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# Crime and Police Personnel in Malaysia: An Empirical Investigation

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## ABSTRAK

Teori ekonomi gelagat jenayah yang diajukan oleh Becker (1968) mencadangkan bahawa meningkatkan jumlah anggota polis dapat mengurangkan kejadian jenayah. Bagaimana pun kajian terkini mendapati hubungan yang positif diantara jumlah anggota polis dengan kadar jenayah. Objektif kajian ini adalah untuk menyiasat kesan anggota polis terhadap 15 kategori jenayah di Malaysia untuk tempoh masa 1973 hingga 2005 dengan mengguna model vektor pembetulan ralat. Hasil kajian mencadangkan bahawa 8 kategori kadar jenayah menyokong teori ekonomi Becker manakala 6 kategori jenayah menyokong hipotesis "jangka panjang kadar semulajadi jenayah".

Kata kunci: Kadar Jenayah, Anggota Polis, Kointegrasi

## *ABSTRACT*

*The economic theory on crime behavior proposed by Becker (1968) suggests that increase in the number of policemen can deter crimes. However, recent studies found a positive relationship between police personnel and crime rates. The purpose of the present study is to investigate the effect of police personnel on 15 categories of crime rates in Malaysia for the period 1973 to 2005 by using the vector error-correction model. Our results suggest that 8 categories of crime rates support Becker's crime economic theory, while 6 categories of crime support the "long-run natural rate of crime" hypothesis.*

*Keywords: Crime Rates, Police Personnel, Cointegration*

## INTRODUCTION

To sustainthe living standard over the long-run, it is important to maintain the long-term growth of the country's output. Increase in output raises the standard of living and studies have shown that the growth rate of the stock of physical and human capitals as well as the rate of technological change is key determinants of long-term economic growth. Accumulated savings channeled to investment in plant, equipment, technology and human capital will enhance growth. Increase in output per person raises income and ultimately leads to the accumulation of wealth. The role of the government in this process is to foster a stable political climate and as well as to define, protect and enforce "property rights".

Property rights is defined as the ownership of goods and services, as well as resources and set limits on the transfer and use of those goods and services (Mabry and Ulbrich, 1989). Without property rights being enforce, one cannot establish who owns them and what rights the owners have. When property can be freely taken by theft and deception no one has the incentive to invest and to accumulate wealth. Thus, the protection of property from been taken forcefully or illegally is the most basic of all property rights (Witte and Witt, 2001). And without government intervention the market cannot work effectively and the strongest will acquire most goods and services rather than those who legitimately acquire the goods from exchange.

Crime has been part of our everyday life. Crime resulted in misery and loss of life. In Malaysia, we identify 15 categories of crime rates, namely: murder, attempted murder, and gang robbery with firearms, gang robbery without firearms, armed robbery, and robbery without armed, rape, assault, daylight burglary, night burglary, lorry-van theft, car theft, motorcycle theft, bicycle theftand other theft. In Malaysia as well as anywhere else criminal activities are clearly an act of brute force engaging in the taking of property and person life and thus violate "property rights". The protection of person and property is the role of government in crime prevention and providing criminal justice system. One common method used by the government to deter crime is to increase budget for police expenditures. With higher budget police department will enable to hire additional police personnel, recruit more qualified persons, to improve their training, to supply them with better equipment – more firepower and sophisticated communication devices to combat crime. Thus, it is expected that higher police expenditures will result in more efficient and effective police force, thereby increasing the probability of arrest and decreasing a criminal's incentive to commit a crime.

However, despite the economic model put forward by Becker (1968) and Ehrlich (1973) that crime does not pay – the war against crime is to increase in police strength and thereby reduce crime (Lin, 2009; Hakim et al., 1979; Vollard and Koning, 2009); numerous studies have suggested the opposite that is an increase in the number of police force increases crime rates (Fajnzylber et al., 2022; Jacob and Rich, 1981; Buck et al., 1983). Yet in other studies, the relationship between crime rates and police personnel is not significant (Bennett and Bennett, 2009; Meera and Jayakumar, 1995; Allison, 1972). This mixed results or "puzzle" has create controversy among the economists and criminologists. Some of the reasons put forward to explain the "puzzle' are due to: endogeneity problem with respect to the relationship between police and crime rates(Decker and Kohfeld, 1985;Lin, 2009); different measures for police strength (Ogilvie et al., 2008); error in the measurement of crime (Chilton, 1982); too few or an incorrect set of social system/economic control variables were included in the equation (Bennett and Bennett, 1983); aggregation and unobserved heterogeneity bias (Cherry, 1999;Cherry and List, 2002).

