DIFFERENT CATEGORIES OF CRIME AND THEIR SOCIO-ECONOMIC DETERMINANTS IN TURKEY: EVIDENCE FROM VECTOR ERROR CORRECTION MODEL

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JEL Codes: D12, K42.

Abstract

The empirical studies on the relationship between crime and economic variables pioneered by Becker (1968) and Ehrlich (1973) have yielded different conclusions. This paper examines the interactions among different categories of crime, a deterrent variable and other socio-economic variables for Turkey in a temporal Granger-causal framework through a multivariate cointegrated analysis. The empirical investigation is applied to for four subcategories of crime defined by Turkish Criminal Law: crime against state or government administration, crime against public, crime against individual and crime against property. The model consists of four independent variables: percent of offences solved, per-capita GDP, rates of divorce and higher education. Results for 1967-2004 tend to suggest no cointegrating relationship for crime against individual. However, independent variables and other three types of crime (against property, against public and against state and government administration) are bound together by long-run equilibrium relationships.

Özet

Becker (1968) ve Ehrlich (1973) öncülüğünde suç ve ekonomik değişkenler arasındaki ilişkiyi araştıran çalışmalar değişik sonuçlar elde etmişlerdir. Bu çalışma, Granger-nedensellik çerçevesi içinde ve çok değişkenli eşbütünleşme yöntemini kullanarak Türkiye'de değişik suç kategorileri, caydırıcı etkenler ve diğer sosyo-ekonomik değişkeler arasındaki ilişkileri incelemektedir. Ampirik araştırma, Türk Ceza Kanunu'nda tanımlanan dört alt kategoriye uygulanmıştır: devletin kişiliğine veya devlet yönetimine karşı suçlar, kamuya karşı suçlar, kişilere karşı suçlar ve mala karşı suçlar. Modelde, dört tane bağımsız değişken kullanılmıştır: karara bağlanan suçların yüzdesi, kişi başına GSMH, boşanma oranı ve yüksek eğitim oranı. 1967-2004 dönemini kapsayan sonuçlar, kişiye karşı suçlar için bir eşbütünleşme ilişkisi göstermemektedir. Ancak, diğer üç tür suç ve bağımsız değişkenler, uzun-dönem ilişkisi içerisinde birbirlerine bağlıdır.

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1. Introduction

Although the economics studies of crime is relatively new, economists have shown an increasing interest in the field of crime, beginning with the seminal papers of Becker (1968) and Ehrlich (1973). Becker (1968:169-170) posits that criminals are rational utility maximizers choosing in conditions of risk. His work is based on the assumption that criminals behave according to the subjective expected utility framework. He argues that individuals are deterred from criminal activities by a higher fine and by a higher probability of detection and conviction. The probability is costly whereas the fine is a costless transfer. Therefore, one should set the fine at its highest value. The probability of detection and conviction is used to complement the fine in deterring individuals. This is known as the high-fine-low-probability result in literature (Garoupa, 1998:4).

There are some empirical findings on criminals' behavior that are not consistent with expected utility theory. Eide (1995:2008) makes reference to studies where criminals tend to overestimate the probability of apprehension and thus a low probability of punishment has a major deterrent effect. Block and Gerety (1995:133) conclude that individuals tend to be risk averse in general but criminals tend to be more sensitive to changes in the probability of punishment whereas noncriminals tend to be more sensitive to changes in the monetary penalties than criminals. The evidence seems to support the analysis of crime as a gamble (at least for financial or property crimes). It is puzzling that people who tend to be risk averse (in the sense of being against losses) commit crimes more frequently than one might expect. Garoupa (1998:10) shows that the maximal fine result holds when the rate at which social planner is just willing to substitute probability for fine is always larger than the rate at which the social planner can change the probability for fine. When the individuals are risk averse, a less-than-maximal-fine may be optimal because individuals care about the expected fine and a risk premium.

Economists approach the behavior of potential criminals in terms of rational choice: the actors choose the best alternatives in terms of costs and benefits within the choices open to them. These actors or potential criminals make a decision about the allocation of their time between legal and illegal activities, taking into consideration the expected costs of criminal acts. Economic analysis of crime shows that the level of crimes and contestable behavior in society is not only dependent on attitudes and values in society but also on the economic consequences of these types of behavior.

The prime focus of economists is therefore on the economic factors in society affecting the crime. In doing so, they have to study the interaction between the micro level of individual decision making and the macro level of the law enforcement system. Data are often only available at macro level (aggregate). Econometric studies at macro level (time series) have the problem that many effects have to be estimated from a limited number of data (van Tulder and van Velthoven, 2003:330).

Early studies of criminal behavior by economists are sometimes criticized for being set in a static framework. Economic models of crime are typically estimated as static models, though there are many reasons to suspect dynamic effects matter, both theoretically through habit formation, interdependence of preferences, capital accumulation, addiction, peer group effects, etc. and empirically through improvements in fit when lagged dependent variables or autocorrelated residuals are included in the model (Witte and Witt, 2000).

