

Crime Rates and Police Efficiency

GREGORY DEANGELO[†], DONALD F. VITALIANO[†], HANNES LANG[†]

[†]Department of Economics, Rensselaer Polytechnic Institute (RPI), 110 Eighth Street, Troy, NY, USA (emails: deangg@rpi.edu; vitald@rpi.edu; langh@rpi.edu)

Abstract:

This paper measures the relative efficiency of 50 municipal police departments in New York State using an output-oriented data envelopment analysis (DEA) programming model and finds that 30 departments are efficient, while 20 could improve their efficiency. Adoption of best practice methods in the 20 laggard agencies could reduce violent crime by an average 173%, and property crime by 64%. We find that four factors show statistically significant effects on violent and property crime ‘output’: the number of community policing officers, the number of employment screening techniques, the number of mobile computer devices deployed and the number officers employed in special drug units.

JEL Codes: K42, H76, R51

Keywords: Law enforcement, Efficiency, Crime.

I. Introduction

According to one of America's leading criminologists, James Q. Wilson, greater efficiency of police departments is one of the four major causes that have driven down the level of crime in the last 40 years (Wilson, 2011). In the face of a growing fiscal crisis, it is more important than ever that policing be carried out as efficiently as possible. For example, Oregon's State Police had to reduce its force by 35% in 2003 solely due to budget cuts, which decreased officer effectiveness (DeAngelo and Hansen, 2010).¹ In New York State, Governor Cuomo proposed a \$60 million budget cut to the New York State Police (Smart, WGXC Hands-on Radio Newsroom, 2011), while other upstate New York cities, such as Rochester, NY unveiled a spending plan that includes laying off 51 full-time positions in the city police department – a story that is echoed throughout upstate New York cities (Voorhees et al., YNN, 2011). In this paper we investigate the comparative efficiency in minimizing serious crimes of 50 local police departments in New York State. An output oriented Data Envelopment Analysis (or DEA) is used to investigate the potential for each police force to reduce crime while holding constant budgeted resources. The results are used to make recommendations about how to increase police efficiency and effectiveness.

The Data Envelopment Analysis method of mathematical programming was first introduced by Charnes, Cooper and Rhodes (1978). Among its advantages, this method does not need a specific parametric function and allows for zero values of inputs or outputs. Its principal shortcoming is the possibility of measurement errors that can lead to outlier observations resulting in a false efficient frontier. A careful examination of the raw data is therefore necessary when DEA is utilized.

The data for our analysis is taken from the 2003 Law Enforcement Management and Administration Statistics (LEMAS) survey (Bureau of Justice Statistics, 2003), the US Census and the Crime Index for New York State. The data is discussed in more detail below.

The paper is structured in the following way: Section II offers a review of the literature on police force efficiency; section III describes the theoretical framework, the output-oriented DEA, which will then be used in section IV to evaluate the efficiency of 50 city police

¹Oregon is, of course, not the only agency facing budget cuts. In 2009, Virginia's State Police had to lay off 104 part-time workers as a result of the budget reductions proposed by Governor Timothy M. Kaine. In the same year the Governor of Michigan, Jennifer Granholm passed budget cuts that reduced the State Police to the lowest number in 40 years. The reduction of 100 police troopers left the force with 968 troopers. Illinois' Governor Pat Quinn recently proposed a cutback that could cost the State Police more than 400 employees and with the recently passed national budget for the fiscal year 2011/2012, more cuts in the budget of law enforcement agencies across the country are expected (Cooper, New York Times, 2011).

departments under investigation. The paper concludes with a description of the findings and recommendations for future research.

II. Literature review

Thanassoulis (1995) analyzes the efficiency of police forces in England and Wales for the years 1992-3 using DEA. The conceptual framework is that of a production function. The inputs used in the analysis are the number of police officers employed, the number of violent crimes, the number of burglaries and the amount of other crimes recorded. As outputs, Thanassoulis (1995) used the clear-up rates² of the three input crime categories. Consideration was given to including socio-economic data, but there were doubts about how accurately the variables would reflect social deprivation. The author concludes that there is a weak correlation between high staffing levels (defined as low manpower efficiencies) and high crime clear-up rates. Only two of forty-one police forces show very high efficiencies in both manpower and clear-up rates.

Grosskopf et al. (1995) employ an input distance function approach to analyze the response to fiscal stress of the Dallas Police Department for the years 1977 to 1987. Their variable inputs are the amount of police officers, amount of sergeants and the amount of civilians, while the fixed inputs are the actual numbers of reported auto thefts and murders. Their two output measurements are the arrest rates for auto theft and murder. They find that the Dallas Police Department handled a period of fiscal stress and increasing crime quite well. Overall they conclude that the efficiency increased while resources became more strained.

Carrington et al. (1997) also use the DEA approach to determine if there is room for improvement in the New South Wales (Australia) police service. They use the number of police officers, the number of civilian employees and the number of police cars as inputs. Outputs are the number of offences, arrests, summons issued, number of major car accidents recorded and the distance traveled by police cars³. This represents an input-oriented production function approach to measuring technical efficiency. They find that higher technical efficiency would lead to a possible 13.5% average decrease in inputs, while keeping outputs constant. A Tobit regression is used to analyze the variation in technical efficiency scores from the DEA. In this regression, socio-economic factors such as the percentage of young people living in an area and a dummy variable for metropolitan areas are included. However they find no significant results, leading to the conclusion that these environmental

² Clear-up rates are the number of crimes resolved compared to the total number of reported crimes.

³ In order to approximate the presence of the police in the community.

variables have no influence on the efficiency. The researchers note that measurement of some of the variables employed such as the distance traveled by a police car, need improvement.⁴ A differentiation in the quality of labor is missing as well and could be dealt with by using full-time equivalent hours of police officers and civilian employees.

Nyhan and Martin (1999) conduct an exploratory DEA on 20 municipal police forces from 10 different U.S. States to investigate the potential of this method in the evaluation of such government service providers.⁵ They use two input variables - total department cost in dollars and amount of total full time equivalent staff - and three output variables - clearance rate, response time and crime rates.⁶ The authors also account for socio-economic factors like population size and median income. Nyhan and Martin use both a constant returns to scale (CCR) and variable returns to scale (BCC) model⁷. The findings suggest that five municipalities could significantly reduce their costs (ranging from \$10 million in Charlotte, North Carolina to \$62 million in Las Vegas, Nevada). Lastly the authors conclude that a DEA can be especially useful for the evaluation of different police precincts within a municipality.

Drake and Simper have authored a series of papers analyzing county police forces in England and Wales (Drake and Simper, 2000, 2001, 2002, 2003 and 2005). They start with a simple input-oriented DEA to estimate the efficiency of the police force production function. The first paper also looks at the existence of categorical scale effects in policing using multiple discriminant analysis. The inputs used in the analysis are employment costs of police officers, premises-related expenses⁸, transport-related expenses⁹, and capital and other costs. For outputs they use the clear-up rate, the total number of traffic offences and the number of breathalyzer tests administered. They find that some regions could decrease their use of resources by up to 31% while maintaining constant outputs if the utilization were more efficient. In general they conclude that the DEA approach in combination with other methods could produce results that lead to an improvement of the efficiency in English and Welsh policing.

⁴ For example, foot, bike and horse patrols are not included here, although they might be significantly large in metropolitan areas.

⁵ The states include Arizona, California, North Carolina, Nevada, Oklahoma, Louisiana, Kansas, Virginia, Texas and Ohio.

⁶ Response times are defined as the time between reception of a call and arrival of the government agency at the crime scene.

⁷ The CCR model named after Charnes, Cooper, and Rhodes 1978, and the BCC model named after Banker, Charnes, and Cooper 1984.

⁸ Such as daily running costs, repair and maintenance of inventory and buildings.

⁹ Such as the running costs and repairs of police vehicles.

In Drake and Simper (2001) the same data from the 2000 paper is used, while expanding their analysis to a one-way ANOVA (Analysis of Variance). Similar to the first paper they find that there are some districts that are inefficient in their usage of resources. Furthermore, they confirm their previous result of diseconomies of scale in the size of police units in the counties. Drake and Simper (2002) compare the results of a parametric vs. nonparametric analysis of English and Welsh police force efficiency. Their findings suggest that the efficiency *rankings* are similar. They also find that the London metropolitan police force is so much greater in size as to require special consideration.