The purpose of the present study is to investigate the impact of police personnel on crime rates in Malaysia using disaggregated crime data as suggested by Cherry (1999) and Cherry and List (2002). Total crime is divided into violent and property crimes. Violent crime is further divided into murder, attempted murder, armed robbery, robbery, rape and assault, while property crime is divided into daylight burglary, night burglary, lorry-van theft, car theft, motorcycle theft, bicycle theftand other theft. To eliminate the problem of simultaneity bias we estimate our crime model using the vector error-correction model proposed by Johansen (1988), and Johansen and Juselius (1990). In this study we are using the number of police personnel as deterrence to crime. Despite caution by Marvell and Moody (1996), Jacob and Rich (1981), Bittner (1974) and Skogan (1980) that not all police personnel are involved in combating crime and only a small fraction of these personnel are dispatched into homicide department, however, as it has been used in other studies, we believe that it is an empirical question to determine the appropriateness of using the number of police to proxy for police strength. Due to data availability our period of study ranges from 1973 to 2005.

The paper is organized as follows. In the next section we review briefly the empirical work related to crime and police personnel, and the method used in the study. In section 3, we discuss the empirical results. The last section contains our conclusion.

## METHODOLOGY

*Related Literature*

The Becker-crime-police (BCP) puzzle arises in recent years over the effect of the police on crime. Numerous empirical evidences found positive impact of increasing police strength on crime rates. Furthermore, some studies do not find any significant impact of police force on crime rates. This is in contrast to the model predicted by Becker (1968) that a way to reduce crime is by increasing the number of police in the area. Cherry and List (2002) and Cherry (1999) advocated that the positive relationship between the police and crime rate is due to aggregation bias. Aggregation and heterogeneity in the unit of observation may lead to spurious relationships that incorrectly imply or exaggerate deterrent effects. In their study they found out that deterrent effects have heterogeneous impacts across crime types.

Allison (1972) proposes the unbalanced growth model of Baumol (1967) in which she claims that the cost of externalities rises more rapidly than the population size does. In other words, as the population rises, the crime rate (an externality) increases at a larger rate. Thus, crime reduction can only be achieved with faster increase in police expenditure than the population. On the other hand, Furlong and Mehay (1981) argue that criminals are more concerned with police performance (arrest, clearance and conviction rates) rather than police inputs (police expenditure, number of policemen, armed and unarmed personnel). Thus, a higher level of inputs does not necessarily deter criminals.

Buck et al. (1983) and Friedman et al. (1989) proposed the "long-run natural rate of crime" to explain the positive effect of police on crime rates. According to Friedman et al. (1989) police can deter crime in the short-run but not in the long-run. In the long-run criminals may learn by doing how to cope with police practices and by committing more crimes they may improve their techniques such that the previously increased policing is no longer effective. Buck et al. (1983), on the other hand, contended that certain crimes (burglaries, robberies, vehicle thefts, and larcenies) are considered the natural level of crime. This crime provides high net returns and is unaffected in the long-run by conventional police outlays. The net expected returns on these crimes are very high and provide a substantial incentive to people who are willing to be involved in illegal activity. Any effort to mobilize police force to curtail this type of crime is futile.

*Testing for Long-Run Relationship between Crime and Police*

In this study, we specify crime-police equation for Malaysia as follows:

$$crime_{it} = \alpha_0 + \alpha_1 police_t + \mu_t \tag{1}$$

where small letters indicate variables in natural logarithm and $\mu_t$ is the error term. The parameters $\alpha's$ are to be estimated and $i$ indicates different types of crime rates. It is a *priori* that we expect $\alpha_1 < 0;\ or\ \alpha_1 > 0$. Police strength has a negative effect on crime rate follows the economic model proposed by Becker (1968). In other words, the presence of more police personnel in an area can deter the occurrence of crime in that area. On the other hand, the positive impact of police on crime rates would suggest that crime does pay as the net expected return is too high to leave the illegal activity.

Estimating Equation (1) using OLS is not straight forward because the estimated equation is subject to the so-called spurious regression results (Granger and Newbold, 1974). According to Granger and Newbold (1974) a spurious regression resulted from estimating an equation containing non-stationary economic variables. Nevertheless, recent advances in time-series analysis have yielded new procedures for estimating long-run and short-run econometric relationships between non-stationary variables. One such procedure which has become widespread in the economic literature is the use of dynamic specification with an error-correction mechanism (ECM) in single-equation and multi-equation macroeconomic forecasting models. However, the ECM model is not of recent origin as it was introduced by Phillips (1954) and first used in economics by Sargan (1964). But, the ECM models have only gained recognition amongst the economists and econometricians since the published work of Davidson et al. (1978). In Davidson et al. (1978), the ECM models which include the dynamics of both short-run (changes) and long-run (levels) adjustment process was used to specify U.K.'s consumption function. The favorable performance of the ECM model relative to the traditional model has inspired other researchers to use the ECM approach in economic modeling. Although the work of Hendry (1979, 1983) and associates on aggregate consumption and money demand has been very influential, it was Granger (1981, 1986) who linked the time-series properties of economic time-series, in particular, to the concept of cointegration and the ECM modeling approach.