In the literature, the determinants of crime are generally summarized in three groups: First group consists of socio-economic variables which include variables such as education level, age structure of the society, urbanization level, male-female percentage of the population, race percentage of the population and social interactions such as family relations. Second group is economic variables including income inequality, median income of families, unemployment, and per capita income. Deterrent variables relating the punishment of criminal behavior are the third group, including police force, severity of punishment, justice and court systems, and prison and jail conditions. Masih and Masih (1996:1101) finds evidence for Austria that these socio-economic, demographic and deterrent variables along with alternative types of crime are bound together with long term equilibrium relationships. They indicate that although some of these variables may not be related to crime in the short run, "in the long run it is the dynamic interactions of all these variables with which each category of crime is ultimately causally related".

In terms of the first group of determinants of crime, the theory predicts that lower education level, urbanization and divorces increase the crime rate. Gümüş (2004:106) investigates the determinants of crime in urban areas by using cross sectional data on US and finds that presence of black population is an important determinant of crime.

There is ambiguity in the empirical studies of crime economics regarding various income variables used to proxy the expected net gains from crime. Earlier studies on income inequality and crime have typically used total income and total earnings. It is quite likely that it is changes in permanent rather than in transitory income that affects crime rates. The results indicate that it is important to separate the two effects, while an increase in the inequality in permanent income yields a positive and significant effect on total crimes and different property crimes; an increase in inequality in transitory income has no significant effect on any type of crime (Dahlberg and Gustavsson, 2005:23).Chisholm and Choe (2005:113) provide a theoretical argument that relates the net expected gains from crime to a measure of income inequality (Gini) and the mean income of a society.

Increases in income may affect crime for three reasons: first, income increases lead to higher number of goods to be stolen and so create more opportunities for potential offenders. This is called the *opportunity effect*. Second, an increased expectation of future legal income decreases the need for illegal profits and decreases crime, which is the *motivation effect*. Finally, an increase in income may lead to an increase in outdoor activities compared to indoor activities. Thus people will spend more time outside and their chance of becoming a victim of crime will increase (*routine-activity effect*) (Beki et. al, 1999:404).

Machin and Meghir (2000:27) show that crime rates are higher where and when wages at the bottom end of the wage distribution are lower, reflecting poorer labor market opportunities, where the probability of being caught is lower, where crime rates are already higher and where the potential returns to crime are high. Increased wages reduce crimes, while increases in the direct economic returns from crime increase criminal activity.

The economic model of crime predicts that rising unemployment rates increase criminal activity as these people fund the maximization of their utility through criminal activities and as they have more opportunities to engage in illegitimate activities (Scorcu and Cellini, 1998: 290-1; Narayan and Smith, 2004:2080). Witt et al. (1998a:1409) and confirms that changes in unemployment are strongly positively correlated with changes in the crime rate.

Increases in the unemployment rate may also reduce the opportunities for the successful accomplishment of criminal activities and reduce crime rates while there may be no significant relationship between unemployment and particular measures of crime (Elliot and Ellingworth, 1998: 528; Narayan and Smith, 2004: 2092). The relationship between unemployment and crime rates seem to depend on the type of crime and the demographic properties of the individuals (such as age and gender distribution of crime) (Masih, 1995: 416, Carmicheal and Ward, 2000: 560; Britt: 2001: 350). In addition, national time series data may fail to indicate a relationship between unemployment and crime as these variables show local variation and national time series data do not allow for such variation (Levitt, 2001: 378-9).

As for the deterrence variables, criminal behavior is found to be more sensitive to changes in sanctions than law enforcement agencies are to changes in crime (Corman, Joyce and Lovitch, 1987: 700).

The aim of this paper is to examine the interactions among different categories of crime, a deterrent variable and other socio-economic variables for Turkey in a temporal Granger-causal framework through a multivariate cointegrated analysis. The empirical investigation is applied to four subcategories of crime defined by Turkish Criminal Law: crime against state or government administration, crime against public, crime against individual and crime against property. The model consists of four independent variables: percent of offences solved, per capita income, rates of divorce and higher education.

As to the knowledge of the authors, this study is the first to examine the economics of crime for Turkey. For this reason, the findings of this analysis are important contributions to the field and valuable for policy implications.

The rest of the paper is organized as follows: the second and third sections present the econometric methodology and data respectively while empirical results are given in the fourth section. The final and fifth section concludes.