Drake and Simper (2003) compare four different methodologies of both parametric and non-parametric distance function models. The results of the DEA and the stochastic input distance function (SIDF) show strong positive correlations. Unfortunately it was not possible to include socio-economic data in their analysis, so that the efficiency scores could not be checked for their sensitivity to socio-economic factors. In their final paper Drake and Simper (2005) again utilize various non-parametric and parametric methods. They expand their analysis by not only looking at differences between police forces, but also among Basic Command Units (BCU) within police forces. They find a strong non-linear relationship between total crime incidents and the resources used for crime-clear-ups.

Diez-Ticio and Mancebón (2002) use DEA to analyze the efficiency of the Spanish police force. They deploy a multiactivity DEA model developed by Mar Molinero (1996) and expanded by Tsai and Mar Molinero (1998) to the Tsai-Mar-Molinero model (TMM), which assumes several institutions with different production functions using shared inputs. A comparison between the results from the ordinary DEA model and the more demanding TMM model shows that the ordinary DEA model gives higher efficiency scores by allowing substitutions between the outputs. A regression model was also used to investigate the characteristics of the efficient and inefficient forces. They find that the ratio of sworn personnel to non-sworn police officers has a positive relationship with the clear-up rate of violent offences.

Sun (2002) analyzes the relative efficiency of fourteen police precincts in Taipei City, Taiwan for the years 1994-6 by employing DEA. He uses the model developed by Charnes, Cooper and Rhodes (1978), with the number of police officers, burglaries, offences and other crimes as the 4 inputs and the clear up rates of the three different crime categories as outputs. He finds that differences in operating environments and socioeconomic factors have no significant influence. Rather the inefficient precincts are experiencing increasing returns to

scale and might be able to improve their output levels with higher manpower levels. Finally he mentions that special consideration has to be given to the fact that this analysis looks at the relative efficiency among peer agencies and therefore leaves room for improvement, even for the efficient precincts. Furthermore, the data does not account for variation in the quality of police work and police officers, which could strengthen the findings.

Barros and Alves (2005) investigate the performance of Lisbon police forces with the help of a stochastic cost-frontier model. Although the DEA method is discussed in the paper, the researchers decide in favor of the econometric frontier because it gives them well-developed statistical tests, the possibility of admitting non-influential variables in the model and allows for the decomposition of deviations from efficient levels between noise and pure inefficiency. They assume a generalized Cobb-Douglas cost function with two input prices (price of labor and price of capital) and four output variables (clear-up rates of theft and burglary, car robberies, clear-up rate of drug related crimes and clear-up rate of minor offenses). Their results give a mean cost efficiency of 54%, which suggests serious waste in the management of police precincts. Barros and Alves (2005) suggest that the inefficient precincts should adopt an enhanced-incentive policy, increasing technical efficiency so that the waste in resources is decreased. The authors state the reasons for waste are principal-agent problems, where the managers of precincts do not have enough incentive to act on behalf of the State, and that job tenure is not linked to the performance of the employees, leading to a “free-rider” problem. Barros (2006) follows up on his previous paper by using the DEA approach for the same data. His approach is input-oriented and finds that most precincts are efficient, and identifies peer groups and their problems among the inefficient ones. Scale economies seem to have a strong influence on the productivity in this sector and hence leave room for improvement for the inefficient precincts.

Gymiah-Brempong (1987) use a multiproduct translog production function in a regression of total police costs on personal crimes, robbery, burglary, larceny, motor vehicle theft and population representing the outputs, and inputs such as sworn police wages, civilian police wages and police fleet value.¹⁰ The data comes from 256 municipalities in Florida for the years 1982 and 1983. He finds that the average municipal police force faces decreasing returns to scale. Gyapong and Gyimah-Brempong (1988) conduct a similar analysis for 260 Michigan municipalities. In their analysis they cannot find statistically significant scale economies, but are able to conclude that economies of scope exist, suggesting that joint

¹⁰ They use population to measure the size of non-crime-related police activity and the fleet value as a proxy for capital.

production of police outputs reduces production cost. However this is not a frontier analysis, so efficiency is implicitly assumed to be one hundred percent.

Gorman and Ruggiero (2008) evaluate State Police performance in the U.S. using a three-stage DEA on data for 49 continental states. They use three outputs - murders, other violent crimes and total property crimes - and the three discretionary inputs - sworn officers and the number of other employees for labor, and the number of vehicles - as a proxy for capital. They also include the percentage of single mothers, the poverty rate and the percent of individuals in the labor force as socio-economic conditions and population and population per square mile as a control for the size of the state. Their three-stage DEA model consists of an OLS and Tobit regression model in the first stage including the socio-economic and control factors to create a so-called overall environmental Cost Index (CI). In the second stage the CI was then applied in a programming model to measure technical efficiency (TE). The third-stage model incorporates the CI into the DEA model in order to derive scale efficiency (SE) of the police forces. Their results find that 34 of the 49 states have a relatively high TE with an average of 94% for all states. Furthermore, most of the efficient states operate at constant returns to scale, while most of the inefficient states face increasing returns to scale. Finally the authors conclude by suggesting further research in lower governmental levels and city police forces.

III. Theoretical framework

In this section we start by introducing the production and cost of policing relevant to this study. In the next step the general features, strengths and weaknesses of the Data Envelope Analysis are described. Lastly the specific DEA model used in this study is presented.

Production and cost of policing

State and local governments purchase inputs such as labor services, capital inputs, materials and supplies in order to produce **direct outputs** such as police patrols. A production function captures the technology of converting inputs into direct outputs:

$$Q = q(L, K, M) \tag{1}$$

Where Q = direct output

L = labor input, such as number of officers and command personnel.

K = capital input, such as patrol cars and precinct houses.

M = materials and supplies, such as computers, revolvers, dogs, etc.

The $q(\cdot)$ function represents the technology, which may be a specific functional form such as Cobb-Douglas or Translog, or unspecified and pieced together from the data in Data Envelopment Analysis (DEA). In cross-section studies we can assume unchanged technology across observational units (e.g. city departments).

One limitation of the single equation production function is that only one output Q can be used as the dependent variable, and in many instances the production process involves multiple outputs. In such cases one may prefer to employ a *distance function*, which shows the maximal outputs for any set of inputs or the minimum inputs required to produce a specified level of output(s) - see Drake and Simper (2005). The production function and the distance function may be fitted using either regression methods (stochastic frontier) or DEA. In either case, one arrives at estimates of technical efficiency, i.e. the degree to which the decision-making unit (DMU) is on or below the relevant production isoquant.

In the case of policing, one question is whether it makes more sense to ask what is the maximum proportional reduction in all inputs that would produce the same output?, or what is the maximum proportional increase in all outputs given the set of inputs? The answer will not be the same unless there are constant returns to scale. The choice generally depends on what managers can control because efficiency ultimately depends on managerial decisions. If police departments or precincts and patrol zones are allocated resources from above then local managers don't control inputs, and asking what is the maximal output given inputs makes more sense in assessing efficiency.

The **cost** of producing any amount of directly produced outputs is merely the sum of the quantity of each input used multiplied by its unit price:

$$C(Q) = wL + rK + pM \quad (2)$$

Where $C(Q)$ is the total cost of the observed level of direct output Q , and w , r and p are the per unit prices of labor (L), capital (K) and materials (M), respectively. This cost is also the observed **expenditure** of the government in providing policing. The efficiency issue here involves whether or not the government has chosen the *cost-minimizing* input quantities. Thus cost-efficiency involves two distinct conceptual issues, is the DMU operating on its isoquant, and is it at the cost-minimizing point on that isoquant? The former is labeled **technical efficiency** and is analogous to the production and distance function methods noted above. The

latter is described as **allocative efficiency**. Note that this concept does *not* refer to allocative efficiency in the conventional sense that output is produced up to the point where marginal cost equals marginal social benefit (or price). It merely asks if the observed level of policing direct output is being produced at least cost, given technology and input prices. Efficiency studies basically ask if observed cost is minimum cost.

