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Crime in the United States of America: testing the 'Broken Window' hypothesis

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ABSTRACT

This study wishes to examine and validate the 'broken window' hypothesis among the fifty one states in the United States. The chosen method for this analysis is Johansen cointegration test to test for cointegration, and if any cointegrating vector is found, we proceed to test for Granger causality based on VECM. We test whether property crime (proxy for minor crime) leads to violent crime (proxy for major crime) in the fifty one states with respect to the period 1960 to 2007. Result of the study indicates that violent crime and property crime are cointegrated in forty eight states out of fifty one states. Further analysis to test for the validity of the broken window hypothesis provides stunning result whereby we found that the hypothesis is indeed valid in forty four out of forty eight states.

Introduction

A normative definition views crime as deviant behavior that violates prevailing norms-cultural standards prescribing how humans ought to behave normally. This approach considers the complex realities surrounding the concept of crime and seeks to understand how changing social, political, psychological, and economic conditions may affect the current definitions of crime and the form of the legal, law enforcement, and penal responses made by society. In the United States since 1930, the Federal Bureau of Investigation (FBI) has tabulated Uniform Crime Reports (UCR) annually from crime data submitted by law enforcement agencies across the United States. Officials compile this data at the city, county, and state levels into the UCR. United States overall crime rate is displayed in two indices. The violent crime index comprises forcible rape, robbery, murder and assault. The property crime index consists of burglary, larceny-theft, and motor vehicle theft. The crime rate is measured by the number of crimes being reported per 100,000 people.

The increase in the public's concern about crime in the United States is generally parallel with the amount of intense media focus on the issue of the abnormally horrendous crimes and on the types of individuals who commit them. Arin (2008) mentioned that Americans have always had a peculiar relationship with crime and criminals. Each generation seems to fret about unprecedented lawlessness, while bestowing on its most outrageous criminals the kind of celebrity reserved for folk heroes and movie stars crime rates vary greatly across the states. Generally looking at the statistics over the period 1960-2007, North Dakota had by far the lowest average crime rates, for violent crime and the most notorious state is Washington D.C. The average crime rates per 100,000 for these states are 64.91 and 1826.87 respectively. Densely populated states such as New York and New Jersey also had crime rates well below the national average. Southern states had the highest overall crime rates.

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Brown (2007) mentioned that one of the great and intractable weaknesses of American democracy is its inability to create and maintain rational criminal law policy. The politics of crime are perennially perverse: the electorate demands that legislatures enact more crimes and tougher sentences, and no interest groups or countervailing political forces lobby against those preferences. Crime in United States could be seen as being on the rise from either a sociological perspective such as an increase in underlying problems in the lives of individuals and in the community or typically economic, social, and/or psychological in nature. While it cannot be denied that genetic and biological factors involved in the development of an individual's propensity towards committing crimes, environment also plays a key role in this arena. Different punishment in different states also contributes to enormously varying crime among the states. People from problematic backgrounds or especially difficult circumstances are not only more likely to participate in criminal activities, but are also more likely to continue their destructive activities to the point at which serious run-ins with the law develop. Unfortunately, there is no reliable data on changes in the economic background of violent criminals. It could be assumed that the numbers had risen faster in poor societies because of the violence that explodes every day, whether it includes gangs or other individual infractions.

Broken window hypothesis is a well known hypothesis and is well debated and well researched; unfortunately it is mostly in the circle of social and psychological areas, and as far as we are concerned, no empirical papers have been presented, thus the main motivation of this study.

This paper is organized as follows. In the following section some related literatures are reviewed. In section 3, we discuss about the crime incidence throughout the period of study for the fifty one states in the United States while in section 4, we discuss the Johansen (1991) cointegration test and Granger causality based on VECM procedure employed in the study. In section 5, empirical results are discussed followed by the last section that contains our conclusion.

