18 districts across a 9-year observation period (i.e.

a 9-year window). We use a window analysis as it assists in analysing trends and potential stability, that is changes in average efficiency across time periods and problems (e.g. civil unrest) across each district (Klopp, 1985). Each DMU (i.e. policing district) is, therefore, represented as if it were a different DMU for each of the nine successive years in the window (2007–2015). This results in an analysis of 162 (16×9) DMUs.

In unreported preliminarily analyses, we examined productivity changes in efficiency over time using the Malmquist productivity index (MPI) (Caves et al., 1982). In doing so, however, we found very little discrimination in our preliminary models. That is, we could only identify very little inefficiency and this is potentially the result of dimensionality rather than the inefficiency of police districts in Hong Kong. We, therefore, employed a pooled frontier analysis across all time periods and then considered the average efficiency across the years for each district and the average efficiency score in each year across districts. Doing so requires an assumption that it is reasonable to use a pooled frontier, so a unit can be compared to units from other time periods – specifically we assume here that the frontier has not changed much during the study period, which arguably is the case.

Critical to this analysis, the use of ratio measures of inputs and outputs may lead to biased estimates of efficiency using traditional DEA methods (CCR and BCC models). It is proposed that these potential biases may influence the convexity of the PPF. In order to reduce potential bias, we apply the Free Disposable Hull (FDH) approach to measuring efficiency as suggested by Olesen et al. (2015). Specifically, a convexity assumption in DEA draws upon possible linear substitutions between input combinations on an isoquant (Drake & Simper, 2003). The DEA efficient frontier is formed based on these isoquants which are derived in a piecewise linear fashion from the DMUs. Hence, each DMU is evaluated in turn relative to this piecewise linear isoquant. FDH does not make any convexity assumption and its isoquant represents a step function, rather than a linear function, through the observed input combinations (Berger & Humphrey, 1997). It is observed that when the convexity assumption is dropped (i.e. move from DEA to FDH), the estimated efficiency scores become higher as the efficient frontier tends to wrap itself closer around the data of each DMU. In line with the benefits that are associated with the FDH, the approach has been applied in a number of contexts including policing in the UK (Drake & Simper, 2003), performance of museums (Mairesse & Vanden Eeckaut, 2002), dynamics of deregulation in the US airline industry (Alam & Sickles, 2000), check processing offices of the Federal Reserve System (Bauer & Hancock, 1993), performance of U.S. life insurance companies (Cummins & Zi, 1998), heuristics for job scheduling problems on parallel machines when there are multiple criteria (Ruiz-Torres & López, 2004), and other local government services (e.g. social, educational, recreational, infrastructure and environmental services) (Geys & Moesen, 2009).

Sample and contextual setting

The Force is responsible for maintaining a safe and stable society by: upholding the rule of law; maintaining law and order; preventing and detecting crime; safeguarding and protecting life and property; and, working in partnership with the community and other agencies (Wong, 2015). The Force is divided into several branches for the day-to-day policing in six regions, which include five land regions (Hong Kong Island, Kowloon East, Kowloon West, New Territories North and New Territories South) and one marine region.

The Hong Kong Marine Police (Marine Police from hereon) is responsible for preserving order in the sea boundaries and waters within and surrounding Hong Kong (Wong, 2015). Apart from the aforementioned duties of the Force, the Marine Police perform additional duties including: assisting with the enforcement of port and maritime regulations; preventing illegal immigration and smuggling; conducting search and rescue operations; providing a casualty evacuation service; assisting the Director of Marine in implementing the International Ship and Port Facility Security (ISPS) Code; and, assisting with the promotion of sea safety and enforcement of related legislation (Wong, 2015). In view of the apparent differences with regards to the duties between the Marine Police and the rest of the Force, the Marine Region is not included in this analysis.

Two other districts, the Airport and Border, are excluded from the analysis as their organisation, operation and style of policing are different to regular civil policing (Force) in other policing divisions. The Airport Security Unit is responsible for airport security, primarily targeting terrorist situations such as aircraft hijacking. Policing in the border with China resembles a military-like operation, which was established in the 1950s during the British colonial period (Wong, 2015). Under the control and command of civilian Hong Kong Police, the British military policed the frontier in collaboration with the Hong Kong police. To date, the Force continues to defend against illegal immigrants and exceptional military situations (e.g. insurgency by bandits).

This study therefore focuses on 18 (out of 21) districts across nine years from 2007 to 2015. The 18 districts provide services to around 98 percent of the population and deal with more than 95 percent of all recorded crimes in Hong Kong. This sample, therefore, provides a sufficiently representative image of the incidence of crime and police activity in Hong Kong. In addition, the number of DMUs (i.e. 162 police districts) included in our study also satisfies the recommended minimum proposed by Golany and Roll (1989) (i.e. n should be greater than the total of two times the number of input and output variables) (in our case $n \geq 2*(2+3) \geq 10$), Friedman and Sinuany-Stern (1998) and Cooper et al. (2007) ($n \geq 3*(2+3) \geq 15$), and Dyson et al. (2001) (n should be greater than the total of two times the product of the number of input and output variables ($n \geq 2*(2*3) \geq 12$)).

Descriptive statistics

Table 1 provides a summary of the average detection rates of violent, property and other crimes as well as the number of detectives and uniformed police officers in 18 districts over the study period (i.e. 2007–15). The reported crime statistics are compiled based on crime cases known to the police and recorded at each successive stage of criminal administration. Similar to the UK system, there are

Table 1 Descriptive statistics of the 18 police districts (2007–2015)