In this study, to test for cointegration and the ECM modeling, we employ the Johansen (1988) and Johansen and Juselius (1990) multivariate maximum likelihood estimation procedure. Detailed exposition on the Johansen-Juselius technique has been provided in Dickey *et al*. (1991), Cuthbertson *et al*. (1992) and Charemza and Deadman (1992). However, a brief discussion on the Johansen-Juselius technique is provided below. We begin with by defining a *k*-lag vector autoregressive (VAR) representation

$$X_t = \alpha + \Pi_1 X_{t-1} + \Pi_2 X_{t-2} + \ldots + \Pi_k X_{t-k} + \nu_t \quad (t=1, 2,\ldots,T) \tag{2}$$

where $X_t$ is a $px1$ vector of non-stationary $I(1)$ variables, $\alpha$ is a $px1$ vector of constant terms, $\Pi_1$, $\Pi_2 \ldots \Pi_k$ are $pxq$ coefficient matrices and $\nu_t$ is a $px1$ vector of white Gaussian noises with mean zero and finite variance. Equation (2) can be reparameterised as

$$\Delta X_t = \alpha + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \ldots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi_k X_{t-k} + \nu_t \tag{3}$$

where $\Gamma_i = -I + \Pi_1 + \Pi_2 + ... + \Pi_i$ $(i=1, 2,...k-1)$ and $\Pi$ is defined as

$$\Pi = -I + \Pi_1 + \Pi_2 + ... + \Pi_k. \tag{4}$$

Johansen (1988) shows that the coefficient matrix $\Pi_k$ contains the essential information about the cointegrating or equilibrium relationships between the variables in the data set. Specifically, the rank of the matrix $\Pi_k$ indicates the number of cointegrating relationships existing between the variables in $X_t$. In this study, for a two case variables, $X_t$ = (crime and unemployment) and so $p=2$. Therefore, then the hypothesis of cointegration between crime and unemployment is equivalent to the hypothesis that the rank of $\Pi_k = 1$. In other words, the rank $r$ must be at most equal to $p-1$, so that $r \leq p-1$, and there are $p-r$ common stochastic trends. If the $r=0$, then there are no cointegrating vectors and there are $p$ stochastic trends.

The Johansen-Juselius procedure begins with the following least square estimating regressions

$$\Delta X_t = \alpha_1 + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \omega_{1t} \tag{5}$$

$$X_{t-p} = \alpha_2 + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \omega_{2t} \tag{6}$$

Define the product moment matrices of the residuals as $S_{ij} = T^{-1} \sum_{t=1}^{T} \varpi_{it} \varpi_{jt}$ (for $i,j=1,2$), Johansen (1988) shows that the likelihood ratio test statistic for the hypothesis of at most $r$ equilibrium relationships is given by

$$-2lnQ_r = -T \sum_{i=r+1}^{p} ln(1-\lambda_i) \tag{7}$$

where $\lambda_1 > \lambda_2 > ...\lambda_p$ are the eigenvalues that solve the following equation

$$/\lambda S_{22} - S_{21} S_{11}{}' S_{12}/=0. \tag{8}$$

The eigenvalue are also called the squared canonical correlations of $\omega_{2t}$ with respect to $\omega_{1t}$. The limiting distribution of the $-2lnQ_r$ statistic is given in terms of a $p$-$r$ dimensional Brownian motion process, and the quantiles of the distribution are tabulated in Johansen and Juselius (1990) for $p$-$r=1,...,5$ and in Osterwald-Lenum (1992) for $p$-$r=1,...10$.

Equation (7) is usually referred to as the trace test statistic which is rewritten as follows

$$L_{trace} = -T \sum_{i=r+1}^{p} ln(1-\lambda_i) \tag{9}$$

where $\lambda_{r+1},...\lambda_p$ are the $p$-$r$ smallest squared canonical correlation or eigenvalue. The null hypothesis is at most $r$ cointegrating vectors. The other test for cointegration is the $L$-maximal eigenvalue test based on the following statistic

$$L_{max} = -T.ln(1-\lambda_{r+1}) \tag{10}$$

where $\lambda_{r+1}$ is the $(r+t)^{th}$ largest squared canonical correlation or eigenvalue. The null hypothesis is $r$ cointegrating vectors, against the alternative of $r+1$ cointegrating vectors. Comparing the two tests, Johansen and Juselius (1990) indicate that the trace test may lack power relative to the maximal eigenvalue test which will produce clearer results.

*Sources of Data*

Following the suggestion by Cherry and List (2002), we used disaggregate data on crime. According to Cherry and List (2002, p. 81), "it is inappropriate to pool crime types into a single decision model and that much of the existing empirical evidence suffers from aggregation bias." Since we recognized that deterrence effect of unemployment is quite heterogeneous across crime types, in this study, we have disaggregated crime offences into fifteen (15) sub-categories of crime, violent and property crime rates, namely: murder, attempted murder, gang robbery with firearms, gang robbery without firearms, robbery with armed, robbery without armed, rape, assault, day house burglary, night house burglary, lorry-van theft, car-theft, motorcycle theft, bicycle theft and other theft. In fact, earlier studies by Cherry (1999), and Cornwell and Trumbull (1994) have pointed out that unobserved heterogeneity in the unit of observation may lead to spurious relationships that incorrectly imply or exaggerate deterrent effects.