A review of related literature

As far as the author's knowledge and information is concerned, there are no researches done on the subject of empirically testing of the 'broken windows' hypothesis. Most of researches on crime originate from the seminal paper by Becker (1968) and Ehrlich (1973).Becker (1968) emphasizes on the fundamental of supply and demand of crime, more specifically, the cost and benefit of crime. Becker's work was later extended by Ehrlich (1973), who initiated a crime model by including the role of opportunity cost between illegal and legal work. One of the researches on crime in the United States was done by Brush (2007), who conducted and compared cross-sectional and time series analyses of United States counties, interestingly, the results are in contradiction, income inequality is positively associated with crime rates in the cross section analysis, but it is negatively associated with crime rates in the time-series analysis. In another research on the United States, Rafael and Juan (2008) explained that some workers become criminals, depending on their luck in the labour market, the expected punishment, and individual shock that they call 'meanness'. It is this meanness level that a penal system based on 'retribution' tries to detect when deciding the severity of the punishment. Magnus and Matz (2008) also in their study in the United States went a step further diverting from the traditional aggregated measures, whereby they separated the effects of permanent and transitory income. They reported that while an increase in inequality in permanent income yields a positive and significant effect on total crimes and property crimes, an increase in inequality in the transitory income and traditional aggregated measures yields insignificant effect. If this holds, it will be interesting to see different states in the United States, performing in our study.

Some stylised facts on crime in the united states

Figure 1 reports the situation of violent crime in the United States for 1960-2007, it can be observed that, crime in the United States has fluctuated considerably over the course of the last half-century, rising significantly in the late 1960s and 1970s, peaking in the 1980s and then decreasing considerably in the growth. Murder is the largest contributor to the violent crime, while assault is the smallest.

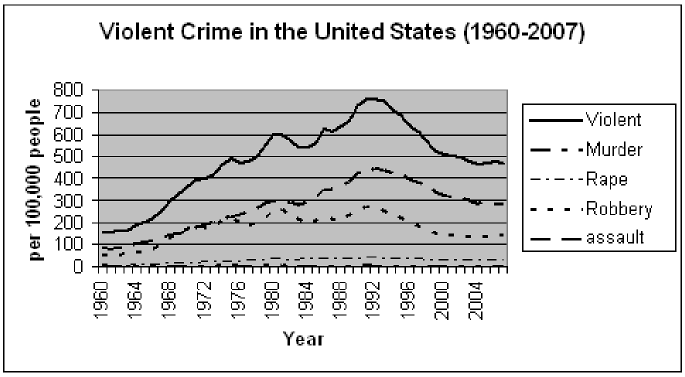

Figure 1. Violent Crime in the United States

Table 1 displays the descriptive statistics for all the fifty one states in the United States. Generally looking at the statistics over the period 1960-2007, North Dakota had by far the lowest average crime rates, for violent crime and the most notorious state is Washington D.C. The average crime rates per 100,000 for these states are 64.91 and 1826.87 respectively.

Johansen Cointegration Analysis

Formally, if two or more non-stationary time series share a common trend, then they are said to be cointegrated. The theoretical framework highlighted are expressed as following: the component of the vector $Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$ are considered to be cointegrated of order *d,b,* denoted Yt ~ CI (*d,b*) if (i) all the component Y_t are stationary after n difference, or integrated of order *d* and noted as $Y_t \sim I(d)$. (ii) Presence of a vector $\beta = (\beta 1, \beta_2, \ldots, \beta_n)$ in such that linear combination $\beta Y_t = \beta_1 y_{1t} + \beta_2 y_{2t} + \ldots + \beta_n y_{nt}$ wherby the vector β is named the cointegrating vector. A few major characteristics of this model are that the cointegration relationship obtained indicates a linear combination of non-stationary variables, in which all variables must be integrated of the same order and lastly if there are *n* series of variables, there may be as many as *n*-1 linearly independent cointegrating vectors.

Johansen's (1991) cointegration test is adopted to determine whether the linear combination of the series possesses a long-run equilibrium relationship. The numbers of significant cointegrating vectors in non-stationary time series are tested by using the maximum likelihood based λ_{trace} and λ_{max} statistics introduced by Johansen (1991) and Juselius (1990). The advantage of this test is it utilises test statistic that can be used to evaluate cointegration relationship among a group of two or more variables. Therefore, it is a superior test as it can deal with two or more variables that may be more than one cointegrating vector in the system.