Police district		Detection rate of violent crime	Detection rate of property crime	Detection rate of other crime	Number of detectives	Number of uniformed police officers
Central	Mean (M)	0.5936	0.2464	0.4629	0.0371	0.2387
	Standard deviation (SD)	0.0340	0.0261	0.0901	0.0017	0.0060
Eastern	M	0.5950	0.4116	0.3662	0.0328	0.1530
	SD	0.0377	0.0510	0.0513	0.0034	0.0150
Kowloon City	M	0.6718	0.3323	0.4750	0.0386	0.1989
	SD	0.0366	0.0304	0.0686	0.0033	0.0140
Kwai Tsing	M	0.6949	0.4251	0.4669	0.0325	0.1708
	SD	0.0260	0.0577	0.0202	0.0058	0.0315
Kwun Tong	M	0.6268	0.3602	0.3512	0.0264	0.1082
	SD	0.0646	0.0307	0.0473	0.0039	0.0130
Lantau	M	0.7102	0.3430	0.4390	0.0460	0.2720
	SD	0.0497	0.0712	0.0506	0.0037	0.0214
Mongkok	M	0.5648	0.3194	0.6030	0.0321	0.0889
	SD	0.0202	0.0381	0.0634	0.0014	0.0042
Sau Mau Ping	M	0.6923	0.3687	0.4165	0.0342	0.1570
	SD	0.0387	0.0400	0.0520	0.0036	0.0157
Sha Tin	M	0.6851	0.4040	0.4228	0.0354	0.1696
	SD	0.0257	0.0423	0.0435	0.0035	0.0160
Sham Shui Po	M	0.6136	0.3176	0.4960	0.0307	0.1305
	SD	0.0307	0.0198	0.0627	0.0029	0.0109
Tai Po	M	0.6352	0.3305	0.4578	0.0356	0.1193
	SD	0.0327	0.0281	0.0397	0.0020	0.0086
Tsuen Wan	M	0.6599	0.3636	0.4785	0.0391	0.1708
	SD	0.0429	0.0559	0.0587	0.0045	0.0165
Tuen Mun	M	0.6545	0.4030	0.4696	0.0377	0.1328
	SD	0.0278	0.0266	0.0503	0.0052	0.0180
Wanchai	M	0.5803	0.3568	0.4805	0.0334	0.1316
	SD	0.0671	0.0667	0.0528	0.0033	0.0122
Western	M	0.6924	0.3589	0.3944	0.0399	0.2129
	SD	0.0712	0.0273	0.0645	0.0038	0.0133
Wong Tai Sin	M	0.6604	0.3324	0.3915	0.0338	0.1687
	SD	0.0170	0.0280	0.0402	0.0033	0.0156
Yau Tsim	M	0.5369	0.3002	0.6150	0.0377	0.1426
	SD	0.0367	0.0289	0.0889	0.0020	0.0073
Yuen Long	M	0.6422	0.3680	0.5409	0.0337	0.1355
	SD	0.0281	0.0230	0.0504	0.0021	0.0095

four main principles adopted for counting crimes: (1) Violent crime against persons – here, one crime is counted for each person against whom an offence has been committed (e.g. murder, wounding). For example, a gang attack involving four victims, where there is one killing and three injuries, would be counted as one offence of murder and three offences of wounding; (2) Crime against property or public order – crime is counted for each distinct offence. For example, a case where two men armed with pistols who rob a bank with 10 customers inside would be counted as one offence of robbery; (3) Crime considered as a continuous offence if repeated (e.g. crimes such as blackmail, deception, and theft by employees). Here, one crime would be counted for each offence or series of similar offences committed by the same offender or group of offenders on different occasions involving the same victim or group of victims. For example, if three offenders blackmailed a shop-owner multiple times in the past three months this would be counted as one offence of blackmail; and (4) Crime associated with other naturally connected offences – here, when multiple related criminal acts are performed, the official statistics would capture the most serious offence as the principle offence. For example, if an offender is arrested for attempting to steal from a vehicle which involves damage to property, the offence of vehicle theft would be counted rather than offence of criminal damage or offence of possession of instruments for unlawful purposes.

According to the data, Lantau appears to have the highest average violent crimes detection rate. This is followed by Kwai Tsing and Western. The detection rate of property crimes is found to be the highest in Kwai Tsing, followed by Eastern and Sha Tin. Yau Tsim, Mongkok and Yuen Long have high, relative to other districts, detection rates in other crime types. Regarding the district inputs, Kwun Tong and Mongkok have a low average proportion of detectives and uniformed police officers compared to other districts.

Results

Window analysis

We found that, across the study period, the average FDH efficiency across districts was 95.37 (SD = 6.24). We conducted a window analysis of FDH efficiencies for the 18 police districts and provide results in Table 2. Findings reveal that 95 of the 162 DMUs were found to be inefficient. The 67 DMUs that had a FDH efficiency rating of 100 percent include Wanchai (2007, 2013, 2014), Western (2007–08), Eastern (2009–11, 2015), Sau Mau Ping (2008–11), Kwun Tong (2007–11, 2015), Yau Tsim (2007–08, 2012), Mongkok (2007–09, 2012–13), Sham Shui Po (2008–10), Kowloon City (2007–09), Yuen Long (2007–09, 2012–13, 2015), Tuen Mun (2007, 2009–2015), Tai Po (2009, 2015), Tsuen Wan (2008, 2012–13), Sha Tin (2007, 2014–15), Kwai Tsing (2007–15), and Lantau (2012, 2014–15).

Table 2 FDH efficiency score for the 18 districts from 2007 to 2015

District	Year	FDH efficiency score
Central	2007	0.972116554
Central	2008	0.89451632
Central	2009	0.940103169
Central	2010	0.806862973
Central	2011	0.761699952
Central	2012	0.838004751
Central	2013	0.691072249
Central	2014	0.799851806
Central	2015	0.765382256
Wanchai	2007	1
Wanchai	2008	0.842872537
Wanchai	2009	0.853247442
Wanchai	2010	0.872807216
Wanchai	2011	0.974637617
Wanchai	2012	0.99784906
Wanchai	2013	1
Wanchai	2014	1
Wanchai	2015	0.999163441
Western	2007	1
Western	2008	1
Western	2009	0.983799915
Western	2010	0.929506695
Western	2011	0.883088395
Western	2012	0.902614845
Western	2013	0.844784709
Western	2014	0.854597047
Western	2015	0.82470253
Eastern	2007	0.973893037
Eastern	2008	0.968639063
Eastern	2009	1
Eastern	2010	1
Eastern	2011	1
Eastern	2012	0.947450332
Eastern	2013	0.951009783
Eastern	2014	0.989785452
Eastern	2015	1
Wong Tai Sin	2007	0.918149112
Wong Tai Sin	2008	0.952450746
Wong Tai Sin	2009	0.943996772
Wong Tai Sin	2010	0.881166648
Wong Tai Sin	2011	0.843042322
Wong Tai Sin	2012	0.956580732
Wong Tai Sin	2013	0.963466556