Conceptually, we can write a total cost function as:

$$Cost = C(Q, w, r, p) \quad (3)$$

Where Q is now defined as a *vector* of direct outputs of police services. It would seem that a cost function is the most policy relevant measure of police efficiency, but it requires a set of input prices be available or separately estimated. The stochastic frontier estimation of the cost function also requires specification of a functional form of $C(\cdot)$, with the Cobb-Douglas the most common in the usual single-equation set-up. The key idea in stochastic frontier regression is the two-part error term:

$$y = \mathbf{B}'x + v + u, \quad (4)$$

where y is cost (in natural log units) and x the vector of right side variables (Q , w , r , and p , also in logs) and \mathbf{B}' is the estimated coefficients vector. The composed error $e = v + u$ consists of the usual normally distributed random error term v , and the one-sided inefficiency parameter u . Much of the literature discusses the choice of the distribution of the u , with a half-normal, exponential or gamma distribution the received options. Recent developments, available in *Limdep* econometric software, for example, allow for various types of heteroscedasticity and calculation of confidence intervals for u . Thus costs are minimum if $u = 0$, or above minimum if $u > 0$, apart from statistical noise v . By contrast, DEA 'envelops' or defines the cost or production frontier with a piecewise linear shape, without any pre-specified functional form, using observed best practice from among the decision-units in the data set. DEA is deterministic, i.e. no explicit allowance is made for statistical noise. DEA will usually identify a number of decision-making units (DMUs) which are 100% efficient whereas frontier regression of the same data will rarely have any cost or production units that are 100% efficient because the regression model cost function is, by definition, least-cost—which is rarely ever attained in practice.

Up to this point police output has been defined as directly observable units such as the number of patrols. But these are really **intermediate inputs** into the final product desired by the public which is prevention and detection of crime and accidents. This is the 'usable output' which should be the ultimate concern of policymakers. Because it is not sold in a competitive

market there is no ready way to value this public good. From the perspective of measuring economic efficiency the problem caused by this distinction between intermediate and final products is the role played by **environmental factors** such as the population characteristics or even the weather in the police jurisdiction. The same quantity of direct outputs Q can result in different amounts of final outputs, which may be represented as follows:

$$G = g(Q, E) = \psi[q(L, K, M), E] \quad (5)$$

Where G = final public good, police protection, and $\psi[\cdot]$ is final output product technology, Q is the vector of direct police outputs, such as patrols, summons issued, alcohol tests and E is the environmental factors affecting crime and accidents, such as percentage of the population under 25 and the extent of poverty.

This simple framework has important empirical ramifications, which is very similar to the case of education. We all understand that the same teachers, classrooms and supplies will achieve different learning outcomes (e.g. test scores) depending upon the characteristics of the student body. If we confine ourselves to measuring the direct outputs Q or the cost thereof then we need not include various environmental variables. But if there are things such as seniority rules, weather, jurisdictional overlap that influence conversion of L , K or M into Q , they should be included.

Our conceptual framework $G = \psi[q(L, K, M), E]$ informs the choice of variables we employ and also permits an assessment of the logical coherence of the existing literature. The complex nature of the nested $\psi[\cdot]$ production function indicates that the choice of a parametric functional form based on tractability is unlikely to capture the relevant technology, which greatly strengthens the case for the non-parametric DEA approach. As noted above, Thanassoulis (1995) treats officers and crimes as inputs, and clearances as the output. Apart from the question of clearances as a proxy for public good G , mixing input L with crime seems problematic, since the inverse of crime is clearly an output desired by the public. Carrington (1997) is using our $Q = q(L, K, M)$ direct output framework, but erroneously includes car accidents among the outputs. Drake and Simper (2000, 2001, 2002, 2003, 2005) are rather ad hoc in their choice of inputs and outputs. They use the expenses of each input rather than the amounts, as indicated by economic theory, and their output vector mixes the public good (G) clearance rate with traffic offences and alcohol testing, the latter a clear example of direct output Q .

In addition to the choice of inputs and outputs, our model sheds light on the issue of returns to scale, to which several papers devote considerable attention, such as Gorman and

Ruggiero (2008) and Barros (2006). Our view is that the spatial nature of policing renders the concept of returns to scale problematic and probably policy-irrelevant. Doubling or halving the number of controllable inputs such as officers and vehicles is not a test of economies or diseconomies of scale because you have not varied the socio-economic environment in which the police operate. Conceptually, you must double or halve the City of Buffalo, for example, and its police relevant socio-economic dimensions to test for returns to scale. In addition, talk of consolidation or breaking-up of police departments to gain from scale efficiencies seems unrealistic for the same spatial-demographic reasons. Furthermore, our model suggests that police relevant environmental variables E be directly included in the DEA production function and treated as fixed input constraints. This will affect the peers that each department is compared to, and make the resulting comparisons much more plausible and policy relevant. This is in contrast to the multi-stage approach of Gorman and Ruggiero (2008) who attempt to tease out environmental effects via an auxiliary set of regressions, which introduce another source of misspecification and lessens the transparency of results for policymakers.

Data envelopment analysis

The nonparametric Data Envelopment Analysis (DEA) method for determining a production frontier to measure efficiency, based on mathematical programming, was first introduced by Charnes, Cooper and Rhodes (1978). Banker, Charnes and Cooper (1984) extended DEA to allow for variable returns to scale. In the ensuing years many methodological and conceptual improvements have appeared.¹¹ Although originally developed to deal with situations where price data was lacking and the focus was on the technical efficiency between inputs and outputs, it is now possible to use DEA to estimate neoclassical cost, profit and revenue frontiers when input and output prices are available. The origin of DEA is reflected in the convention of referring to the units of observation as Decision Making Units (DMUs), rather than firms, in order to allow for government or non-profit organizations. Chief among the strengths of DEA is that it does not require specification of a parametric function to represent the underlying technology, and allows for zero values of inputs or outputs. A Cobb-Douglas, translog, Leontief and other econometric functional forms are at best a simplified approximation to a complicated process, and they have the potential to yield erroneous results if the approximation is poor.¹² In addition, a DEA production function readily permits

¹¹ More than three thousand DEA-related publications are recorded (Ray, 2004, 1).

¹² For example, fitting a logarithmic production or cost function can never yield zero marginal products of inputs, even when the firm is using more inputs than is technically necessary.

multiple outputs to be included. In the case of a police agency, 'outputs' can refer to the reduction of violent crime and property crime, for example. The main criticism of DEA is that it is deterministic, i.e., no explicit account is taken of measurement error in solving the linear program to construct the production or cost frontier. However, recent developments in the DEA literature address its statistical shortcomings. Banker and Natarajan (2004) provide a statistical foundation for DEA and show the conditions when DEA estimators are statistically consistent and maximum likelihood, and they develop parametric and non-parametric tests of various hypotheses.¹³ The absence of an explicit error term probably accounts for the slowness with which DEA has spread among economists, who are mostly brought up in the econometric tradition.¹⁴ The programming approach 'envelops' all the observed data points and uses outlier observations to define the efficient frontier. If these outliers are data errors, the resulting frontier is correspondingly compromised. Against this, DEA uses as its benchmark observed best practice of peer DMUs, which many observers feel is more appropriate than the parametric approach whose reference is the theoretical maximum output, revenue or profit or, minimum cost. In addition, DEA identifies the specific *reference set* of efficient DMUs with which to compare an inefficient one. In other words, if police department A is shown to be only 66% efficient relative to the frontier, DEA identifies the specific departments against which A's performance is benchmarked, thus allowing the investigator to examine management practices in A versus those in the efficient peer group. The reference set for any DMU consists of those with which it is most directly comparable in terms of the mix of inputs and outputs. In most cases there is no single reference DMU with exactly the same output/input mix as department A. In this case a *virtual* DMU lying on the production frontier is constructed from those most similar to A. The solution to the DEA programming model generates the weights required to construct the virtual frontier.

The DEA model

We employ the Banker, Charnes and Cooper (BCC) output oriented DEA model. With an output orientation, the police agency decision-making unit (DMU) is viewed as having been provided with a certain amount of resources and its objective is to produce the largest possible

¹³ Banker and Natarajan (2004) demonstrate that DEA efficiency scores are consistent estimators if the probability of observing a nearly efficient decision making unit (DMU) is strictly positive. Tests comparing the efficiency of two groups of DMUs, of returns to scale, allocative efficiency, input separability, shifts in the frontier and others are also presented.

¹⁴ Noteworthy is the inclusion of a DEA module in the 2007 version of *Limdep* and 2010 version of *Stata*, two of the more popular econometric software programs.

output using at most the given inputs. An output orientation better describes the management of a police agency than does input orientation, which takes the output level as given and then seeks to minimize the inputs used.