Prior to testing for the number of significant cointegrating vectors, the likelihood ratio (LR) tests are performed to determine the lag length of the vector autoregressive system. In the Johansen procedure, following a vectorautoregressive (VAR) model, it involves the identification of rank of the *n* X *n* matrix ∏ in the specification given by :

$$\Delta \boldsymbol{Y_t} = \boldsymbol{\delta} + \sum_{i=1}^{k-1} \boldsymbol{\Gamma_i} \Delta \boldsymbol{Y_{t-i}} + \prod \boldsymbol{Y_{t-k}} + \boldsymbol{\varepsilon_t} \qquad (3.5)$$

where Y_t is a column vector of the *n* variables, Δ is the difference operator, Γ and ∏ are the coefficient matrices, *k* denotes the lag length and δ is a constant. In the absence of cointegrating vector, ∏ is a singular matrix, which means that the cointegrating vector rank is equal to zero. On the other hand, in a cointgrated scenario, the rank of ∏ could be anywhere between zero. In other words, the Johansen Cointegration test can determine the number of cointegrating equation and this number is named the *cointegrating rank*.

The Johansen Maximum likelihood test provides a test for the rank of ∏, namely the trace test (λ_{trace}) and the maximum eigenvalue test (λ_{max}). Firstly, the λ_{trace} statistics test whether the number of cointegrating vector is zero or one. Then, the λ_{max} statistic tests whether a single cointegration equation is sufficient or if two are required. Both test statistics are given as follows:

$$\boldsymbol{\lambda_{trace}(r) = -T \sum_{i=r+1}^{p} \ln(1 - \hat{\lambda})} \qquad (3.6)$$

$$\boldsymbol{\lambda_{trace}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})} \qquad (3.7)$$

Where P is the number of separate series to be analysed, T is the number of usable observations and λ is the estimated eigenvalues obtained from the (i+1) x (i+1) cointegrating matrix.

Table 1: Descriptive Statistics (number of violent crime per 100 000)

	Mean	Maximum	Minimum	Std. Dev.
ALABAMA	464.219	872.0	200.0	157.1525
ALASKA	515.926	766.0	149.0	167.7939
ARIZONA	527.381	715.0	192.0	131.9858
ARKANSAS	389.667	595.0	136.0	127.7367
CALIFORNIA	715.310	1120.0	282.0	219.2979
COLORADO	419.476	579.0	153.0	103.0738
CONNECTICUT	330.191	554.0	70.0	125.5251
DELAWARE	500.621	762.4	111.1	171.4389
FLORIDA	818.831	1244.3	299.5	251.9374
GEORGIA	495.052	756.3	189.3	152.6593
HAWAII	226.555	299.5	69.1	64.83486
IDAHO	222.624	322.0	66.4	69.31066
ILLINOIS	695.312	1039.2	322.7	188.2206
INDIANA	341.993	537.0	137.1	104.7307
IOWA	207.117	354.4	38.7	91.27651
KANSAS	336.433	510.8	107.1	104.1352
KENTUCKY	284.295	535.5	108.9	87.01267
LOUISIANA	628.612	1061.7	66.3	232.417
MAINE	133.307	224.7	44.0	44.95634
MARYLAND	754.702	1000.1	285.1	156.8829
MASSACHUSETS	488.160	804.9	98.5	185.59
MICHIGAN	618.783	803.9	297.6	124.0722
MINNESOTA	242.141	359.0	86.5	72.02544
MISSISSIPPI	314.388	502.8	113.8	91.83831
MISSOURI	511.521	763.0	235.4	125.7825
MONTANA	188.143	365.0	72.2	72.88078
NEBRASKA	261.426	451.4	57.7	96.81764
NEVADA	638.926	1001.9	216.6	194.0145
NEW HAMPSHIRE	115.314	179.8	23.3	41.40538
NEW JERSEY	450.029	647.6	153.9	139.7823
NEW MEXICO	627.524	961.4	198.9	207.8986
NEW YORK	778.491	1180.9	325.4	247.677
NORTH CAROLINA	474.652	681.0	259.6	104.0176
NORTH DAKOTA	64.914	127.9	27.7	21.67608
OHIO	378.574	561.8	124.8	100.9657
OKLAHOMA	415.212	664.1	134.5	149.6973
OREGON	398.917	551.1	120.6	127.8874
PENNSYLVANIA	344.781	480.3	131.0	91.55285
RHODE ISLAND	306.191	462.0	78.5	91.60317
SOUTH CAROLINA	667.033	1030.5	177.2	251.3506
SOUTH DAKOTA	147.733	227.6	59.0	42.2566
TENNESSEE	519.762	789.7	138.7	200.9663
TEXAS	519.379	840.1	199.3	156.087
UTAH	240.612	334.0	89.5	63.75156
VERMONT	110.374	184.2	19.8	39.10197
VIRGINIA	309.410	380.9	227.6	38.47368
WASHINGTON	373.581	534.5	103.0	107.8165
WASHINGTON DC	1826.876	2921.8	722.8	491.5986
WEST VIRGINIA	182.929	350.7	78.0	63.10818
WISCONSIN	189.817	284.0	46.1	72.36753
WYOMING	238.148	430.1	75.6	81.38964