Table 2 (continued)

District	Year	FDH efficiency score
Wong Tai Sin	2014	0.911752396
Wong Tai Sin	2015	0.894943506
Sau Mau Ping	2007	0.993494413
Sau Mau Ping	2008	1
Sau Mau Ping	2009	1
Sau Mau Ping	2010	1
Sau Mau Ping	2011	1
Sau Mau Ping	2012	0.993120392
Sau Mau Ping	2013	0.944746049
Sau Mau Ping	2014	0.974012617
Sau Mau Ping	2015	0.939062933
Kwun Tong	2007	1
Kwun Tong	2008	1
Kwun Tong	2009	1
Kwun Tong	2010	1
Kwun Tong	2011	1
Kwun Tong	2012	0.986653354
Kwun Tong	2013	0.92680416
Kwun Tong	2014	0.964877759
Kwun Tong	2015	1
Yau Tsim	2007	1
Yau Tsim	2008	1
Yau Tsim	2009	0.935617978
Yau Tsim	2010	0.823685099
Yau Tsim	2011	0.8847657
Yau Tsim	2012	1
Yau Tsim	2013	0.910124419
Yau Tsim	2014	0.848696381
Yau Tsim	2015	0.873050492
Mongkok	2007	1
Mongkok	2008	1
Mongkok	2009	1
Mongkok	2010	0.925996319
Mongkok	2011	0.947607881
Mongkok	2012	1
Mongkok	2013	1
Mongkok	2014	0.949091986
Mongkok	2015	0.969480574
Sham Shui Po	2007	0.992773362
Sham Shui Po	2008	1
Sham Shui Po	2009	1
Sham Shui Po	2010	1
Sham Shui Po	2011	0.954286444

Table 2 (continued)

District	Year	FDH efficiency score
Sham Shui Po	2012	0.969157015
Sham Shui Po	2013	0.905060052
Sham Shui Po	2014	0.875545233
Sham Shui Po	2015	0.885205895
Kowloon City	2007	1
Kowloon City	2008	1
Kowloon City	2009	1
Kowloon City	2010	0.96295064
Kowloon City	2011	0.848081557
Kowloon City	2012	0.857224341
Kowloon City	2013	0.878351459
Kowloon City	2014	0.829972263
Kowloon City	2015	0.950026909
Yuen Long	2007	1
Yuen Long	2008	1
Yuen Long	2009	1
Yuen Long	2010	0.980176431
Yuen Long	2011	0.914433829
Yuen Long	2012	1
Yuen Long	2013	1
Yuen Long	2014	0.958834941
Yuen Long	2015	1
Tuen Mun	2007	1
Tuen Mun	2008	0.980046606
Tuen Mun	2009	1
Tuen Mun	2010	1
Tuen Mun	2011	1
Tuen Mun	2012	1
Tuen Mun	2013	1
Tuen Mun	2014	1
Tuen Mun	2015	1
Tai Po	2007	0.940107368
Tai Po	2008	0.980954436
Tai Po	2009	1
Tai Po	2010	0.906433608
Tai Po	2011	0.976045651
Tai Po	2012	0.931295372
Tai Po	2013	0.933209648
Tai Po	2014	0.924936136
Tai Po	2015	1
Tsuen Wan	2007	0.8820954
Tsuen Wan	2008	1
Tsuen Wan	2009	0.966759963

Table 2 (continued)

District	Year	FDH efficiency score
Tsuen Wan	2010	0.999781084
Tsuen Wan	2011	0.965659395
Tsuen Wan	2012	1
Tsuen Wan	2013	1
Tsuen Wan	2014	0.972840265
Tsuen Wan	2015	0.98163013
Sha Tin	2007	1
Sha Tin	2008	0.952842525
Sha Tin	2009	0.985572539
Sha Tin	2010	0.981907615
Sha Tin	2011	0.996941148
Sha Tin	2012	0.987554873
Sha Tin	2013	0.97584781
Sha Tin	2014	1
Sha Tin	2015	1
Kwai Tsing	2007	1
Kwai Tsing	2008	1
Kwai Tsing	2009	1
Kwai Tsing	2010	1
Kwai Tsing	2011	1
Kwai Tsing	2012	1
Kwai Tsing	2013	1
Kwai Tsing	2014	1
Kwai Tsing	2015	1
Lantau	2007	0.874537488
Lantau	2008	0.843059613
Lantau	2009	0.879339198
Lantau	2010	0.815515708
Lantau	2011	0.987440247
Lantau	2012	1
Lantau	2013	0.993710788
Lantau	2014	1
Lantau	2015	1

Table 3 compares districts by their mean efficiency score and variance. Kwai Tsing has the highest mean efficiency score of 100, followed by Tuen Mun (99.78). The district with the lowest average efficiency score was Central (83). Those districts with a high average efficiency score also had a low variance, indicating a more stable performance in the detection of crime over the reporting period. Previous research (e.g. Sun, 2002) suggests that low mean efficiency scores tend to be accompanied by high variances across years. In the current study, Central, Lantau, Western, Yau Tsim and Kowloon City appear to follow such a pattern.

Table 3 Mean efficiency score and variance by district

District	FDH Efficiency		Technical efficiency (VRS model for comparison)	
	Mean	Variance	Mean	Variance
Central	83	9.09	80.62	8.25
Eastern	98.12	2.16	92.46	5.77
Kowloon City	92.52	7.13	89.20	7.11
Kwai Tsing	1	-	97.95	2.37
Kwun Tong	98.65	2.53	95.43	5.20
Lantau	93.26	7.77	90.59	7.68
Mongkok	97.69	2.95	94.12	4.69
Sau Mau Ping	98.27	2.46	93.89	3.39
Sha Tin	98.67	1.55	93.76	2.73
Sham Shui Po	95.36	5.17	88.87	4.77
Tai Po	95.48	3.48	90.71	2.74
Tsuen Wan	97.43	3.76	91.54	4.84
Tuen Mun	99.78	0.67	96.90	1.86
Wanchai	94.9	7.04	88.68	7.02
Western	91.3	6.83	89.22	6.98
Wong Tai Sin	91.84	4.03	86.74	2.42
Yau Tsim	91.95	6.83	88.49	7.63
Yuen Long	98.37	2.96	94.24	3.98

Some potential stability issues are highlighted in Table 2. Substantial reductions in efficiency (> 10% drop) were found for Central (2010, 2013), Wanchai (2008), Yau Tsim (2010), and Kowloon City (2011). Substantial rises in efficiency (> 10% increase) were found for Central (2012, 2014), Wanchai (2011), Wong Tai Sin (2012), Yau Tsim (2012), Kowloon City (2015), Tsuen Wan (2008), and Lantau (2011).