Data on crime and their sub-categories for the period 1973 to 2005 were collected from the Royal Police of Malaysia (PDRM). The total crime activities are classified into 15 categories: murder, attempted murder, gang armed robbery, gang robbery, armed robbery, robbery, rape and assault (these comprise the violent crime); day house burglary, night house burglary, lorry-van theft, car theft, motorcycle theft, bicycle theft and other theft (comprise the property crime). All crime rates were measured as per 100,000 populations. For police strength we proxy using the number of police personnel. All variables were transformed into natural logarithm.

## THE EMPIRICAL RESULTS

*Results for Total Crime Rate, Violent and Property Crime Rate*

Before testing for cointegration by using the Johansen-Juselius procedure, we test for the order of integration of all variables for all crime rates. Table 1 show the results of the unit root test for the test of the order of integration of police, total crime, violent and property crime rates. Clearly, in all cases, the augmented Dickey-Fuller test (Dickey and Fuller, 1979, 1981) statistics indicate that the four series are difference stationary, in other words, they are $I(1)$ in levels.

Having noted that both (crime and police) series are of the same order of integration, we run the cointegration test following the procedure provide by Johansen and Juselius (1990). These results are tabulated in Table 2. The null hypothesis of no cointegration can be rejected in all three cases of the crime-police nexus using both the trace and *L*-max statistics at the 5 percent significance level. This result implies that there is no long-run relationship between the three crime categories with police personnel in Malaysia for the period 1973 to 2005.

Nevertheless, knowing that the Johansen-Juselius cointegration procedures are distorted in small sample, we prefer employing the vector error-correction model to infer cointegration among the series. As a matter of fact, according to the 'Granger Representation Theorem' (Engle and Granger, 1987) not only does cointegration imply the existence of an error correction model but also the converse applies, that is, the existence of an error-correction model implies cointegration of the variables. Recent developments in cointegration and error-correction model as pointed by Pesavento (2004) suggest that the Johansen's test for cointegration has low power in both large and small sample compared to the error-correction model. In fact, Kremers et al. (1992) have argued that the standard *t*-ratio for the coefficient on the error-correction term in the dynamic equation is a more powerful test for cointegration. Banerjee et al. (1986) and Kremers et al. (1992) show that standard asymptotic theory can be used when conducting the test in the context of an error-correction model (ECM); specifically, the *t*-statistics on the error-correction term coefficients have the usual distribution.

Therefore, we specify the following two-variable vector error-correction models (VECM) as

$$\Delta y_t = a_0 + \sum_{i=1}^{k}\alpha_i \Delta y_{t-i} + \sum_{j=1}^{k}\alpha_j \Delta x_{t-j} + \gamma_1 ecm_{t-1} + \varepsilon_{1t} \tag{11}$$

$$\Delta x_t = b_0 + \sum_{i=1}^{k}\beta_i \Delta y_{t-i} + \sum_{j=1}^{k}\beta_j \Delta x_{t-j} + \gamma_2 ecm_{t-1} + \varepsilon_{2t} \tag{12}$$

where $ecm_{t-1}$ is the lagged residual from the cointegration between $y_t$ (say,crime) and $x_t$ (police) in level. Granger (1988) points out that based on Equation (11), the null hypothesis that $x_t$ does not *Granger* cause $y_t$ is rejected not only if the coefficients on the $x_{t-j}$, are jointly significantly different from zero, but also if the coefficient on $ecm_{t-1}$ is significant. The VECM also provides for the finding that $x_{t-j}$ *Granger* cause $y_t$, if $ecm_{t-1}$ is significant even though the coefficients on $x_{t-j}$ are not jointly significantly different from zero. Furthermore, the importance of $\alpha$'s and $\beta$'s and represent the short-run causal impact, while $\gamma$'s gives the long-run impact. In determining whether $y_t$ *Granger* cause $x_t$, the same principle applies with respect to Equation (12). Above all, the significance of the error correction term (ecm) indicates cointegration, and the negative value for $\gamma$'s suggest that the model is stable and any deviation from equilibrium will be corrected in the long-run.

The results of estimating Equations (11) and (12) are presented in Table 3. From the VECM results in Table 3, we presented the *t*-statistics of the error-correction term, $ecm_{t-1}$, where we can infer the long-run causality between the variables. The significance (at least one) of the error correction term at the 5 percent level implies cointegration or exhibit long-run relationship between crime and police force. In other words, both these two variables are bound together by the long-run relationships. Further, the results suggest that *Granger* long-run causality runs from police to total crimeand property crime. For the violent crime, Granger long-run causality runs from violent crime to police.

Our main interest is to determine the sign and the size of the long-run (elasticities) parameter estimates, $\alpha_1$ in Equation (1). The result of the long-run elasticities of crime rate responses to changes in the police force is given in Table 4. The result indicates that only in the case of violent crime that police is significantly different from zero. The result suggests that a 1 percent increase in the police strength will reduce violent crime rates by 1.2 percent. As for total crime and property crime, police has no effect on crime rates in Malaysia.