Table 2. Unit Root Test (ADF)

		Violent				Property		
	Level		1st Difference		Level		1st Difference	
Alabama	-1.5642		-4.1225	*	-1.3326		-3.6578	*
Alaska	-2.4562		-3.5689	*	-1.2457		-3.2230	*
Arkansas	-2.0111		-3.6658	*	-1.8854		-4.3265	*
Arizona	-2.2233		-3.1452	*	-2.1133		-4.3320	*
California	-1.8875		-3.2564	*	-2.0045		-4.7244	*
Colorado	-1.8562		-3.1245	*	-1.8977		-4.2361	*
Connecticut	-1.9965		-3.8564	*	-1.8631		-4.6532	*
Delaware	-2.1114		-4.2331	*	-2.1127		-3.9985	*
Florida	-2.0321		-4.1566	*	-2.0123		-4.2896	*
Georgia	-2.4562		-4.1544	*	-1.2654		-3.9961	*
Idaho	-2.1233		-3.3310	*	-1.5648		-4.2331	*
Illinois	-1.5670		-3.2230	*	-1.8896		-4.5261	*
Indiana	-1.8883		-4.3320	*	-1.3658		-4.4785	*
Iowa	-1.9854		-3.9861	*	-1.5687		-3.5689	*

Kansas	-2.0560		-4.2220	*	-2.3331		-5.2314	*
Kentucky	-2.3212		-4.1230	*	-2.4562		-4.1658	*
Louisiana	-2.2096		-3.8293	*	-2.3860		-7.4581	*
Maryland	-1.7081		-4.7244	*	-2.9949		-4.8552	*
Massachussets	-1.1946		-6.1144	*	-2.9037		-4.8068	*
Maryland	-1.9965		-3.8564	*	-2.0408		-4.5786	*
Maine	-1.7025		-7.4004	*	-0.8679		-5.8715	*
Michigan	-1.4336		-4.6271	*	-2.3117		-5.1704	*
Minnesota	-2.2386		-5.2111	*	-1.6372		-5.5541	*
Missouri	-1.8216		-6.9408	*	-0.0667		-7.0012	*
Montana	-1.8037		-6.5631	*	-0.7203		-8.1153	*
North Carolina	-1.8228		-1.8228	*	-0.9734		-6.0808	*
North Dakota	-4.1221		-9.4884	*	-0.9456		-7.2641	*
Nebraska	-1.3739		-6.3450	*	-1.0058		-5.6832	*
New Hampshire	-1.7854		-6.3985	*	-1.4971		-4.8915	*
New Jersey	-1.6985		-5.9867	*	-1.5829		-4.9367	*
New Mexico	-1.6987		-7.3265	*	-1.8294		-6.1144	*
Nevada	-1.8963		-5.9861	*	-2.2233		-3.1452	*
New York	-1.6358		-5.6986	*	-1.5782		-7.2301	*
Ohio	-1.9987		-6.3698	*	-1.8820		-5.4468	*
Oklahoma	-1.6587		-6.9863	*	-1.7829		-4.7244	*
Oregon	-1.6988		-5.9833	*	-1.7922		-4.8936	*
Pennsylvania	-1.9963		-5.1037	*	-2.1106		-6.5560	*
Rhode Island	-1.4698		-3.9998	*	-1.6729		-4.7590	*
South carolina	-1.3658		-4.2780	*	-1.0027		-6.8903	*
South Dakota	-1.9964		-5.8367	*	-2.0002		-4.3687	*
Tennesee	-1.9947		-7.9871	*	-1.5823		-3.9848	*
Texas	-1.7541		-3.9875	*	-2.0198		-3.8904	*
Utah	-1.6980		-6.1144	*	-1.6389		-4.2201	*
Virginia	-1.6931		-3.7684	*	-1.6937		-3.8902	*
Vermont	-1.6998		-3.6894	*	-2.1167		-6.8095	*
Washinghton DC	-1.9356		-3.7890	*	-1.2987		-5.9821	*
Washinghton	-1.6654		-3.7683	*	-1.8392		-4.9456	*
Wisconsin	-1.6980		-3.9980	*	-1.7829		-5.0768	*
West Virginia	-1.9867		-5.2938	*	-1.8923		-3.9897	*
Wyoming	-1.3265		-7.0182	*	-1.3896		-5.3899	*
Mississippi	-1.6598		-4.7248	*	-1.9012		-6.1144	*
* denotes significant at 5% level								