According to the correlation analyses, districts with higher crime rates (in any of the three categories) tend to have a: (i) lower detection rate in violent and property crime and a higher detection rate in other crimes; (ii) lower uniformed police-crime ratio (i.e. heavier caseload for uniformed police); and (iii) lower FDH efficiency score (see Table 4). Progress in time (i.e. subsequent reference years) also reveals: (i) an increase in the detection rate of property crime; (ii) an increase in the number of detectives per case; (iii) an increase in the number of uniformed police officers per case; and (iv) a decrease in efficiency score.

DEA-CCR and DEA-BCC results are provided in Appendix Table 6 so interested readers can compare them with the FDH estimates. We note however that some of the values in the inputs are small and close to zero in some districts. This may affect the feasibility of the linear programming model in DEA. Previous studies have overcome this problem by adding a constant to make the values positive and larger than

Table 4 Correlations between district crime rates, efficiency score, inputs and outputs

	Output: Detection rate of violent crime	Output: Detection rate of property crime	Output: Detection rate of other crime	Input: Number of detectives per case	Input: Number of uniformed police officers per case	Violent crime rate	Property crime rate	Other crime rate	Overall crime rate	FDH efficiency score	Year
Output: Detection rate of violent crime	1										
Output: Detection rate of property crime	0.297**	1									
Output: Detection rate of other crime	-0.130	-0.277**	1								
Input: Number of detectives per case	0.116	0.224**	-0.095	1							
Input: Number of uniformed police officers per case	0.329**	0.034	-0.272**	0.744**	1						
Violent crime rate	-0.579**	-0.479**	0.628**	-0.067	-0.221**	1					
Property crime rate	-0.618**	-0.517**	0.593**	-0.087	-0.213**	0.950**	1				

Table 4 (continued)

	Output: Detection rate of violent crime	Output: Detection rate of property crime	Output: Detection rate of other crime	Input: Number of detectives per case	Input: Number of uniformed police officers per case	Violent crime rate	Property crime rate	Other crime rate	Overall crime rate	FDH efficiency score	Year
Other crime rate	-0.587**	-0.419**	0.552**	-0.025	-0.190*	0.931**	0.948**	1			
Overall crime rate	-0.612**	-0.488**	0.595**	-0.066	-0.210**	0.968**	0.992**	0.978**	1		
FDH efficiency score	0.415**	0.571**	0.263**	-0.240**	-0.373**	-0.226**	-0.269**	-0.240**	-0.257**	1	
Year	-0.147	0.408**	-0.463**	0.468**	0.222**	-0.156*	-0.112	0.014	-0.081	-0.161*	1

** $p < 0.01$; * $p < 0.05$

0 (Sarkis, 2006). To overcome this potential problem, the additive method has been adopted where an integer is added to both inputs and outputs to handle the concern regarding small values as proposed by Sarkis (2006), Ali and Seiford (1990) and Pastor (1996). The above authors proposed that this method does not alter the efficient frontier for DEA formulations and thus are translation invariant. For detailed strengths and limitations of this method please consult Sarkis (2006). We note that results, especially the DEA-BCC efficiency scores, do not markedly change when the additive method is applied.

Discussion

This study utilises a well-established economic technique for identifying how the process of detection of crime can be modified so that police districts can improve their detection of violent, property and/or other crimes based on the current deployment of officers and detectives. Efficiency in policing is significantly different to other activities where employees and resources can be laid off or hired in response to short-term changes in demand. Here, police presence is always required as not only does it act to respond to incidents of crime but also is critical to the prevention of crime. This study aims to examine which police districts are more or less efficient in translating their limited resource inputs (i.e. officers and detectives) into outputs (i.e. detection of crimes). This is important for the police and government in justifying to the general population that public money is being utilised in the most efficient and effective manner. In addition, it allows police to make informed decisions that will assist in improving: (i) the rate of detection; and (ii) the efficiency of all police activities without compromising institutional targets (e.g. deterring crime and maintaining social order and promoting police-citizen relationships).

The analysis holds the contribution of each unit of input (i.e. officer-to-crime ratio) constant. In other words, the analysis assumes that each individual detective/officer contributes equally to the detection of crime. Inefficiencies identified in our results are based on the distance between the DMU and the benchmark on the FDH PPF frontier revealing a potential improvement in detecting more crimes based on the same level of inputs. Identified inefficiencies might reveal a limit to officers' performance due to district-specific factors or variations in terms of operational priorities (i.e. trade-offs of pursuing different institutional targets/spending more resources in detecting a particular type of crime). Our results imply that police commanders in less efficient districts could strategically focus resources in improving the detection of certain types of crime in order to be as efficient as the benchmark DMUs. Also, inefficient districts could benefit from making modifications to officer deployment in order to enhance their efficiency with respect to the detection of crime. To approach the benchmark DMU, those inefficient DMUs could benefit from discussions with those efficient districts regarding their deployment of human resources and other context-specific policing factors which may be useful for adaptation in enhancing the detection of crime.

Findings of the correlation analyses reveal relationships between the efficiency scores and contextual variables as well as the inputs and outputs of our efficiency model. Findings highlight an interesting pattern of police personnel allocation, where high crime areas with heavier caseloads per officer demonstrate a unique ability to achieve a high efficiency. This pattern may be attributed to better management and/or highly skilled police working in districts with a high crime rate.

The current version of our efficiency model provides insights to the use of publicly accessible administrative data to study police efficiency of crime detection. It should be noted that the findings alone are not sufficient to fully reveal the complex and dynamic process of crime recording and detection. The model can potentially be enhanced by the use of multivariate analyses that examine the influence of other contextual factors (e.g. the varying ability of police officers, employment rate, social cohesion, community satisfaction of police effectiveness) on the detection of crime. We discuss this issue further in the limitations section of this paper.