*Results for Disaggregated Crime Categories*

The results pertaining to all fifteen sub-categories of crime in Malaysia are reported in Tables 5 to 8. In Table 5 we report the results for the order of integration for the sub-categories of criminal activities, which suggest that except murder and rape, all other crime rates are integrated of order one at the five percent level. However, at the one percent level we can safely said that both murder and rape are also integrated of order one. Therefore, we conclude that all the fifteen sub-categories of crime in Malaysia are *I*(1) time-series variables.

Table 6 shows the result of the cointegration test between police and the crime rates for each sub-category. The null of no cointegration can be rejected in 11 out of 15 categories. The long-run relationship are shown between police and murder, attempted murder, gang robbery with firearms, armed robberies, robberies without armed, rape, assault, day house burglary, motorcycle, bicycle and other theft. For motorcycle theft, based on the trace test, the null hypothesis of no cointegration can be rejected. According to Cheung and Lai (1993), the trace test shows more robustness to both skewness and excess kurtosis in the residuals than does the *L*-max test; therefore, we can emphasis on the use of trace statistics to make inferences for non-cointegration between other theft and police in this study.

Despite having shown eleven sub-categories of crime rate that are cointegrated between crime and police by using the Johansen multivariate cointegration test, we further infer the long-run relationship from the ECM framework as suggested by Pasavento (2004), Kremers et al. (1992) and Banerjee et al. (1986). The results of the error-correction model estimations are presented in Table 7. Interestingly, in all cases the error-correction term is significantly different from zero at the 5 percent level. Thus, we conclude that there is long-run relationship between all the 15 sub-categories of crime rates and police personnel in Malaysia for the period 1973-2009. The significant of the ECM term indicate that one-way *Granger* long-run causality runs from police to gang robbery with firearms, armed robberies, day house burglary, night house burglary, and other theft. On the other hand, a one-way *Granger* long-run causality runs from attempted murder, gang robbery without firearms, robberies without armed, rape, lorry-van theft, car theft, motorcycle theft and bicycle theft to police personnel. A bi-directional *Granger* long-run causality is detected in the cases of murder and assault and police personnel.

The long-run impact of police on the crime rates is shown in Table 8. As shown in Table 8, the estimated long-run coefficient or elasticities ($\alpha_1$) are significantly different from zero at least at the 5 percent level. Only in the cases of robbery without armed and other theft that police has impact on the crime rates at the 10 percent level. Nevertheless, police personnel have no effect on day house burglary in Malaysia. Out of the 14 cases, police presence impacted negatively on crime rates in 8 out of the 14 cases; and these criminal activities are murder, gang robbery without firearms, robberies without armed, rape, assault, lorry-van theft, car theft, and motorcycle theft. On the other hand, police impacted positively on attempted murder, gang robbery with firearms, armed robberies, night house burglary, bicycle theft and other theft. The responses of crime rates to a 1 percent changes in police personnel reduce crime rates that ranges from 0.5 percent in the case of murder to 5.8 percent in the case of lorry-van theft. On the other hand, the responses of crime rates to a 1 percent changes in police personnel increases crime rates that ranges from 0.4 percent in the case of other theft to 3.0 percent in the case of armed robberies.

## CONCLUSION

The purpose of the present study is to investigate the long-run and causal relationship between police personnel and 15 categories of the criminal activities in Malaysia for the period 1973 to 2005. In this study, we employ the Johansen multivariate cointegration test and the error-correction model framework to infer cointegration between crime rates and police personnel. We have investigated several measures of crime rates at both the aggregated and disaggregated level: total crime, violent and property crime rates. The sub-categories of crime rates are namely: murder, attempted murder, gang robbery with firearms, gang robbery without firearms, armed robberies, and robbery without armed, rape, assault, day house burglary, night house burglary, lorry-van theft, car-theft, motorcycle theft, bicycle theft and other theft.

Our long-run model suggests police personnel has negative effect on violent crime, murder, gang robbery without firearms, robberies without armed, rape, assault, lorry-van theft, car theft, and motorcycle theft, thus, supporting Becker's crime model. On the other hand, positive effect of police personnel on crime is supported in the cases of attempted murder, gang robbery with firearms, armed robberies, night house burglary, bicycle theft and other theft. We contend that the positive effect of police personnel on crime would support the "long-run natural rate of crime" hypothesis.

## REFERENCES


Allison, J.P. (1972). Economic factors and the rate of crime. *Land Economics*, 48, 193-196.

Banerjee, A., Dolado, J.J., Hendry, D.F. & Smith, G.W. (1986). Exploring equilibrium relationship in econometric through static models: Monte Carlo evidence. *Oxford Bulletin of Economics and Statistics*, 48, 253-277.

Baumol, W.J. (1967). Macroeconomics of unbalanced growth: The anatomy of urban crisis. *American Economic Review*, 57, 415-426.

Becker, G.S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76, 169-217.

Bennett, R.R. & Bennett, S.B. (1983). Police personnel levels and the incidence of crime: A cross-national investigation. *Criminal Justice Review*, 8, 32-40.