Table 3. Cointegration Test

	Null Hypothesis		Trace test		L-max test
States					
California	Ho: r = 0		20.76243***		19.48721***
	Ho: r ≤ 1		2.39543		2.39543
Alabama	Ho: r = 0		18.48711**		18.38777**
	Ho: r ≤ 1		0.56198		0.56198
Alaska	Ho: r = 0		18.44982**		17.9083**
	Ho: r ≤ 1		0.65092		0.65092
Alabama	Ho: r = 0		23.78651**		21.29831**
	Ho: r ≤ 1		0.019823		0.019823
Arizona	Ho: r = 0		22.58894**		21.88324**
	Ho: r ≤ 1		0.20651		0.20651
Arkansas	Ho: r = 0		24.54722**		24.54548**
	Ho: r ≤ 1		0.001744		0.001744
California	Ho: r = 0		16.98761**		16.97354**
	Ho: r ≤ 1		2.65191		2.65191
Colorado	Ho: r = 0		22.87693**		22.60921**
	Ho: r ≤ 1		0.29865		0.29865
Connecticut	Ho: r = 0		21.38294**		20.3398**
	Ho: r ≤ 1		0.02876		0.02876
Delaware	Ho: r = 0		22.45954**		20.21665**
	Ho: r ≤ 1		2.242883		2.242883
Florida	Ho: r = 0		22.93868***		20.84632**
	Ho: r ≤ 1		0.86989		0.86989
Georgia	Ho: r = 0		19.4845**		19.86341**
	Ho: r ≤ 1		2.08932		2.08932
Hawaii	Ho: r = 0		18.40362**		17.93721**
	Ho: r ≤ 1		0.38674		0.38674
Iowa	Ho: r = 0		27.55957**		19.83376**
	Ho: r ≤ 1		3.725805		3.725805
Idaho	Ho: r = 0		19.56235**		18.73562**
	Ho: r ≤ 1		1.87345		1.87345