We also note that the nature and content of policing tasks is broad and dynamic. The Force, as a law enforcement agency, is required to perform a range of tasks including responding to and detecting crime. This highlights the important concept of 'attributable fraction' where resources can be utilised for multiple purposes. In our study, time allocated for police personnel to detect crime may depend on the changing priority of other demands (e.g. patrolling to facilitate crime deterrence and maintaining public order and crowd control during events of social movement). Our findings, therefore, need to be interpreted with the following assumptions: (i) an ongoing demand of crime investigation and detection which arguably exists as a key priority of the Force; and (ii) the time required for handling crime is evenly distributed across districts (i.e. there was not a particular district or some districts being subjected to a particular level of challenging and time-consuming cases). Future research which attempts to gauge the proportion of time uniform officers and detectives spend exclusively on crime detection will need to adopt either a top-down (e.g. institutional requirement or estimate) or bottom-up (e.g. reported or recorded officer time spent on different tasks) approach to yield an estimate of such a fraction.

It is important to recognise that those DMUs identified as being less efficient than their benchmark peers are potentially limited with regards to how many crimes can be detected relative to their level of police strength. Factors that contribute to a district's efficiency or inefficiency may also include district-specific factors. Examples include the size of the population, the geographical size of the district, the socio-economic status of the population and public willingness to engage with police in crime prevention and detection activities. With regards to the final example, a proxy may be whether or not citizens engage with police in activities such as neighborhood watch or other community policing interventions. In addition, there may be districts where there is a greater presence of private security organizations either formally protecting the entrances of buildings and apartments or undertaking routine security checks or the electronic monitoring of premises during times where there is less public presence (e.g. after hours and during the night).

A final note, other efficiency measures based on directional distance functions such as slack-based and hyperbolic measures of efficiency are not employed here but could be avenues for future research. We did not use these methods as the properties of such models, related computational methods and methodological issues need further examination before their inclusion can be validated. This is beyond the scope of this paper.

Conclusions

To verify the aforementioned speculation, further research is required that includes the above variables in the analysis. By doing so, the researcher can regress these potential explanatory variables to ascertain their contribution to the efficiency level of a given police district. Such analyses are critical to police operations as they assist in unpacking the complexity of the relationship between police and the detection of crime. Results are also beneficial to police from an operational and financial perspective. With regards to the former, police may wish to replicate an intervention in another district but are unsure what resources may be required to meet outcomes that were achieved in the benchmark district. Here, the results of an extended efficiency analysis (i.e. with the inclusion of districts-specific and relevant variables) can assist in command decisions regarding the deployment of both frontline and investigative officers – sensitive to specific district contextual variation. With regards to finance, police commanders can use the evidence derived from the extended efficiency analysis to make formal requests, which is supported by evidence, for additional resources to assist in the deployment of officers that are engaged to enhance the detection of crime in their district.

This research should be considered as the initial step in assisting police in the detection of crime and the allocation of resources to improve the efficiency of detection. A challenge concerning the use of district level administrative data is that we are unable to fully disaggregate officer time spent on different tasks. As such, we are unable to accurately measure the attributable fraction of time spent by an officer on crime detection. Also, these data do not allow for the differentiation of arrests that are made during social movements (e.g. the 2014 Umbrella Movement pro-democracy protest) from those outside such movements. Since social movement protesters might be arrested under a wide range of principle offences, it is not possible to distinguish protest arrests from other arrests. This may lead to a potential bias in which detection rates appear high. To address this potential bias, we undertake a separate analysis, which excludes specific districts (e.g. Central-2014) in which a protest took place in 2014. The exclusion of this district does not appear to affect the overall performance of the analysis where we find changes to mean efficiency scores are less than 0.001 and all benchmark police stations remain unchanged in models with and without the inclusion of Central-2014.

Also, as argued above, frontline uniformed police play a role in both the prevention and the detection of crime. Detectives, however, may play less a role in the prevention of crime than frontline police as criminals will not have access to data regarding the performance of detectives in solving crimes. As such, the criminal cannot make any accurate assessments of the probability of their crimes being detected, which in turn may act as a deterrence. In terms of the reallocation of police resources based on the results, commanders should be conscious of the fact that this analysis does not take into account an estimate of the preventative influence of frontline uniform police. This is a limitation of this study. Future research could focus on developing an attributable fraction regarding the proportion of police resources that are dedicated to different policing activities. Such data could then be included into weighting the inputs for a more refined and accurate analysis regarding the detection of crime. We however, note that the current study assists commanders in focussing resources on the efficiency in detecting certain crime types. As such, they are able to reallocate resources (possibly without changing the inputs – for example number of officers – in a given district) to focus on crimes that are currently identified in the analysis to be less efficiently detected. This will assist in improving the efficiency of the given district.

Finally, while the current research focuses on detection, the method employed can be applied to multiple targets and goals that are of interest to police. Examples of outcomes include the deterrence of crime, the maintenance of social order and the promotion of police-citizen relationships.

Appendix

Table 5 Selected studies focusing on the relationship between police numbers and/or arrests and crime

Study/country/sample	Method	Findings
Marvell and Moody (1996) US Pooled data from 49 states and 56 cities, 1973–1992	Observational study Multiple Time Series with fixed effects (with Granger causality test) Main explanatory variable: police numbers per capita Response variable(s): crime rate (incidence divided by population)	Causality in both directions, with stronger effect of police numbers on crime. This effect was much stronger at the city rather than the state level. At the state level, significant negative association between police numbers and homicide, robbery and burglary. At city level, statistical effects for homicide, robbery, burglary, larceny, auto theft and total crime all significant
Levitt (1997) US Panel of 59 cities, 1970–1992	Observational study Two-stage least squares using electoral cycle (election year or not) as an instrumental variable Main explanatory variable: 'sworn officers' per capita Response variable: crime rate	Increases in police reduce crime. Estimates elasticity of crime to be -0.3: however, see McCrary's (2002) critique, which nullified these findings
Corman and Mocan (2000) US Monthly time series data from New York, 1970–1996	Observational study Regression analysis with lagged effects Main explanatory variables: number of arrests and number of police officers. Response variable: Absolute numbers of crimes	Significant effect of arrests on murders, robberies, burglaries and motor-vehicle thefts; significant effect of police numbers on robberies and burglaries but not on murder or motor vehicle theft. Reports average elasticity of crime with respect to police numbers as -0.45
McCrary (2002) US Panel of 59 cities, 1970–1992	Observational study Re-analysis of Levitt (1997)	Results reveal negative elasticities for violent (-0.66) and property crime (-0.11)
Levitt (2002) US Panel of 122 cities, 1975–1995	Observational study Two-stage least squares using number of firefighters per capita as an instrumental variable Main explanatory variable: police per capita Response variables: violent crime rate and property crime rate	Negative effect of police numbers on both violent and property crime rates. Evidence is strongest for murder and robbery