In this paper there are three police agency final outputs G : the inverse of the per capita incidence of violent crimes, the inverse of the per capita incidence of property crimes and the number of functions the department fulfills in its jurisdiction. Violent crimes consist of murder, forcible rape, robbery and aggravated assault. Property crimes include burglary, larceny and motor vehicle theft. These definitions are those employed in the Uniform Crime/Incident-based reporting system developed by the Federal Bureau of Investigation. These index crimes are used to track overall crimes in New York State, but are not necessarily identical with the definitions in New York statutes. They are, however, reported by New York police agencies to the New York State Bureau of Criminal Justice Services, which is our source. The basic idea is simple: a police agency is doing more to reduce the harm and anxiety caused by crime the lower is the per capita number of these seven index crimes. Thus, a lower crime rate represents more output, and vice versa.

The inputs under the control of police managers include the number of full and part-time sworn officers, considered separately, the number of full and part-time civilian police personnel, considered separately, the number of police vehicles (marked and unmarked) and the number of police stations, including the headquarters building. The preceding list of inputs is uncontroversial. More difficult to address are the environmental circumstances within which the agency operates. Crime will be greater in a poor, gang and drug-infested neighborhood than in an upscale suburb. Some analysts advocate including only those inputs in the production function over which management has direct control. Efficiency scores are then to be adjusted or modified for uncontrollable external environmental variables in a second stage analysis, usually a regression equation. Our method is a hybrid approach. We include two key population characteristics as non-controllable inputs directly into the DEA model - the percentage of the population aged 18 to 24 residing in the police agency's jurisdiction and the census-reported poverty rate. One might imagine other environmental variables to include, but the need to conserve degrees of freedom with a sample of just 50 police agencies dictates that we should confine ourselves to those judged to be critical. Section IV of the paper describes the data sources in more detail and presents descriptive statistics. We also perform a second stage Tobit and probit regression to explain the DEA results as well as account for omitted variables.

The following BCC envelopment form of the DEA model is employed (Cooper, Seiford and Tone, 2007), whose "DEA Solver" software is employed:

$$\begin{aligned}
 & \text{Max } \eta & (6) \\
 \text{Subject to } & X^C \lambda \leq x_o^C \\
 & \eta y_o^C \leq Y^C \lambda \\
 & x_o^N = X^N \lambda \\
 & y_o^N = Y^N \lambda \\
 & e\lambda = 1 \\
 & \lambda > 0
 \end{aligned}$$

Upper case letters refer to matrices and lower case to vectors. Outputs are denoted with Y and y , inputs with X and x . The superscripts C and N refer to controllable and non-controllable outputs or inputs, respectively. The subscript o denotes the DMU under consideration. The efficient amount of inputs must be no more than the existing amounts, and the efficient output must be at least as large as current output. The second set of constraints employ equalities because non-controllable inputs and outputs must be the same as the initial levels under the optimal solution to the programming problem. The $e\lambda = 1$ constraint imposes convexity on the production frontier and thus allows variable returns to scale; e is a row vector with all elements unity and λ a column vector with non-negative elements. Lambda (λ) is the optimal set of weights used to construct the virtual frontier with which each DMU is compared, i.e., the optimal reference set. A DMU is fully efficient only if the scalar $\eta = 1$ and all slacks are zero. The envelopment model determines the maximum *proportional* increase in outputs ($\eta > 1$) by basically comparing each DMU sequentially with all other DMUs to determine if output expansion is possible. The reference set are those DMUs that are most similar to DMU $_o$, i.e., closest to it on the frontier. Because the convex production frontier is piece-wise linear, slacks can arise because not all outputs or inputs can be varied by the same proportion. The above programming model determines the maximal radial output expansion for each non-efficient DMU, and also generates output and input slacks. Output slacks s^+ are defined as $\hat{y}_o = \eta^* y_o + s^+$, and input slacks s^- are $\hat{x}_o = x_o - s^-$, where optimal values have hats and η^* is the maximum radial expansion of output for the DMU under consideration.

The optimal solution $(\eta^*, \lambda^*, s^{+*}, s^{-*})$ is solved in two steps. In the first step η is maximized and, in the second step, the sum of the output and input slacks is maximized subject to $\eta = \eta^*$. The optimal outputs and inputs are obtained using λ^* .

In the analysis below we focus on the ratio of optimal to actual output for each DMU or \hat{y}_0^i/y_0^i , which includes both the radial output expansion and output slacks of any inefficient DMU. In other words, we seek to answer the question of how much a police agency could increase its crime-fighting output, given the resources at its disposal.

IV. Data

The data about the city police departments in New York State is taken from the 2003 Law Enforcement Management and Administrative Statistics (LEMAS) survey, provided by the U.S. Bureau of Justice Statistics, which is the most recent survey available to the public. Since 1987 the LEMAS-survey has been conducted every 3-4 years. The survey collects information on agency personnel, expenditures and pay, operations, community policing initiatives, equipment, computers and information systems, and written policies of over 3,000 publicly funded state and local law enforcement agencies in the United States. For our analysis the survey results for 50 City Police Departments in the State of New York are examined (Bureau of Justice Statistics, 2003).¹⁵ There are numerous upstate New York cities that are relatively comparable to one another, making New York State an excellent case study. Moreover, while it might seem useful to increase the number of cities by examining multiple states, we have opted not to do so, as there are likely cross-state legal and cultural differences that would confound the analysis. The mean population is 38,548, ranging from 2,196 to 285,018. Socio-economic variables are from the U.S. Census Bureau. We include the percentage of the population between ages 18 and 24, as well as the percentage considered “poor”¹⁶. The data for the violent crime rate and the property crime rate in the year 2003 is taken from the New York State Division of Criminal Justice Services.

The following table describes the summary statistics for the 8 inputs and 3 outputs used in the DEA analysis:

¹⁵ We have excluded New York City from this analysis because the DEA analysis uses comparison cities in determining relative efficiency and there is not a comparable city for New York City.

¹⁶The poverty thresholds in 2003 range from \$8,825 for a single retired individual to \$37,656 for a family of nine or more.

TABLE 1

Summary Statistics of the variables used in the Data Envelopment Analysis

<i>Variables</i>	<i>Description</i>	<i>Min / Max</i>	<i>Mean</i>	<i>Standard Deviation</i>
<i>Inputs</i>				
Capital	Number of precinct stations including the headquarters	1 - 14	2.32	2.824
FTSWRN	Number of Full-time Sworn Officers	2 - 865	110.8	179.829
PTSWRN	Number of Part-time Sworn Officers	0 -12	1.34	2.703
FTNonSW	Number of Full-time Non-Sworn employees	0 -198	23.82	45.318
PTNonSW	Number of Part-time Non-Sworn employees	0 - 34	6.38	9.808
Vehicles	Number of Vehicles	2 - 506	55.88	105.799
Aged18_24	Percentage of population between 18 and 24	3.8 - 44.6	10.034	6.045
PctPoor	Percentage of population considered "poor".	2.3 - 35.6	13.92	7.802
<i>Outputs</i>				
INVCPC	The inverse of the rate of violent crime per capita	72.63 - 15066	880.173	2142.984
INPCPC	The inverse of the rate of property crime per capita	13.69 - 131.77	45.231	26.005
Functions	Number of different activities the department is involved in ¹⁷	12 - 29	21.54	3.884

K=50

¹⁷ The variable measures the amount of functions the agency had as a primary responsibility as answered on the LEMAS 2003 survey (question 1). Those responsibilities are subcategories of Law enforcement functions, traffic and vehicle-related functions, criminal investigation, court-related functions, special public safety functions, special operations, detention-related functions and other functions.

DEA results

The mean output efficiency score (η) is 95.6% across the 50 departments studied, of which 30 are judged 100% efficient. The mean score for the 20 inefficient departments is 89.5%. But these numbers refer only to the potential proportional increase in all outputs simultaneously, and thus do not include the significant output slacks arising from the piecewise linear efficiency frontier. Inclusive of slacks, the mean ratio of the potential reduction of actual violent crime and property crime is a startling 173% and 64%, respectively. These two numbers are the headline, takeaway numbers of this paper, thus suggesting that significant opportunities to reduce crime exist in forty percent of the departments under investigation.

Figure 1 below shows the 20 inefficient departments and their ratio of actual to potential violent crime rates. A larger circle means that more room for improvement for the respective city police department regarding the violent crimes.

FIGURE 1

Actual to potential violent crime rates for the 20 inefficient city police departments.