Illinois	Ho: r = 0		22.56932**		22.12395**
	Ho: r ≤ 1		0.54976		0.54976
Indiana	Ho: r = 0		18.94532**		17.96345**
	Ho: r ≤ 1		0.57253		0.57253
Kansas	Ho: r = 0		20.48479**		19.88618**
	Ho: r ≤ 1		0.598607		0.598607
Kentucky	Ho: r = 0		19.18966**		11.91841**
	Ho: r ≤ 1		0.7271256		0.7271256
Louisiana	Ho: r = 0		20.67302***		20.68401***
	Ho: r ≤ 1		1.649087		1.649087
Massachusets	Ho: r = 0		21.91473***		15.72743***
	Ho: r ≤ 1		3.1873		3.1873
Maryland	Ho: r = 0		23.50734***		21.86596***
	Ho: r ≤ 1		1.641385		1.641385
Maine	Ho: r = 0		25.74653**		17.36237**
	Ho: r ≤ 1		3.38416		3.38416
Michigan	Ho: r = 0		16.39236**		16.39039**
	Ho: r ≤ 1		0.00197		0.00197
Minnesota	Ho: r = 0		24.54722**		24.54548**
	Ho: r ≤ 1		0.001744		0.001744
Missouri	Ho: r = 0		25.13715**		17.40874**
	Ho: r ≤ 1		4.728406		4.728406
Montana	Ho: r = 0		3.57494		3.0231
	Ho: r ≤ 1		0.551836		0.551836
North Carolina	Ho: r = 0		27.55957**		19.83376**
	Ho: r ≤ 1		3.725805		3.725805
North Dakota	Ho: r = 0		17.29493**		16.87844**
	Ho: r ≤ 1		0.416494		0.416494
Nebraska	Ho: r = 0		23.82999**		17.35988**
	Ho: r ≤ 1		3.470113		3.470113
New Hampshire	Ho: r = 0		3.57494		3.0231
	Ho: r ≤ 1		0.551836		0.551836
New Jersey	Ho: r = 0		22.45954**		20.21665**
	Ho: r ≤ 1		2.242883		2.242883
New Mexico	Ho: r = 0		21.72819***		20.40218***
	Ho: r ≤ 1		1.326012		1.326012
Nevada	Ho: r = 0		3.35671		3.056432
	Ho: r ≤ 1		0.55342		0.55342
New York	Ho: r = 0		19.83576**		!8.98345**
	Ho: r ≤ 1		1.07893		1.07893
Ohio	Ho: r = 0		21.98443**		21.45231**
	Ho: r ≤ 1		2.09823		2.09823
Oklahoma	Ho: r = 0		19.56235**		18.73562**
	Ho: r ≤ 1		1.87345		1.87345
Oregon	Ho: r = 0		22.45987***		21.94563**
	Ho: r ≤ 1		2.09812		2.09812
Pennsylvania	Ho: r = 0		19.35967**		19.35642**
	Ho: r ≤ 1		0.84563		0.84563
Rhode Island	Ho: r = 0		18.94532**		17.96345**
	Ho: r ≤ 1		0.57253		0.57253
South carolina	Ho: r = 0		23.67893**		20.78998**
	Ho: r ≤ 1		1.89332		1.89332
South Dakota	Ho: r = 0		19.44886**		17.92267**
	Ho: r ≤ 1		0.77383		0.77383
Tennesee	Ho: r = 0		16.98761**		16.97354**
	Ho: r ≤ 1		2.65191		2.65191
Texas	Ho: r = 0		23.78651**		21.29831**
	Ho: r ≤ 1		0.019823		0.019823
Utah	Ho: r = 0		18.69375**		16.99674**
	Ho: r ≤ 1		0.008952		0.008952
Virginia	Ho: r = 0		17.9327**		17.91342**
	Ho: r ≤ 1		0.08567		0.08567
Vermont	Ho: r = 0		22.48667**		20.83976**
	Ho: r ≤ 1		1.38677		1.38677
Washinghton DC	Ho: r = 0		20.96843**		19.99528**
	Ho: r ≤ 1		0.08943		0.08943
Washinghton	Ho: r = 0		21.98443**		21.45231**
	Ho: r ≤ 1		2.09823		2.09823
Wisconsin	Ho: r = 0		19.96873**		19.04563**
	Ho: r ≤ 1		0.09278		0.09278
West Virginia	Ho: r = 0		22.67398**		21.68345**
	Ho: r ≤ 1		0.56738		0.56738

Wyoming	Ho: r = 0		16.98761**		16.97354**
	Ho: r ≤ 1		2.65191		2.65191
Mississippi	Ho: r = 0		19.35967**		19.35642**
	Ho: r ≤ 1		0.84563		0.84563

Table 3. Error Correction Model Based on VECM

States	Dependent Variable	*t*-statistics of ecmt-1 in VECM Models
California	Δ Violent Crime	[-2.14235]**
Alabama	Δ Violent Crime	[-2.26502]**
Alaska	Δ Violent Crime	[-2.85635]***
Alabama	Δ Violent Crime	[-3.87638]**
Arizona	Δ Violent Crime	[-3.90401]***
Arkansas	Δ Violent Crime	[-4.23663]***
California	Δ Violent Crime	[-2.98234]**
Colorado	Δ Violent Crime	[-3.04210]***
Connecticut	Δ Violent Crime	[-5.40412]***
Delaware	Δ Violent Crime	[-4.01500]***
Florida	Δ Violent Crime	[-4.96845]***
Georgia	Δ Violent Crime	[-2.49398]***
Hawaii	Δ Violent Crime	[-3.81392]***
Iowa	Δ Violent Crime	[-4.83156]***
Idaho	Δ Violent Crime	[-5.16798]***
Illinois	Δ Violent Crime	[-2.06070]**
Indiana	Δ Violent Crime	[-3.05244]***
Kansas	Δ Violent Crime	[-4.62541]**
Kentucky	Δ Violent Crime	[-2.61622]**
Louisiana	Δ Violent Crime	[-1.36273]
Massachusets	Δ Violent Crime	[-3.83925]**
Maryland	Δ Violent Crime	[-4.34286]**
Maine	Δ Violent Crime	[-3.9398]
Michigan	Δ Violent Crime	[-3.94641]*
Minnesota	Δ Violent Crime	[-5.20485]**
Missouri	Δ Violent Crime	[-1.34976]
Montana	Δ Violent Crime	-
North Carolina	Δ Violent Crime	[-3.39631]**
North Dakota	Δ Violent Crime	[-1.37275]
Nebraska	Δ Violent Crime	[-2.40659]***
New Hampshire	Δ Violent Crime	-
New Jersey	Δ Violent Crime	[-4.32767]*
New Mexico	Δ Violent Crime	[3.91472]**
Nevada	Δ Violent Crime	-
New York	Δ Violent Crime	[2.9493]**
Ohio	Δ Violent Crime	[3.33967]**
Oklahoma	Δ Violent Crime	[2.93995]**
Oregon	Δ Violent Crime	[3.00563]***
Pennsylvania	Δ Violent Crime	[2.00987]**
Rhode Island	Δ Violent Crime	[2.33419]**
South carolina	Δ Violent Crime	[3.11754]**
South Dakota	Δ Violent Crime	[2.99456]**
Tennesee	Δ Violent Crime	[2.88954]**
Texas	Δ Violent Crime	[3.00987]**
Utah	Δ Violent Crime	[2.09081]***
Virginia	Δ Violent Crime	[1.8965]**
Vermont	Δ Violent Crime	[1.99557]**
Washinghton DC	Δ Violent Crime	[2.98243]**
Washinghton	Δ Violent Crime	[3.24356]**
Wisconsin	Δ Violent Crime	[3.85764]**
West Virginia	Δ Violent Crime	[2.87945]**
Wyoming	Δ Violent Crime	[3.09056]**
Mississippi	Δ Violent Crime	[2.90678]**