Table 5 (continued)

Study/country/sample	Method	Findings
Kovandzic and Sloan (2002) US Yearly data from Florida counties, 1980–1998	Observational study Multiple Time Series with fixed effects (with Granger causality test) Main explanatory variable: police per capita Response variables: crime rates	'Significant and substantial' impacts of police levels on robbery, burglary and larceny and total crime (with relatively small elasticities – 0.14 for total crime). However no effect of police numbers on aggravated assault or murder
Di Tella and Schargrodsky (2004) Argentina City blocks in Buenos Aires	Natural experiment A terrorist bomb led to police guard being placed on every block containing a Jewish institution in Buenos Aires. A difference-in-difference approach is used to analyse the impact on car-theft in those blocks Main explanatory variable: dummy variables representing police presence at or near block Response variable: Absolute number of car thefts	Find 'a large, negative and highly local effect of police presence on car theft'. Note that this effect is highly local and this paper is more akin to those that look at 'hot-spot' policing
Corman and Mocan (2005) US Monthly time series data from New York, 1974–1999	Observational study Regression analysis with lagged effects Main explanatory variables: absolute numbers of police officers and arrests. Response variable: absolute number of crimes	Significant associations between felony arrests and murder, burglary, assault, robbery, motor-vehicle theft, grand larceny and rape. Significant associations between misdemeanor arrests and robbery, motor-vehicle theft and grand larceny
Klick and Tabarrok (2005) US Washington DC	Natural experiment Uses changes to terror alert status to examine potential effect on crime of police mobilisation on high-alert days Main explanatory variable: dummy variable representing high alert day Response variable: Absolute number of reported crimes	Report that non-violent crime, particularly auto-theft and theft from auto was significantly reduced on high-alert days Suggest that overall elasticity of crime in relation to police presence of about -0.3
Vollaard and Koning (2009) Netherlands Five waves of PMB victimisation survey that covers the entire country	Observational study Combines survey data on victimisation and precaution-taking with data on police expenditure and numbers Main explanatory variable: police per capita Response variable: reported victimisation	Conclude that there are significant negative effects of higher police levels on property and violent crime, public disorder, and precaution taking Elasticitites range from -0.2 to -0.5. No effect of police numbers on assault or robbery with violence

Table 5 (continued)

Study/country/sample	Method	Findings
Lin (2009) US Panel of '51' States, 1970–2000	Observational study Two-stage least squares using state sales tax as an instrumental variable Main explanatory variable: police numbers per capita Response variables: crime rate	Significant negative associations between numbers of police and levels of property crime, murder, robbery, burglary, larceny and auto theft Estimates elasticity for property crime of about -0.9
Draca et al. (2011) UK Central London Boroughs	Natural experiment Deployment of extra police in central London after 7/7 bombings used to examine impact on crime rates of increased police numbers in certain areas Main explanatory variable: police deployment (hours worked per 1,000 population) Response variable: crime rate	Conclude that 'susceptible' crime – violence and sexual offences, theft and handling and robbery – fell significantly in the treatment areas compared with control areas. 'Non- susceptible' crime – burglary and criminal damage – not affected. Note that this distinction seems rather arbitrary. The authors state that burglary and criminal damage are less susceptible in this context because they occur more in residential areas or at night, but provide no supporting evidence in this regard. Estimate an elasticity of crime with respect to the police of approximately -0.38
Garrett and Ott (2011) US 20 cities 1983–2004	Observational study OLS panel regression with city- and year-specific dummy variables (e.g. seasonality, unemployment rate, minimum wage) and lag effects	Elasticity estimates differ across cities. Suggested heterogeneity in the crime and arrest relationship across cities. Overall a significant negative elasticity was found for robbery (-0.07)
Chalfin and McCrary (2013) US 242 cities (at least one city in 45 states) 1960–2010	Observational study Least square conditional on both the UCR and the ASG measures of the growth rate in the city's population and year effects with an additional regression with state-by-year effects Two stage least squares of the growth rate in each of the nine crime rates on the first lag of the growth rate in the number of per capita sworn police officers. All models are estimated using 2010 city population weights	Significant negative associations between numbers of police and levels of murder, rape, robbery, assault, burglary, larceny, and motor vehicle theft. Elasticity for violent and property crimes is -0.34 and -0.17, respectively