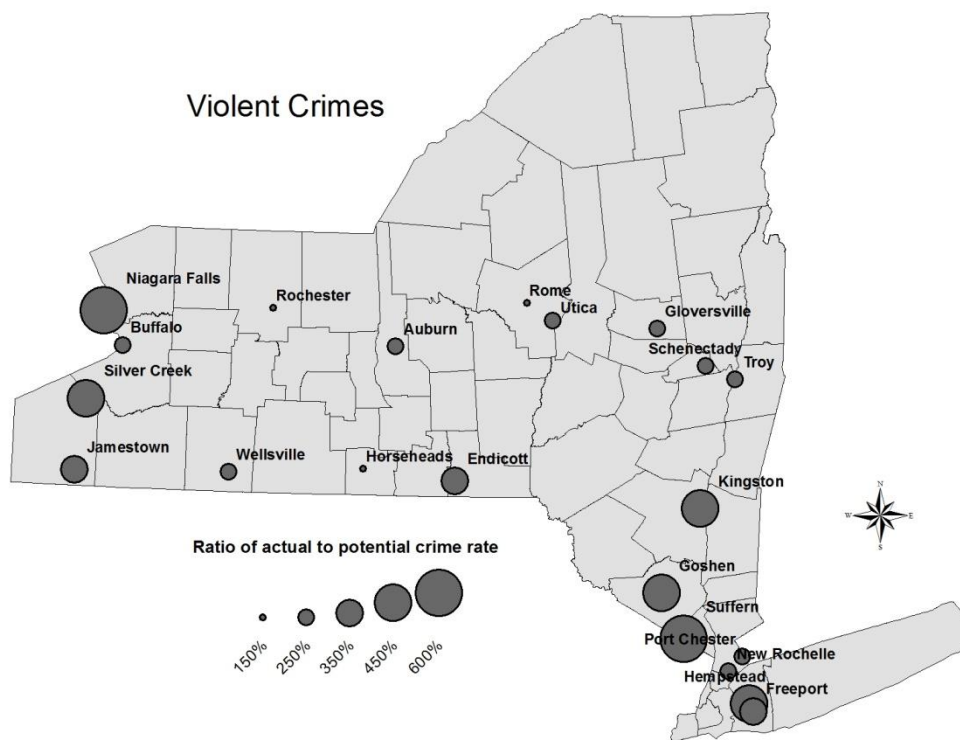
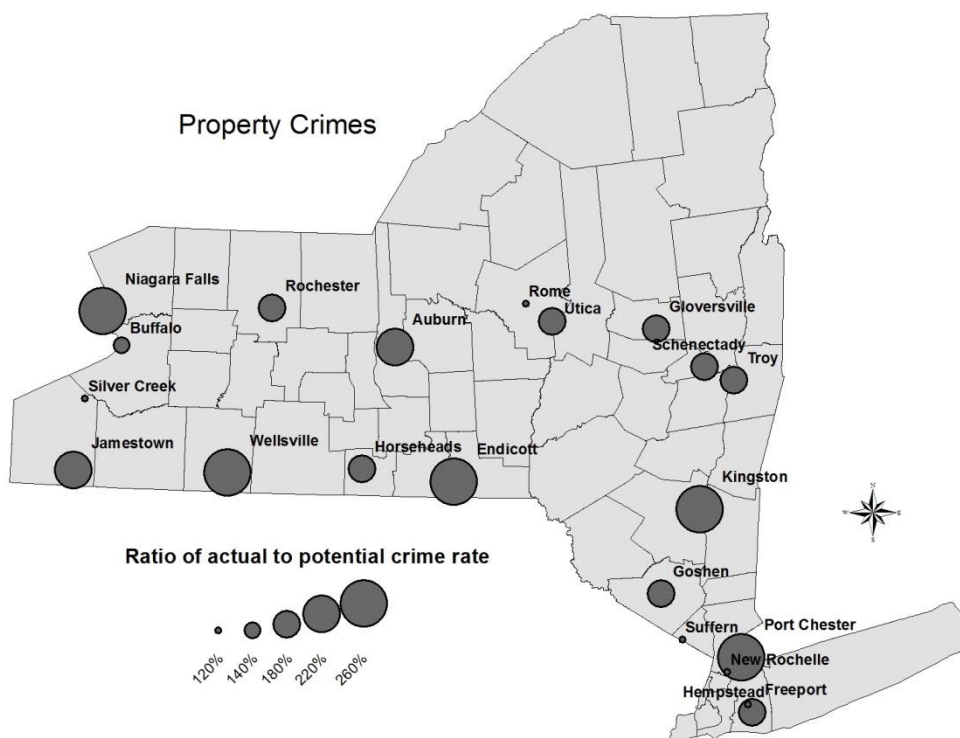


Figure 2 below shows the ratio of actual to potential property crime rates for the 20 inefficient city police departments.

FIGURE 2

Ratio of actual to potential property crime rates for the 20 inefficient city police departments.



The Appendix shows the actual and the projected (efficient) inverse crime rates for the inefficient departments, as well as the reference departments against which each is benchmarked. Having determined that outputs could be significantly increased without additional resources the next question is what policies and procedures might account for the poor performance of some departments and thus suggests changes that could be adopted by police chiefs and other responsible officials.

Regression analysis of DEA results

*****We estimate Tobit/probit regressions to identify police department characteristics linked to inefficiency. The data in the second part of the analysis is also based on the LEMAS survey. Out of the 62 questions asked on the survey, only four shows statistically significant influence on the two dependent variables, the ratios of potential to actual violent and property crime rates (inverted), denoted as the VCRatio and PCRatio. Factors such as requiring

education beyond high school, hours of academy and field training, unionization, and the salaries of police officers and supervisors (including the chief) all proved insignificant. On the other hand, the number of officers in a dedicated drug task force is linked to reduced violent and property crime. Surprisingly, community policing officers and more extensive officer screening methods are both associated with *more* criminal activity. Table 2 presents the description of the data used in the regressions.

TABLE 2

Summary Statistics of the variables used in the Tobit and Probit Models (N = 50)

<i>Variable</i>	<i>Description</i>	<i>Min - Max</i>	<i>Mean</i>	<i>Standard Deviation</i>
<i>Dependent Variables</i>				
VCRatio	Ratio of the optimal violent crime rate to the actual	1.00 - 6.00	1.69*	1.13
PCRatio	Ratio of the optimal property crime rate to the actual	1.00 - 2.58	1.26	0.43
<i>Independent Variables</i>				
SCREENS	Number of screening techniques used in hiring new employees	1 - 14	10.1	2.34
COMMPOL	Number of community policing officers	0 -30	4.04	6.64
NONCOMP	Sum of vehicle mounted and portable computer devices NOT-USED by the department ¹⁸	5 - 9	7.38	1.16
DRUGUNIT	Number of officers employed in a special drug unit	0 - 57	4.88	9.93

* This means crime could be decreased by 69% across the 50 departments.

¹⁸Question 49 on the LEMAS survey asks for the usage of vehicle mounted or portable computers used by the police officers in the department. This variable counts the amount of "Agency does not use" checked boxes for the 9 possible different appliances.

Both the VCRatio and PCRatio are bounded below by 1, which drives the need to use a Tobit regression model when examining the relationship between property and violent crime rates and police characteristics. Table 3 shows the correlation coefficients between actual crime rates per capita and the PCRatio and VCRatio. Interestingly, the inefficiency ratios are more correlated with each other (0.605) than are property and violent crime rates per capita (0.25), which could be evidence of spillover inefficiencies between property and violent crime rates. Additionally, the crime rates per capita and inefficiency ratios (for both property and violent crimes) show a negative relationship. The negative correlation between actual crime rates and crime inefficiency suggests that high-crime departments are actually more efficient. In other words, a high crime department has a lower ratio of potential to actual crime reduction.

TABLE 3:

Correlation Between Crime Rate and Inefficiency (N = 50)

	<i>Property Crime Rate per capita</i>	<i>Violent Crime Rate per capita</i>	<i>PCRatio</i>	<i>VCRatio</i>
<i>Property Crime Rate per capita</i>	1.000			
<i>Violent Crime Rate per capita</i>	0.250	1.000		
<i>PCRatio</i>	-0.391	-0.173	1.000	
<i>VCRatio</i>	-0.104	-0.185	0.605	1.000

Table 4 presents the coefficient estimates, partial derivatives evaluated at the means (marginal effects), standard errors and p-values for a Tobit regression of VCRatio on number of community policing officers (commpol), number of officer employment screens (screens), the non-use of in-field computing (noncomp) and the number of drug unit officers (drugunit).¹⁹ We find that all four variables are highly statistically significant. The coefficients for commpol and screens have positive signs, suggesting that more officers assigned to community policing and more screens that are used *increase the inefficiency* of the

¹⁹In order to determine whether we are implementing the correct specification, we conduct a Lagrange multiplier test and find that the value of 6.731 in the LM test is less than the critical Chi-square value of 11.07, thus the hypothesis that a Tobit model is appropriate in our regression is not rejected.

departments regarding the violent crime rate. The variable *drugunit* has a negative sign for its coefficient. This shows that having a larger drug unit has a positive effect on the violent crime rate-efficiency of the police department. Because a higher value of the *noncomp* variable means that *less* computing equipment is used in cars, the negative sign of its coefficient leads to the conclusion that a greater reliance on technology also increases the inefficiency with regard to the violent crime rate.