Granger-causality based on VECM

As pointed out by Engle and Granger (1987) even though individual time series are non-stationary, linear combinations of them can be, because equilibrium forces tend to keep such series together in the long run. Moreover, if cointegration is detected then the Granger causality must be conducted in Vector Error Correction Model (VECM) to avoid problem of misspecification (Granger, 1988). Otherwise, the analysis may be conducted as a standard vector autoregressive (VAR) model. VECM is a special case of VAR that imposes cointegration on its variables.

Engle and Granger (1987) showed that if two series are cointegrated, there must be exists an error correction representation and conversely if an error correction representation exists, the two series are cointegrated. In addition, the existence of a cointegration relationship between two series implies that there is at least a causal effect running from one variable to another. However, the cointegration test does not indicate the direction of the causality between variables. This direction of the Granger causality can only be detected through the VECM derived from the long-run cointegrating vectors. In addition to indicate the direction of causality amongst variables, the VECM also allow us to distinguish between short-run and long-run Granger causality.

Granger causality based on VECM also measures precedence and information content as a test of information efficiency of an asset variable, X causes another variable, Y if the past history of X can be used to predict Y more accurately than simply using the past history of Y alone. Therefore, if the results show that the level of trade of country X causes level of trade of country Y, it can be claimed that trade variability of X is fundamentally linked to trade of Y and the change in trade of X or leads the trade of Y.

The direction of short-run causality effects running from one variable to another can be determined by using the VECM derived from the long-run cointegrating vectors. The Granger causality can be exposed either through the statistical significance of:

i) The lagged Error Correction Terms (ECTs) by separate t-test or

ii) A joint test applied to the significance of the sum of the lags of each explanatory variables by a joint F or Wald χ^2 test or

iii) A joint test of all the set of terms described in (i) and (ii) by a joint F or Wald χ^2 test taking each of the terms separately.

The F-test or Wald χ^2 of the explanatory variables (in first differences) indicates the short run causal effects while the long-run causal relationship is implied through the significance of the lagged ECTs which contains the long-run information. According to Granger (1988), if the variable in a system are cointegrated, then the causal analysis need to incorporate the error correction term for the adjustments of deviation from its long-run equilibrium and avoid misspecification of model. The equations estimated in VECM are as follow:

$$\Delta \ln(x_t) = \alpha_1 + \sum_{i=1}^{m_1} \beta_{1i} \Delta \ln(x_{t-i}) + \sum_{i=1}^{m_2} \beta_{2i} \Delta \ln(y_{t-i}) + \gamma_1 ECT_{1,t-1} + u_{1t} \qquad (3.8)$$

$$\Delta \ln(y_t) = \alpha_2 + \sum_{i=1}^{m_3} \beta_{3i} \Delta \ln(x_{t-i}) + \sum_{i=1}^{m_4} \beta_{4i} \Delta \ln(y_{t-i}) + \gamma_2 ECT_{2,t-1} + u_{2t} \qquad (3.9)$$

Subsequently, the short-run Granger causality dynamic is tested by calculating the F-statistic and based on the null hypothesis that the set of coefficient on lagged values of independent variables are not statistically different from zero. The statistic employed is:

$$F = \frac{m(RSS_R - RSS_{UR})}{RSS_R} \sim \chi_p^2 \qquad (3.10)$$

where p is the number of restricted coefficient, m is the number of observation, RSS_R and RSS_{UR} are the residual sum of squares obtained by least square estimation with and without imposing the restrictions respectively.