Bittner, E. (1974). Florence Nightingale in pursuit of Willie Sutton: A theory of the police. In H. Jacob (ed.). *The Potential for Reform of Criminal Justice*. Beverly Hills, California: Sage Publications.

Buck, A.J., Gross, M., Hakim, S. & Weinblatt, J. (1983). The deterrence hypothesis revisited. Regional Science and Urban Economics, 13, 471-486.

Charemza, W.W. & Deadman, D.F. (1992). *New Direction in Econometric Practice*. England: Edward Elgar.

Cherry, T.L. (1999). Unobserved heterogeneity bias when estimating the economic model of crime. *Applied Economics Letters*, 6, 753-757.

Cherry, T.L. and List, J.A. (2002). Aggregation bias in the economic model of crime. *Economics Letters*, 75, 81-86.

Cheung, Y. and Lai, K. (1993). Finite-sample sizes of Johansen's likelihood ratio tests for cointegration. *Oxford Bulletin of Economics and Statistics*, 55, 313-328.

Cornwell, C. & Trumbull, W.N. (1994). Estimating the economic model of crime with panel data. *The Review of Economics and Statistics*, 76, 360-365.

Cuthbertson, K., Hall, S.G. & Taylor, M.P. (1992). *Applied Econometric Techniques*. New York: Harvester Wheatsheaf.

Decker, S. & Kohfeld, C. (1985). Crimes, crime rates, arrests and arrest ratios: Implications for deterrence theory. *Criminology*, 23, 437-

Dickey, D.A. & Fuller, W.A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica*, 49, 1057-1077.

Dickey, D.A., Jansen, D.W. & Thronton, D.L. (1991). A primer on cointegration with an application to money and income. *Federal Reserve Bank of St. Louis Review*, 73, 58-78.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy*, 81, 521-564.

Engle, R.F. & Granger, C.W.J. (1987). Cointegration and error-correction: Representation, estimation and testing. *Econometrica*, 55, 251-276.

Fajnzylber, P., Lederman, D. & Loayza, N. (2002). What causes violent crime? *European Economic Review*, 46, 1323-1357.

Friedman, J., Hakim, S. & Spiegel, U. (1989). The difference between short and long run effects on police outlays on crime: Policing deters criminals initially, but later they may 'learning by doing'. *American Journal of Economics and Sociology*, 48, 177-191.
Furlong, W. & Mehay, S. (1981). Urban law and enforcement in Canada: A empirical analysis. *Canadian Journal of Economics*, 14, 44-57.
Granger, C.W.J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37, 428-438.
Hakim, S., Ovadia, A., Sagi, E. & Weinblatt, J. (1979). Interjurisdictional spillover of crime and police expenditure. *Land Economics*, 55, 200-212.
Jacob, H. & Rich, M.J. (1981). The effects of the police on crime: A second look. *Law & Society Review*, 15, 109-122.
Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12, 231-254.
Johansen, S. & K. Juselius. (1990). Maximum likelihood estimation and inference on cointegration: With application to the demand for money. *Oxford Bulletin of Economics and Statistics*, 52, 169-210.
Kremers, J.J.M., Ericsson,N.R. & Dolado, J.J. (1992). The power of cointegration test. *Oxford Bulletin of Economics and Statistics*, 54, 325-348.
Levitt, S. (1996). The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *Quarterly Journal of Economics*, 111, 319-351.
Lin, M.J. (2009). More police, less crime: Evidence from US state data. *International Review of Law and Economics*, 29, 73-80.
Marvell, T.B. & Moody, C.E. (1996). Specification problems, police levels and crime rates, *Criminology*, 34, 609-646.
Meera, A.K., & Jayakumar, M.D. (1995). Determinants of crime in a developing country: A regression model. *Applied Economics*, 27, 455-460.
Ogilvie, J.M., Allard, T.J. & Stewart, A.L. (2008). Impact of police numbers on crime. Justice Modelling @ Griffith (JMAG).
Pesavento, E. (2004). Analytical evaluation of the power of tests for the absence of cointegration. *Journal of Econometrics*, 122, 349-384.
MacKinnon, J.G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, 11, 601-618.
MacKinnon, J.G., Haug, A.A. & Michelis, L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics*, 14, 563-577.
Marby, R.H. & Ulbrich, H.H. (1989). *Introduction to Economic Principles*. New York: McGraw-Hill Book Company.
Osterwald-Lenum, M. (1992). A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Economics and Statistics*, 54, 461-472.
Skogan, W. (1980). Presentation before the police services committee, City of Evanston, April 16, 1980.
Vollaard, B. & Koning, P. (2009). The effect of police on crime, disorder and victim precaution. Evidence from a Dutch victimization survey. *International Review of Law and Economics*, 29, 336-348.
Witte, A.D. & Witt, R. (2001). What we spend and what we get: Public and private provision of crime prevention and criminal justice. *Fiscal Studies*, 22, 1-40.