The partial derivatives are significant as well and show the magnitude of the effects. Since all of the explanatory variables are measured in numbers, interpretation is relatively straightforward. For example, allocating one additional individual to the drug crimes unit reduces the ratio of optimal to actual crime rate by 0.067. Similar interpretations can be offered for the other explanatory variables.

While the above results are interesting, possible endogeneity remains a concern. For example, drug units will likely be set up in departments that have high violent crime rates, since drugs and violence are linked. Thus, we would expect to find that agencies that select to have drug units are more acutely aware of violent crime related issues and have already set up measures that are intended to reduce the violent crime rate. To test for potential endogeneity in the Tobit regression, we have performed a test for exogeneity in a Tobit model (Smith and Blundell, 1986). We find that mobile computing and community policing suffer from endogeneity in the violent crime specification. Therefore, in the bottom panel of table 4, we include the effect of the endogenous variables based on a simultaneous equations model.²⁰ After correcting for endogeneity, two major changes occur. First, we find that the community policing coefficient increases from 0.146 to 0.225. In other words, increasing the number of community police officers by one individual increases the ratio of optimal to actual violent crimes. Second, after correcting for endogeneity the coefficient estimates associated with *noncomp* becomes insignificant. Thus, we conclude that community policing and employment screens make agencies *less* efficient, while drug units increase efficiency in fighting violent crimes.

²⁰ Smith and Blundell (1986) provide a test for exogeneity that consists of estimating separate OLS regressions for each of the potentially endogenous variables. The explanatory variables used are population, percent poor, percent of population aged 18-24 and the amount of state aid. The residuals from each of these OLS equations is then appended to the original Tobit model and the hypothesis of exogeneity is rejected based on the statistical significance of coefficients of these residual explanatory variables (i.e. if they are significant, then the corresponding variable is assumed to be endogenous).

TABLE 4

Tobit regression – VCRatio (Corrected for heteroscedasticity)

<i>Dependent Variable VCRatio</i>				
<i>Variable</i>	<i>Coefficient</i> <i>(Standard Errors)</i>	<i>p-value</i>	<i>Partial Derivatives</i> <i>(Standard Errors)</i>	<i>p-value</i>
Constant	3.880 (2.669)	0.146	1.134 (0.955)	0.235
Commpol	0.146 (0.034)	0.000‡	0.043 (0.011)	0.000‡
Screens	0.435 (0.120)	0.000‡	0.127 (0.043)	0.003‡
Noncomp	-1.018 (0.303)	0.000‡	-0.297 (0.127)	0.019†
Drugunit	-0.230 (0.072)	0.001‡	-0.067 (0.032)	0.036†

Test for Tobit specification: LM test [df] for Tobit = 6.731 [5]

Number of obs. = 50; Standard Errors in parentheses; p-values: † < 0.05, ‡ < 0.01

<i>Variable</i>	<i>Coefficient</i> <i>(Standard Errors)</i>	<i>p-value</i>	<i>Partial Derivatives</i> <i>(Standard Errors)</i>	<i>p-value</i>
Commpol	0.225 (0.095)	0.018†	0.216 (0.087)	0.013†
Noncomp	-3.247 (12.906)	0.801	-3.169 (12.693)	0.803

Table 5 conducts an analogous estimation exercise for property crimes similar to the violent crime estimation exercise in Table 4, with the exception that a probit model is implemented. The use of the probit model (1 = inefficient, 0 = efficient) resulted from a Lagrange Multiplier test that rejected the hypothesis of a Tobit model as appropriate in this case. Specification testing suggests that the four variables considered help explain the probability of a police department being inefficient with respect to property crime, but not the extent of inefficiency. A parallel example might be a model explaining fire damage to buildings where the age of the building affects the probability of a fire but not the extent of

damage, perhaps because older building are worth less or built with inferior fire retardant materials.

TABLE 5
Probit regressions – PCRatio

<i>Dependent VariablePCDummy (=1 if inefficient, = 0 if efficient)</i>		
<i>Variable</i>	<i>Coefficient</i>	<i>p-value</i>
Constant	-0.377 (0.220)	0.087
Commpol	0.024 (0.009)	0.010†
Screens	0.140 (0.057)	0.013†
Noncomp	-0.161 (0.067)	0.017†
Drugunit	-0.040 (0.017)	0.017†

Correct predictions = 58.000%

Number of obs. = 50; Standard Errors in parentheses; p-values: † < 0.05

We observe the same directions of the effects as in the Tobit model for the VCRatio. More community policing officers and screening techniques in the hiring process decrease the efficiency of the department regarding the property crime rate. The size of specialized drug units increases the efficiency, while more computers in cars and portable devices have a negative influence on the efficiency. All coefficients are significant and the model tells us that 58% of predictions are correct.²¹

While the interpretation of the marginal effects from both the property and violent crime estimates discussed above are useful in understanding the impact of the explanatory variables on the outcome variable, we offer the following interpretations, which are more policy relevant. Using the marginal coefficients for the number of officers assigned to

²¹ A similar test for endogeneity (Smith and Blundell, 1986) was conducted for the probit property crime regression and none of the explanatory variables were determined to be endogenous. As a result, we do not need to re-estimate the coefficient estimates or marginal effects, as we did in Table 4.

community policing and drug units, what is the predicted effect on violent crime of transferring *one* officer from community policing to a drug unit? For the 20 inefficient police departments, the mean number of officers in each unit is 5. The relevant coefficients are in bold face in Tables 4 and 5, and the calculation is: $-1(0.216) + 1(-0.067) = -0.283$. The mean violent crime inefficiency for the 20 departments is reduced from 173% (ratio of efficient to actual) to 145.5% or, a 16% reduction as a consequence of reallocating one officer.

V. Conclusion

This analysis concludes that there exists considerable room for improvement in the crime-fighting outcomes of municipal police departments. While sixty percent of the departments are fully efficient, the remaining forces could reduce per capita violent crime by an average 173% and property crimes by 64% –without additional resources –by behaving more like their peers. As an illustration, the per capita violent crime rate in Wellsville, NY was 0.004975 in 2003. The DEA analysis projects a crime rate of .002132 if it was fully efficient, amounting to a 133% reduction.

Identifying the precise sources of greater or lesser police efficiency is very challenging, and we identify only four department practices and policies with the potential for reducing crime. Shifting officers to dedicated drug crime units reduces both violent and property crimes. An obvious question and research agenda is to identify the tactics used by specialized units that make them more effective. Contrary to conventional wisdom, community policing worsens both types of crimes, perhaps because officers are diverted from crime fighting to public relations. The negative or limited impact of mobile computers may merely reflect more accurate record-keeping. More background screening, along with pay and training also have negative or zero impact on measured crime. An obvious question is the role of incentives and performance-related compensation. As in public education, if individual officers' pay was linked to their crime fighting results, as compared to across-the-board or seniority-based pay, then spending more on police pay may yield positive crime-reduction.

Extending the sort of efficiency analysis presented in this paper requires the U.S. Justice Department to continue the LEMAS surveys and more timely release of the data to researchers.