Table 6 DEA and FDH efficiency scores

District	Year	DEA-CCR efficiency score	DEA-CCR efficiency score (additive model*)	DEA-BCC efficiency score	DEA-BCC efficiency score (additive model*)	FDH efficiency score
Central	2007	0.742	0.997	0.951	0.949	0.972
Central	2008	0.661	0.992	0.877	0.876	0.895
Central	2009	0.665	0.994	0.896	0.895	0.940
Central	2010	0.560	0.987	0.796	0.795	0.807
Central	2011	0.537	0.986	0.751	0.750	0.762
Central	2012	0.511	0.989	0.801	0.798	0.838
Central	2013	0.432	0.982	0.673	0.671	0.691
Central	2014	0.491	0.987	0.784	0.782	0.800
Central	2015	0.440	0.985	0.729	0.729	0.765
Wanchai	2007	0.855	0.991	0.866	0.849	1.000
Wanchai	2008	0.754	0.990	0.817	0.812	0.843
Wanchai	2009	0.705	0.990	0.794	0.788	0.853
Wanchai	2010	0.675	0.990	0.804	0.802	0.873
Wanchai	2011	0.690	0.994	0.876	0.875	0.975
Wanchai	2012	0.718	0.998	0.966	0.964	0.998
Wanchai	2013	0.784	1.000	1.000	1.000	1.000
Wanchai	2014	0.703	0.997	0.950	0.948	1.000
Wanchai	2015	0.673	0.996	0.908	0.907	0.999
Western	2007	0.701	1.000	1.000	1.000	1.000
Western	2008	0.672	1.000	0.997	0.996	1.000
Western	2009	0.586	0.997	0.952	0.952	0.984
Western	2010	0.567	0.993	0.890	0.890	0.930
Western	2011	0.525	0.992	0.866	0.864	0.883
Western	2012	0.475	0.992	0.869	0.866	0.903
Western	2013	0.458	0.988	0.805	0.802	0.845
Western	2014	0.464	0.990	0.832	0.829	0.855
Western	2015	0.539	0.990	0.819	0.817	0.825
Eastern	2007	0.740	0.994	0.893	0.891	0.974
Eastern	2008	0.687	0.992	0.852	0.851	0.969
Eastern	2009	0.751	0.995	0.933	0.907	1.000
Eastern	2010	0.754	0.997	0.960	0.936	1.000
Eastern	2011	0.786	0.999	1.000	0.987	1.000
Eastern	2012	0.676	0.993	0.874	0.859	0.947
Eastern	2013	0.665	0.991	0.843	0.820	0.951
Eastern	2014	0.735	0.998	0.966	0.963	0.990
Eastern	2015	0.717	1.000	1.000	0.999	1.000
Wong Tai Sin	2007	0.683	0.992	0.864	0.863	0.918
Wong Tai Sin	2008	0.689	0.995	0.904	0.904	0.952
Wong Tai Sin	2009	0.619	0.993	0.876	0.875	0.944
Wong Tai Sin	2010	0.566	0.990	0.837	0.835	0.881

Table 6 (continued)

District	Year	DEA-CCR efficiency score	DEA-CCR efficiency score (additive model*)	DEA-BCC efficiency score	DEA-BCC efficiency score (additive model*)	FDH efficiency score
Wong Tai Sin	2011	0.507	0.989	0.819	0.817	0.843
Wong Tai Sin	2012	0.627	0.993	0.882	0.881	0.957
Wong Tai Sin	2013	0.600	0.993	0.873	0.872	0.963
Wong Tai Sin	2014	0.548	0.993	0.885	0.882	0.912
Wong Tai Sin	2015	0.578	0.993	0.866	0.864	0.895
Sau Mau Ping	2007	0.722	0.997	0.954	0.950	0.993
Sau Mau Ping	2008	0.701	0.998	0.973	0.970	1.000
Sau Mau Ping	2009	0.649	1.000	0.996	0.992	1.000
Sau Mau Ping	2010	0.732	0.998	0.960	0.959	1.000
Sau Mau Ping	2011	0.671	0.996	0.938	0.937	1.000
Sau Mau Ping	2012	0.683	0.996	0.934	0.933	0.993
Sau Mau Ping	2013	0.596	0.994	0.904	0.901	0.945
Sau Mau Ping	2014	0.622	0.994	0.888	0.887	0.974
Sau Mau Ping	2015	0.606	0.994	0.902	0.900	0.939
Kwun Tong	2007	1.000	1.000	1.000	1.000	1.000
Kwun Tong	2008	0.867	0.998	0.972	0.971	1.000
Kwun Tong	2009	0.862	1.000	0.998	0.997	1.000
Kwun Tong	2010	0.888	0.999	0.985	0.984	1.000
Kwun Tong	2011	0.854	0.998	0.971	0.968	1.000
Kwun Tong	2012	0.819	0.996	0.933	0.931	0.987
Kwun Tong	2013	0.708	0.994	0.882	0.880	0.927
Kwun Tong	2014	0.702	0.993	0.849	0.837	0.965
Kwun Tong	2015	0.834	1.000	1.000	1.000	1.000
Yau Tsim	2007	0.817	1.000	1.000	1.000	1.000
Yau Tsim	2008	0.822	0.999	0.982	0.981	1.000
Yau Tsim	2009	0.773	0.995	0.911	0.911	0.936
Yau Tsim	2010	0.647	0.987	0.775	0.774	0.824
Yau Tsim	2011	0.735	0.991	0.842	0.842	0.885
Yau Tsim	2012	0.766	0.997	0.961	0.959	1.000
Yau Tsim	2013	0.658	0.992	0.844	0.843	0.910
Yau Tsim	2014	0.571	0.991	0.840	0.836	0.849
Yau Tsim	2015	0.590	0.990	0.809	0.807	0.873
Mongkok	2007	1.000	1.000	1.000	1.000	1.000
Mongkok	2008	1.000	1.000	1.000	1.000	1.000
Mongkok	2009	0.959	0.999	0.992	0.989	1.000
Mongkok	2010	0.797	0.993	0.876	0.874	0.926
Mongkok	2011	0.868	0.995	0.920	0.917	0.948
Mongkok	2012	0.946	0.996	0.954	0.953	1.000
Mongkok	2013	0.917	0.995	0.940	0.937	1.000
Mongkok	2014	0.803	0.994	0.872	0.867	0.949

Table 6 (continued)