As conclusion, by using the Granger causality on VECM, the causal relations of the estimates of the VECM can be examined. When property crime index (*X*) is regressed on violent crimel index (*Y*) and the estimate of the models show that the error correction terms (ECTs) is significant in the VECM equation, this suggest that property crime index (*X*) adjust to the previous equilibrium error, past violent crime index (*Y*) has significant explanatory power for current property crime index (*X*), and violent crime index (*Y*) is significant in predicting the changes in the property crime (*X*). The data set of this study consists of annual number of violent crime per 100 000 of each state in United States and the average violent crime per 100 000 of United States as the main reference. The data originates from the Federal Bureau of Investigation (FBI), and subsequently made available on the internet by United States Disaster Center The total sample is spanning from 1960 to 2006. All variables were expressed in natural logs.

Results and Conclusion

Table 2 shows the results of the unit root test (ADF) and it is overwhelmingly clear that both the violent crime and property crime in all the fifty one states are *I (1)*, clearing our way to proceed with the cointegration test, whereby the precondition is the variables to be tested need to be in the same integrating order..Table 3 reports the results of the Johansen cointegration test, and it can clearly observed that property crime and violent crime are cointegrated in forty eight out of the fifty one states in the United States of America, thus we proceeded to test for Granger causality based on VECM only for these forty eight countries.

Our results for the Granger causality test shows that out of these forty eight states, property crime seems to Granger cause violent crime in forty four states, or in other words, the broken window hypothesis is indeed valid in these forty four states. Looking from a broader perspective, policy makers, and enforcement agencies should take a serious account of this, and should make preventive and pre-emptive steps to stop the incidence of minor crime, which we believe and have been proven empirically that they would eventually get out of control and lead to major crimes.

Proper policy crimes especially those on minor crimes should be formulated precisely and clearly, in order to prevent or at least minimize the minor crimes, and this in the long run would ultimately reduce major crimes. the findings of this paper is not only interesting, it also validate the broken window hypothesis, and is expected to at least stress the policy makers to take note of the seriousness of minor crimes, if left unchecked. it might lead to a surge in major crimes and it be detrimental and cause severe damage to an economy.

References

Arin, G. (2008) Making crime pay, *ABA Journal*, **94**(6), 11-11

Becker, G.S. (1968) Crime and punishment: An economic approach. *Journal of Political Economy* **76,** 1169-1217.

Brown, D.K. (2007) Democracy and Decriminalization, *Texas Law Review*, **86**(2) 224-278

Brush, J. (2007) Does income inequality lead to more crime? A comparison of cross-sectional and time series analyses of United States countries. *Economic Letters* **96**, 264-268.

Chong, T.T.-L., Hinich, M.J., Liew, V.K.S. and Lim, K.P. (2008) Time Series Test of Nonlinear Convergence and Transitional Dynamics, *Economics Letters*, doi:10.1016/j.econlet.2008.02.025

Datta, A. (2003) Time Series Test of Convergence and Transitional Dynamics, *Economics Letters*, **81**, 233-240.

Ehrlich, I. (1973) Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy* **38**(3), 521-565.

Kapetanios, G., Shin, Y. and Snell, A. (2003) Testing For A Unit Root In the Nonlinear STAR Framework, *Journal of Econometrics,* **112**, 359-379.

Magnus, G. and Matz, D. (2008) Inequality and crime: Separating the effects of permanent and transitory income. *Oxford Bulletin of Economics & Statistics,* **70**(2), 129-153.

Oxley, L. and Greasley, D. (1995) A Time Series Perspective On Convergence: Australia, UK and USA Since 1870, *Economic Record*, **71**, 259-270.

Rafael, D.T. and Juan, D. (2008) Crime and punishment in the "American Dream", *Journal of Public Economics,* **92**(7), p1564-1584