Appendix A

TABLE A.1

DEA - Rank and Score of Inefficient City Police Departments

<i>DMU</i>	<i>Rank</i>	<i>Score</i>
GOSHEN POLICE DEPT	30	0.980327
NEW ROCHELLE POLICE	31	0.975029
GLOVERSVILLE POLICE	32	0.965356
WELLSVILLE POLICE DE	33	0.955423
ENDICOTT POLICE DEPT	34	0.948298
UTICA POLICE DEPT	35	0.946018
SUFFERN POLICE DEPT	36	0.943297
ROME POLICE DEPT	37	0.932286
HORSEHEADS POLICE DE	38	0.92965
BUFFALO POLICE DEPT	39	0.928481
HEMPSTEAD VILLAGE PO	40	0.920804
SILVER CREEK VILLAGE	41	0.914417
PORT CHESTER POLICE	42	0.90908
NIAGARA FALLS POLICE	43	0.885044
ROCHESTER POLICE DEP	44	0.880074
TROY POLICE DEPT	45	0.866127
SCHENECTADY POLICE D	46	0.861304
AUBURN POLICE DEPT	47	0.834563
KINGSTON POLICE DEPT	48	0.774944
JAMESTOWN POLICE DEP	49	0.761863
FREEPORT POLICE DEPT	50	0.698058

TABLE A.2

Computing the dependent variables of the Tobit and probit regression

<i>AGENCY</i>	<i>Actual</i> <i>(O)INVPCPC</i>	<i>Actual</i> <i>(O)INPCPC</i>	<i>Target</i> <i>(O)INVPCPC</i>	<i>Target</i> <i>(O)INPCPC</i>	<i>VCRatio</i>	<i>PCRatio</i>
ALBANY POLICE DEPT	80.965	18.821	80.965	18.821	1	1
WATERVLIET POLICE DEPT	402.080	45.279	402.080	45.279	1	1
WELLSVILLE POLICE DEPT	201.375	27.460	469.018	61.414	2.329078	2.236455
BINGHAMTON POLICE DEPT	254.451	23.785	254.451	23.785	1	1
ENDICOTT POLICE DEPT	314.049	24.294	888.709	62.767	2.829843	2.583624
AUBURN POLICE DEPT	365.208	27.788	656.831	56.057	1.798513	2.017327
JAMESTOWN POLICE DEPT	187.354	24.980	525.957	48.497	2.807297	1.941411
SILVER CREEK VILLAGE POLICE DEPT	190.467	60.787	726.374	66.709	3.813654	1.097412
ELMIRA POLICE DEPT	183.855	18.657	183.855	18.657	1	1
HORSEHEADS POLICE DEPT	795.375	32.799	951.278	51.389	1.196012	1.566795
BUFFALO POLICE DEPT	72.635	17.263	160.271	23.393	2.206538	1.355053
GLOVERSVILLE POLICE DEPT	400.711	23.792	754.084	38.600	1.881868	1.62238
LEROY POLICE DEPT	1457.667	31.688	1457.667	31.688	1	1
ILION POLICE DEPT	253.636	59.362	253.636	59.362	1	1
BROCKPORT POLICE DEPT	197.488	37.313	197.488	37.313	1	1
ROCHESTER POLICE DEPT	105.853	13.693	158.660	23.432	1.498873	1.71118
AMSTERDAM POLICE DEPT	748.917	90.322	748.917	90.322	1	1
FREEPORT POLICE DEPT	240.253	45.125	732.809	64.643	3.05016	1.432547
GARDEN CITY POLICE DEPT	1675.923	79.225	1675.923	79.225	1	1
HEMPSTEAD VILLAGE POLICE DEPT	139.533	48.594	513.319	52.774	3.678844	1.086008
NIAGARA FALLS POLICE DEPT	89.534	16.475	536.852	41.073	5.996074	2.493052
CAMDEN POLICE DEPT	191.667	63.889	191.667	63.889	1	1
ROME POLICE DEPT	676.706	46.263	905.086	49.623	1.337487	1.072632
UTICA POLICE DEPT	154.506	26.090	315.182	38.021	2.039928	1.457293

SYRACUSE POLICE DEPT	105.961	18.648	105.961	18.648	1	1
CLIFTON SPRINGS POLICE DEPT	732.000	64.588	732.000	64.588	1	1
GENEVA POLICE DEPT	422.406	35.109	422.406	35.109	1	1
GOSHEN POLICE DEPT	383.571	61.724	1529.554	101.134	3.987664	1.638491
MONROE POLICE DEPT	1342.000	31.331	1342.000	31.331	1	1
HOOSICK FALLS POLICE DEPT	422.875	105.719	422.875	105.719	1	1
TROY POLICE DEPT	166.038	22.744	373.343	33.977	2.248547	1.493898
SUFFERN POLICE DEPT	440.560	92.555	2012.188	98.118	4.567341	1.060111
SCHENECTADY POLICE DEPT	126.327	23.495	312.285	39.292	2.472038	1.672378
AMITYVILLE POLICE DEPT	955.100	60.449	955.100	60.449	1	1
MONITCELLO POLICE DEPT	166.487	21.862	166.487	21.862	1	1
KINGSTON POLICE DEPT	197.407	20.724	197.407	20.724	1	1
LYONS POLICE DEPT	156.043	23.927	156.043	23.927	1	1
BRIARCLIFF MANOR POLICE DEPT	1976.500	131.767	1976.500	131.767	1	1
CROTON POLICE DEPT	1560.200	61.425	1560.200	61.425	1	1
LARCHMONT POLICE DEPT	1630.750	76.741	1630.750	76.741	1	1
MT. VERNON POLICE DEPT	169.737	41.710	169.737	41.710	1	1
NEW ROCHELLE POLICE DEPT	284.635	44.150	700.997	47.646	2.462791	1.079192
PELHAM VILLAGE POLICE DEPT	914.143	45.063	914.143	45.063	1	1
PORT CHESTER POLICE DEPT	307.198	35.748	752.784	79.404	2.450487	2.221204
RYE POLICE DEPT	15066.000	65.504	15066.000	65.504	1	1
SCARSDALE POLICE DEPT	3585.800	78.982	3585.800	78.982	1	1
TARRYTOWN POLICE DEPT	518.682	82.094	518.682	82.094	1	1
WHITE PLAINS POLICE DEPT	248.444	33.353	248.444	33.353	1	1
YONKERS POLICE DEPT	224.560	52.095	224.560	52.095	1	1
ATTICA POLICE DEPT	2525.000	26.302	2525.000	26.302	1	1

TABLE A.3

Inefficient Agencies and correspondent reference set

<i>AGENCY</i>	<i>SCORE</i>	<i>REFERENCE SET (Lambda-Value)</i>				
WELLSVILLE POLICE DEPT	0.955	CLIFTON SPRINGS PD (0.2715285)	HOOSICK FALLS PD (0.309764)	MONITCE LLO PD (0.368788)	CROTON PD (4.99E-02)	
ENDICOTT POLICE DEPT	0.948	AMSTERDAM PD (0.5128888)	MONROE PD (0.136731)	MONITCE LLO PD (0.263024)	SCARSDALE PD (7.66E-02)	WHITE PLAINS PD (1.08E-02)
AUBURN POLICE DEPT	0.835	AMSTERDAM PD (0.4070972)	MONROE PD (0.21483)	MONITCE LLO PD (0.161893)	MT. VERNON PD (0.21618)	
JAMESTOWN POLICE DEPT	0.762	AMSTERDAM PD (0.3208562)	MONROE PD (0.135807)	MONITCE LLO PD (0.307664)	MT. VERNON PD (0.08085)	WHITE PLAINS PD (0.154823)
SILVER CREEK VILLAGE POLICE DEPT	0.914	CLIFTON SPRINGS PD (0.7440093)	HOOSICK FALLS PD (0.118941)	MONITCE LLO PD (5.91E-02)	CROTON PD (7.80E-02)	
HORSEHEADS POLICE DEPT	0.930	ILION PD (6.77E-02)	CLIFTON SPRINGS PD (0.185517)	MONROE PD (0.536995)	HOOSICK FALLS PD (0.166667)	MONITCELL O PD (4.31E-02)
BUFFALO POLICE DEPT	0.929	ALBANY PD (0.2684036)	MONITCELL O PD (0.527364)	WHITE PLAINS PD (0.204232)		
GLOVERSVILLE POLICE DEPT	0.965	AMSTERDAM PD (0.187196)	MONROE PD (0.406678)	MONITCE LLO PD (0.399869)	WHITE PLAINS PD (6.26E-03)	
ROCHESTER POLICE DEPT	0.880	ALBANY PD (0.2979735)	MONITCELL O PD (0.486594)	WHITE PLAINS PD (0.215433)		
FREEPORT POLICE DEPT	0.698	AMSTERDAM PD (0.4044773)	MONROE PD (0.180235)	SCARSDA LE PD (1.20E-02)	TARRYTOW N PD (0.165442)	WHITE PLAINS PD (0.237821)
HEMPSTEAD VILLAGE POLICE DEPT	0.921	AMSTERDAM PD (0.3383743)	SYRACUSE PD (6.18E-02)	GENEVA PD (0.599784)		
NIAGARA FALLS POLICE DEPT	0.885	AMSTERDAM PD (0.2147869)	MONROE PD (0.192351)	MONITCE LLO PD (0.359133)	WHITE PLAINS PD (0.233728)	
ROME POLICE DEPT	0.932	AMSTERDAM PD (0.3010711)	MONROE PD (0.387705)	MONITCE LLO PD (0.194843)	MT. VERNON PD (8.50E-02)	SCARSDALE PD (0.031356)
UTICA POLICE DEPT	0.946	AMSTERDAM PD (0.1784058)	GENEVA PD (0.10313)	MONITCE LLO PD (0.494041)	WHITE PLAINS PD (0.224423)	