District	Year	DEA-CCR efficiency score	DEA-CCR efficiency score (additive model*)	DEA-BCC efficiency score	DEA-BCC efficiency score (additive model*)	FDH efficiency score
Mongkok	2015	0.827	0.996	0.917	0.915	0.969
Sham Shui Po	2007	0.835	0.996	0.944	0.939	0.993
Sham Shui Po	2008	0.848	0.995	0.922	0.911	1.000
Sham Shui Po	2009	0.835	0.995	0.915	0.912	1.000
Sham Shui Po	2010	0.824	0.996	0.936	0.936	1.000
Sham Shui Po	2011	0.752	0.995	0.916	0.913	0.954
Sham Shui Po	2012	0.735	0.994	0.888	0.887	0.969
Sham Shui Po	2013	0.645	0.992	0.849	0.847	0.905
Sham Shui Po	2014	0.577	0.991	0.817	0.815	0.876
Sham Shui Po	2015	0.602	0.991	0.812	0.811	0.885
Kowloon City	2007	0.741	1.000	1.000	1.000	1.000
Kowloon City	2008	0.731	1.000	0.992	0.990	1.000
Kowloon City	2009	0.616	0.997	0.946	0.945	1.000
Kowloon City	2010	0.572	0.995	0.905	0.905	0.963
Kowloon City	2011	0.489	0.990	0.817	0.815	0.848
Kowloon City	2012	0.527	0.990	0.826	0.825	0.857
Kowloon City	2013	0.481	0.992	0.857	0.854	0.878
Kowloon City	2014	0.443	0.988	0.794	0.791	0.830
Kowloon City	2015	0.517	0.994	0.892	0.889	0.950
Yuen Long	2007	0.895	1.000	1.000	1.000	1.000
Yuen Long	2008	0.813	1.000	1.000	1.000	1.000
Yuen Long	2009	0.737	0.998	0.969	0.968	1.000
Yuen Long	2010	0.696	0.996	0.919	0.918	0.980
Yuen Long	2011	0.715	0.993	0.877	0.877	0.914
Yuen Long	2012	0.734	0.996	0.933	0.931	1.000
Yuen Long	2013	0.719	0.997	0.957	0.954	1.000
Yuen Long	2014	0.643	0.995	0.908	0.906	0.959
Yuen Long	2015	0.668	0.996	0.918	0.916	1.000
Tuen Mun	2007	0.719	0.999	0.983	0.978	1.000
Tuen Mun	2008	0.769	0.998	0.964	0.963	0.980
Tuen Mun	2009	0.814	1.000	1.000	1.000	1.000
Tuen Mun	2010	0.753	0.999	0.975	0.972	1.000
Tuen Mun	2011	0.790	0.999	0.976	0.975	1.000
Tuen Mun	2012	0.743	0.999	0.984	0.978	1.000
Tuen Mun	2013	0.659	0.997	0.943	0.938	1.000
Tuen Mun	2014	0.652	0.997	0.943	0.937	1.000
Tuen Mun	2015	0.642	0.998	0.952	0.946	1.000
Tai Po	2007	0.711	0.994	0.904	0.896	0.940
Tai Po	2008	0.689	0.992	0.854	0.850	0.981
Tai Po	2009	0.778	0.996	0.921	0.917	1.000

Table 6 (continued)

District	Year	DEA-CCR efficiency score	DEA-CCR efficiency score (additive model*)	DEA-BCC efficiency score	DEA-BCC efficiency score (additive model*)	FDH efficiency score
Tai Po	2010	0.712	0.994	0.887	0.882	0.906
Tai Po	2011	0.746	0.996	0.927	0.921	0.976
Tai Po	2012	0.746	0.995	0.918	0.910	0.931
Tai Po	2013	0.729	0.994	0.911	0.903	0.933
Tai Po	2014	0.639	0.994	0.887	0.879	0.925
Tai Po	2015	0.683	0.998	0.955	0.951	1.000
Tsuen Wan	2007	0.590	0.990	0.814	0.814	0.882
Tsuen Wan	2008	0.721	0.997	0.952	0.951	1.000
Tsuen Wan	2009	0.674	0.994	0.900	0.900	0.967
Tsuen Wan	2010	0.621	0.996	0.923	0.921	1.000
Tsuen Wan	2011	0.559	0.994	0.900	0.896	0.966
Tsuen Wan	2012	0.551	0.997	0.964	0.958	1.000
Tsuen Wan	2013	0.575	0.999	0.990	0.983	1.000
Tsuen Wan	2014	0.549	0.994	0.883	0.879	0.973
Tsuen Wan	2015	0.613	0.996	0.911	0.909	0.982
Sha Tin	2007	0.701	0.999	0.990	0.989	1.000
Sha Tin	2008	0.620	0.995	0.916	0.915	0.953
Sha Tin	2009	0.670	0.996	0.920	0.920	0.986
Sha Tin	2010	0.644	0.995	0.908	0.906	0.982
Sha Tin	2011	0.701	0.995	0.908	0.901	0.997
Sha Tin	2012	0.687	0.996	0.938	0.936	0.988
Sha Tin	2013	0.634	0.997	0.946	0.944	0.976
Sha Tin	2014	0.662	0.997	0.938	0.937	1.000
Sha Tin	2015	0.660	0.998	0.974	0.972	1.000
Kwai Tsing	2007	1.000	1.000	1.000	1.000	1.000
Kwai Tsing	2008	0.770	0.996	0.940	0.933	1.000
Kwai Tsing	2009	0.849	0.997	0.996	0.937	1.000
Kwai Tsing	2010	0.749	0.997	0.969	0.947	1.000
Kwai Tsing	2011	0.721	0.997	0.944	0.936	1.000
Kwai Tsing	2012	0.746	1.000	1.000	1.000	1.000
Kwai Tsing	2013	0.698	0.998	0.966	0.965	1.000
Kwai Tsing	2014	0.740	1.000	1.000	1.000	1.000
Kwai Tsing	2015	0.725	1.000	1.000	1.000	1.000
Lantau	2007	0.456	0.990	0.850	0.841	0.875
Lantau	2008	0.481	0.989	0.825	0.819	0.843
Lantau	2009	0.457	0.991	0.861	0.853	0.879
Lantau	2010	0.433	0.987	0.773	0.770	0.816
Lantau	2011	0.506	0.996	0.937	0.933	0.987
Lantau	2012	0.432	0.997	0.967	0.960	1.000
Lantau	2013	0.490	0.996	0.941	0.940	0.994

Table 6 (continued)

District	Year	DEA-CCR efficiency score	DEA-CCR efficiency score (additive model*)	DEA-BCC efficiency score	DEA-BCC efficiency score (additive model*)	FDH efficiency score
Lantau	2014	0.500	1.000	1.000	1.000	1.000
Lantau	2015	0.572	1.000	1.000	1.000	1.000
	Average	**0.683**	**0.995**	**0.913**	**0.909**	**0.954**

*The additive method has been adopted where an integer is added to both inputs and outputs to handle the concern regarding small values as proposed by Sarkis (2006), Ali and Seiford (1990) and Pastor (1996). The above authors proposed that this method does not alter the efficient frontier for DEA formulations and thus are translation invariant. For detailed strengths and limitations of this method please consult Sarkis (2006)

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