TABLE 1: Results of Unit Root tests for Total, Violent and Property Crime Index

| **Criminal activities** | **ADF unit root tests:** | |
|---|---|---|
| | **Levels** | **First-differences** |
| Total crime: | -2.50 (1) | -3.60**(0) |
| Violent crime | -2.91 (1) | -4.05**(0) |
| Property crime | -2.43 (1) | -3.60**(0) |
| Police | -2.32 (0) | -5.10**(0) |

Notes: Asterisk (**) denotes statistically significance at the 5% level. Critical values are taken from MacKinnon (1996). Series in levels were estimated with constant and trend, while series in first-differences were estimated with constant only. Figures in parentheses denote lag length chosen by SBC criterion

TABLE 2: Results of Bi-variate Cointegration Tests (VAR=2)

| **Criminal activities** | **Null hypothesis** | **Trace test** | **Lamda-max test** |
|---|---|---|---|
| Total crime | $H_o$: r = 0 | 7.46 | 6.83 |
| | $H_o$: r ≤ 1 | 0.63 | 0.63 |
| Violent crime | $H_o$: r = 0 | 12.23 | 11.95 |
| | $H_o$: r ≤ 1 | 0.28 | 0.28 |
| Property crime | $H_o$: r = 0 | 7.80 | 7.01 |
| | $H_o$: r ≤ 1 | 0.79 | 0.79 |

Notes: Asterisk (**) denotes statistically significance at the 5% level. Critical values are taken from MacKinnon-Haug-Michelis (1999).

TABLE 3: Results of Long-run Relationship Between Crime and Police Personnel

| **Criminal activities** | **Dependent variable** | ***t*-statistics of ecm$_{t-1}$ in VECM model** |
|---|---|---|
| Total crime | ΔTotal crime | -2.32** |
| | ΔPolice | -0.94 |
| Violent crime | Δ Violent crime | -1.69 |
| | ΔPolice | -2.97** |
| Property crime | ΔProperty crime | -2.45** |
| | ΔPolice | -0.67 |

Notes: Asterisk (**) denotes statistically significance at the 5% level.

TABLE 4: Results of Long-run Elasticities

| **Criminal activities** | **The long-run model** |
|---|---|
| Total crime | $11.598 - 0.8859(1.5516)police_t$ |
| Violent crime | $11.010 - 1.1655 ** (2.3488)police_t$ |
| Property crime | $11.044 - 0.8164(1.4587)police_t$ |

Notes: Asterisk (**) denotes statistically significance at the 5% level.

TABLE 5: Results of Unit Root Tests for the Disaggregate Crime Activities

| **Criminal activities** | **ADF unit root tests:** | |
|---|---|---|
| | **Levels** | **First-differences** |
| Violent crime: | | |
| Murder | -3.80**(0) | -6.88**(0) |
| Attempted murder | -2.58 (0) | -7.37**(0) |
| Gang robbery with firearms | -2.58 (0) | -5.80**(0) |
| Gang robbery without firearms | -1.91 (1) | -4.59**(0) |
| Armed robberies | -2.49 (0) | -5.53**(0) |
| Robberies without armed | -2.42 (1) | -4.53**(0) |
| Rape | -3.60**(1) | -5.61**(0) |
| Assault | -2.68 (1) | -4.38**(0) |
| Property crime | | |
| Day house burglary | 3.38 (1) | -3.55**(0) |
| Night house burglary | -2.22 (6) | -3.63**(0) |
| Lorry-van theft | -2.78 (0) | -5.49**(0) |
| Car theft | -3.24 (7) | -4.42**(0) |
| Motorcycle theft | -2.38 (1) | -3.96**(0) |
| Bicycle theft | -1.71 (0) | -6.03**(0) |
| Other theft | -3.26 (5) | -2.96**(7) |

Notes: Asterisk (**) denotes statistically significance at the 5% level. Critical values are taken from MacKinnon (1996). Series in levels were estimated with constant and trend, while series in first-differences were estimated with constant only. Figures in parentheses denote lag length chosen by SBC criterion

TABLE 6: Results of Bi-variate Cointegration Tests (VAR=2)

| **Criminal activities** | **Null hypothesis** | **Trace test** | **Lamda-max test** |
|---|---|---|---|
| Violent crime: | | | |
| Murder | $H_o$: r = 0 | 20.55** | 18.18** |
| | $H_o$: r ≤ 1 | 2.36 | 2.36 |
| Attempted murder | $H_o$: r = 0 | 25.13** | 23.18** |
| | $H_o$: r ≤ 1 | 1.95 | 1.95 |
| Gang robbery with firearms | $H_o$: r = 0 | 38.73** | 36.17** |
| | $H_o$: r ≤ 1 | 2.56 | 2.56 |
| Gang robbery without firearms | $H_o$: r = 0 | 10.60 | 10.60 |
| | $H_o$: r ≤ 1 | 0.00 | 0.00 |
| Armed robberies | $H_o$: r = 0 | 17.87** | 16.88** |
| | $H_o$: r ≤ 1 | 0.98 | 0.98 |
| Robberies without armed | $H_o$: r = 0 | 10.19 | 10.16 |
| | $H_o$: r ≤ 1 | 0.02 | 0.02 |
| Rape | $H_o$: r = 0 | 23.92** | 23.60** |
| | $H_o$: r ≤ 1 | 0.31 | 0.31 |
| Assault | $H_o$: r = 0 | 18.28** | 16.34** |
| | $H_o$: r ≤ 1 | 1.93 | 1.93 |
| Property crime: | | | |
| Day house burglary | $H_o$: r = 0 | 17.02** | 16.44** |
| | $H_o$: r ≤ 1 | 0.58 | 0.58 |
| Night house burglary | $H_o$: r = 0 | 9.48 | 7.66 |
| | $H_o$: r ≤ 1 | 1.82 | 1.82 |
| Lorry-van theft | $H_o$: r = 0 | 21.28** | 21.26** |
| | $H_o$: r ≤ 1 | 0.02 | 0.02 |
| Car theft | $H_o$: r = 0 | 14.13 | 14.00 |