GOSHEN POLICE DEPT	0.980	BROCKPORT PD (1.83E-02)	MONROE PD (0.228301)	HOOSICK FALLS PD (0.159032)	BRIARCLIFF MANOR PD (0.573244)	PELHAM VILLAGE PD (2.11E-02)		
TROY POLICE DEPT	0.866	ALBANY PD (5.45E-02)	GENEVA PD (0.815407)	MONITCE LLO PD (8.12E-02)	YONKERS PD (4.89E-02)			
SUFFERN POLICE DEPT	0.943	BROCKPORT PD (2.60E-03)	AMSTERDA M PD (0.145057)	MONROE PD (8.39E-03)	HOOSICK FALLS PD (0.248915)	BRIARCLIFF MANOR PD (0.21489)	SCARSDAL E PD (0.37971)	TARR YTOW N PD (4.34E- 04)
SCHENECTADY POLICE DEPT	0.861	ALBANY PD (0.1726895)	BINGHAMT ON PD (0.162786)	AMSTERD AM PD (0.216864)	MONITCELL O PD (0.204366)	WHITE PLAINS PD (0.243294)		
KINGSTON POLICE DEPT	0.775	AMSTERDAM PD (0.1427869)	MONROE PD (0.40629)	HOOSICK FALLS PD (0.125)	MONITCELL O PD (0.290827)	WHITE PLAINS PD (3.51E-02)		
NEW ROCHELLE POLICE DEPT	0.975	ALBANY PD (3.53E-02)	AMSTERDA M PD (0.270383)	MONROE PD (0.295499)	WHITE PLAINS PD (0.398823)			
PORT CHESTER POLICE DEPT	0.909	AMSTERDAM PD (0.599593)	GENEVA PD (7.50E-02)	MONROE PD (0.148273)	HOOSICK FALLS PD (0.166667)	WHITE PLAINS PD (1.05E-02)		

Reference

- Banker, R.D., Charnes, A. and Cooper, W.W. (1984). 'Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis', *Management Science*, Vol. 30, pp.1078-1092.
- Banker, R.D. and Natarajan, R. (2004). 'Statistical Tests Based on DEA Efficiency Scores', in: Cooper W.W., Seiford L.M. and Zhu J. (eds), *Handbook on Data Envelopment Analysis*, Kluwer Academic Publishers, Boston, pp. 299 – 322.
- Barros, C.P. (2006). 'Productivity Growth in the Lisbon Police Force', *Public Organization Review*, Vol. 6, pp. 21-35.
- Barros, C.P. and Alves, F.P. (2005). Efficiency in crime prevention: a case study of the Lisbon precincts. *International Advances in Economic Research*, Vol. 11, pp. 315–328.
- Bureau of Justice Statistics. (2003). 'Law Enforcement Management and Statistics, 2003', Available online at <http://www.icpsr.umich.edu/icpsrweb/NACJD/studies/04411/version/1> (10/24/2011).
- Charnes, A., Cooper, W.W. and Rhodes, E. (1978). 'Measuring Efficiency of Decision Making Unit', *European Journal of Operational Research*, Vol. 2, pp. 429-444.
- Carrington, R., Puthuchery, N. and Rose, D. (1997). 'Performance measurement service provision: the case of police services in New South Wales', *Journal of Productivity Analysis*, Vol. 8, pp. 415–430.
- DeAngelo, G. and Hansen, B. (2010). 'Life and Death in the Fast Lane: Police Enforcement and Roadway Safety'. *Working paper*.
- Cooper, M. (2011). 'Spending Agreement Hurts Police and Fire Agencies'. *The New York Times* 04/15/2011. Available Online at: <http://www.nytimes.com/2011/04/15/us/politics/15safety.html> (10/21/2011).
- Cooper, W.W., Seiford, L.M. and Tone, K. (2007). *Data Envelopment Analysis*, Second Ed., Springer, New York.
- Diez-Ticio, A, and Mancebon, M-J. (2002). 'The efficiency of the Spanish police service: an application of the multiactivity DEA model', *Applied Economics*, Vol. 34, pp. 351-362.
- Drake, L., and Simper, R. (2000). 'Productivity estimation and the size-efficiency relationship in English and Welsh police forces. An application of data envelopment analysis and multiple discriminant analysis', *International Review of Law and Economics*, Vol. 20, pp. 53-73.
- Drake, L. and Simper, R. (2001). 'The Economic Evaluation of Policing Activity: An Application of a Hybrid Methodology', *European Journal of Law and Economics*, Vol. 12, pp. 173-192.
- Drake, L. and Simper, R. (2002). 'X-efficiency and scale economies in policing: a comparative study using the distribution free approach and DEA', *Applied Economics*, Vol. 34, pp. 1859-1870.
- Drake, L. and Simper, R. (2003). 'The measurement of English and Welsh police force efficiency: A comparison of distance function models', *European Journal of Operational Research*, Vol. 147, pp. 165-186.
- Drake, L. and Simper, R. (2005). 'Police Efficiency in Offenses Cleared: An Analysis of English 'Basic Command Units''. *International Review of Law and Economics*, Vol. 25, pp. 186-208.

- Gorman, M.F. and Ruggiero, J. (2008). 'Evaluating US state police performance using data envelopment analysis', *International Journal of production economics*, Vol. 113, pp. 1031-1037.
- Greene, W.H. (2007). *Econometric Modeling Guide. Limdep Econometric Software, Version 9.0*, Econometric Software, Inc Plainview, N.Y.:
- Grosskopf, S., Hayes, K. and Hirschberg, J. (1995). 'Fiscal stress and the production of public safety: A distance function approach', *Journal of Public Economics*, Vol. 57, pp. 277-296.
- Gyimah-Brempong, K. (1987). 'Economies of scale in municipal police departments: the case of Florida', *Review of Economics and Statistics*, Vol. 69, pp. 352-356.
- Gyapong, A., Gyimah-Brempong, K. (1988). 'Factor substitution, price elasticity of factor demand and returns to scale in police production: Evidence from Michigan', *Economic Journal*, Vol. 54, pp. 863-878.
- Mar Molinero, C. (1996). 'On the Joint Determination of Efficiencies in a Data Envelopment Analysis Context', *The Journal of the Operational Research Society*, Vol. 47, pp. 1273-1279.
- Nyhan, R.C. and Martin, L.L. (1999). 'Comparative Performance Measurement: A Primer on Data Envelopment Analysis', *Public Productivity & Management Review*, Vol. 22, pp. 348-364.
- Ray, S.C. (2004). *Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research*, Cambridge University Press, New York.
- Smart, P. (2011). 'Cuomo questions state police car use', WGXC Hands-on Radio Newsroom 02/07/2011. Available online at: <http://newsroom.wgxc.org/archives/8763> (10/21/2011).
- Smith, R.J. and Blundell, R.W. (1986). 'An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply', *Econometrica*, Vol. 54, pp. 679-685.
- Sun, S. (2002). 'Measuring the relative efficiency of police precincts using data envelopment analysis', *Socio-Economic Planning Sciences*, Vol. 36, pp. 51-71.
- Thanassoulis, E. (1995). 'Assessing police forces in England and Wales using Data Envelopment Analysis', *European Journal of Operational Research*, Vol. 87, pp. 641-657.
- Tsai, P.F. and Mar Molinero, C. (1998). 'The Joint Determination of Efficiencies in DEA: An Application to the UK Health Service', *IDEAS*, Economic Research Division of the Federal Reserve Bank of St. Louis.
- Voorhees, S. and George, L. (2011). 'Rochester Mayor Tom Richards Releases Proposed Budget', Your News Now (YNN) 05/20/2011. Available Online at: http://rochester.ynn.com/content/top_stories/544078/rochester-mayor-tom-richards-releases-proposed-budget/ (10/21/2011).
- Wilson, J.D. (2011). 'Crime and the Great Recession', *City Journal*, Vol. 21,