| | | | |
|---|---|---|---|
| | $H_o$: r ≤ 1 | 0.12 | 0.12 |
| Motorcycle theft | $H_o$: r = 0 | 14.45 | 14.34** |
| | $H_o$: r ≤ 1 | 0.11 | 0.11 |
| Bicycle theft | $H_o$: r = 0 | 18.69** | 15.50** |
| | $H_o$: r ≤ 1 | 3.19 | 3.19 |
| Other theft | $H_o$: r = 0 | 21.06** | 19.56** |
| | $H_o$: r ≤ 1 | 1.50 | 1.50 |

Notes: Asterisk (**) denotes statistically significance at the 5% level. Critical values are taken from MacKinnon-Haug-Michelis (1999).

TABLE 7: Results of Long-run Relationship Between Crime and Police Personnel

| **Criminal activities** | **Dependent variable** | ***t*-statistics of $ecm_{t-1}$ in VECM model** |
|---|---|---|
| Violent crime: | | |
| Murder | ΔMurder | -2.34** |
| | ΔPolice | -3.11** |
| Attempted murder | ΔAttempted murder | -1.45 |
| | ΔPolice | 3.45** |
| Gangrobbery with firearms | ΔGang robbery with firearms | -7.37** |
| | ΔPolice | -0.91 |
| Gangrobbery without firearms | ΔGangrobbery without firearms | -1.49 |
| | ΔPolice | -2.11** |
| Armed robberies | ΔArmed robberies | -3.01** |
| | ΔPolice | 1.50 |
| Robberies without armed | ΔRobberies without armed | -1.46 |
| | ΔPolice | -2.65** |
| Rape | ΔRape | -1.44 |
| | ΔPolice | -5.29** |
| Assault | ΔAssault | -2.82** |
| | ΔPolice | -3.19** |
| Property crime: | | |
| Day house burglary | ΔDaylight house burglary | -3.75** |
| | ΔPolice | -1.56 |
| Night house burglary | ΔNighttime house burglary | -2.61** |
| | ΔPolice | -0.37 |
| Lorry-van theft | ΔLorry-van theft | -0.53 |
| | ΔPolice | -4.88** |
| Car theft | ΔCar theft | -0.33 |
| | ΔPolice | -3.28** |
| Motorcycle theft | ΔMotorcycle theft | -1.39 |
| | ΔPolice | -3.15** |
| Bicycle theft | ΔBicycle theft | -0.63 |
| | ΔPolice | 3.79** |
| Other theft | ΔOther theft | -3.98** |
| | ΔPolice | 0.88 |

Notes: Asterisk (**) denotes statistically significance at the 5% level.

TABLE 8: Results of Long-run Elasticities

| **Criminal activities** | **The long-run model** |
|---|---|
| Violent crime: | |
| Murder | $3.8987 - 0.5217 ** (3.7907) police_t$ |
| Attempted murder | $-6.7119 + 0.9109 ** (2.4521) police_t$ |
| Gang robbery with firearms | $-6.9779 + 0.9515 ** (5.7187) police_t$ |
| Gang robbery without firearms | $20.098 - 3.1189 ** (3.1529) police_t$ |
| Armed robberies | $-17.316 + 3.0587 ** (5.6952) police_t$ |
| Robberies without armed | $11.112 - 1.2626 (1.7334) police_t$ |
| Rape | $13.476 - 1.9978 ** (6.1820) police_t$ |
| Assault | $8.1403 - 0.8857 ** (2.9399) police_t$ |
| Property crime: | |
| Day house burglary | $5.7707 - 0.3978 (1.2101) police_t$ |
| Night house burglary | $-0.5061 + 0.8357 ** (2.4858) police_t$ |
| Lorry-van theft | $37.071 - 5.8796 ** (6.1471) police_t$ |
| Car theft | $17.072 - 2.3591 ** (2.9049) police_t$ |
| Motorcycle theft | $25.279 - 3.4484 ** (3.7116) police_t$ |
| Bicycle theft | $-12.857 + 2.6431 ** (2.3718) police_t$ |
| Other theft | $2.2347 + 0.4797 (1.8218) police_t$ |

Notes: Asterisk (**, *) denotes statistically significance at the 5% and 10% level respectively.