2. Methodology

It is a standard practice to begin the analysis by examining the time-series properties of the data. The first step is to determine whether the variables that are used are stationary or non-stationary. If they are non-stationary, then the issue is to what degree they are integrated. We utilize two asymptotically equivalent procedures for detecting unit roots in the data: the Augmented Dickey-Fuller (ADF) and the Phillip and Perron (PP) tests (see Dickey and Fuller, 1981; Phillips and Perron, 1988). If all the variables in a multivariate model are integrated to the order one, i.e. I(1), then the next step is to find out whether they are cointegrated using Johansen's framework (Johansen (1988) and Johansen and Juselius (1990)).[1]

Before determining the number of cointegrating vectors, it is necessary to choose the order of the lags in the vector autoregressive model (VAR), which should be large enough to ensure that the error terms in the equations are not autocorrelated, but small enough to enable estimation. In addition, it has been suggested that the Johansen-Juselius tests of cointegration rank are contingent upon the presence or absence of deterministic components in the dynamic

[1] Apart from being multivariate, the Johansen procedure has several appealing features. First, it allows more than one cointegrating relation among the variables being examined. Second, the Johansen procedure accommodates dynamics in the cointegration analysis.

model. Johansen (1992) suggests the need to test the joint hypothesis of both the rank order and the deterministic components based on the so-called Pantula principle.

Johansen's method sets out a maximum likelihood procedure for estimating and determining the presence of cointegrating vectors in VAR system. Suppose the vector of p-variables, $Z_t = (Z_{1t},..., Z_{pt})'$, is generated by the k-order vector autoregressive process with Gaussian errors:

$$Z_t = A_1 Z_{t-1} + ... + A_k Z_{t-k} + \mu + \varepsilon_t \qquad t=1, ..., T \qquad (1)$$

where Zt is a $p \times 1$ vector of stochastic variables, $\varepsilon_1,..., \varepsilon_T$ are iid Np $(0, \Sigma)$ and μ is a vector of constants. Since we want to distinguish between stationarity by linear combinations and by differencing this process may be written in error correction form as:

$$\Delta Z_t = \Gamma_1 \Delta Z_{t-1} + ... + \Gamma_{k-1} \Delta Z_{t-k-1} + \Pi Z_{t-k} + \mu + \varepsilon_t \qquad t=1, ..., T \qquad (2)$$

The matrix Π contains information about the long-run relationship between the variables in the vector. Information about the number of cointegrating vectors is found in the rank of Π. In other words, the rank of Π determines how many linear combinations of Z_t are stationary. If the $p \times p$ matrix Π has rank zero, $r = 0$, then all elements of Z_t are non-stationary. Thus there is no cointegrating relationship between the variables. If Π is of full rank, $r = p$, then all elements of Z_t are stationary, Thus, any combination of the variables results in a stationary series, that is, cointegrated. In the intermediate case $r < p$, there are r nonzero cointegrating vectors among the elements of Z_t and $p - r$ common stochastic trends. If a non-zero relationship is indicated by the test, a stationary long-run relationship is implied.

Johansen (1988) and Johansen and Juselius (1990) derived the likelihood ratio test for the hypothesis of r cointegrating vectors. The cointegrating rank, r, can be tested with two statistics, namely trace and maximal eigenvalue. Since the method is now widely used in the literature, a description of the specific details of the test is omitted here. The appropriate critical values for the tests are provided in Osterwald-Lenum (1992).

Testing linear restrictions on the cointegrating vectors will allow us to investigate whether all the variables in the model should enter into a long-run equilibrium relationship. The hypothesis of long-run exclusion of each variable when $r = 1$ is tested using a likelihood ratio test which is asymptotically distributed as Chi-square with degrees of freedom equal to the number of restrictions tested. Significance of the variables implies that the concerned variables should be present in the long-run equilibrium relationship.

The next step involves Granger causality test. According to Granger (1988), if the variables are cointegrated, the finding of Granger non-causality is ruled out. However, it does not indicate the direction of causality between variables. The direction of Granger causality can only be detected through the vector-error correction model (VECM) derived from the long-run cointegrating vectors, which is now widely used in the literature (see for example Masih and Masih, 1996). The VECM is a restricted form of VAR that incorporates co-integration restrictions. This specification restricts the behavior of co-integrating variables to converge to their long-run equilibrium. In addition to the direction of causality, the VECM also allows us to distinguish between short-run and long-run Granger-causality. The F-test of the explanatory variables (in first differences) indicates the short-run causal effect, while the long-run causal relationship is implied through the significance of the lagged error-correction term (ECT) which contains the long-run information.

The *F*- and *t*-tests on VECM may be interpreted as within-sample causality tests since they only indicate the Granger-exogeneity or endogeneity of the dependent variable within the sample period (see Masih and Masih, 1996). They do not provide information regarding the relative strength of the Granger-causal chain amongst the variables beyond the sample period. In order to analyze the dynamic properties of the system, the forecast error variance decompositions (VDCs) are computed.

3. Data

Dependent Variables

The crime data obtained from the Turkish Statistical Institute is based on the Turkish Criminal Law which defines crime or felonies in ten categories: against state, against liberty, against government administration, against judicial system, against public order, against public security, against public welfare, against public decency and family order, against individuals, against property. In addition, there are misdemeanors in four groups as against public order, against public welfare, against public morality, against property rights.

Convicts received into prisons based on each of these fourteen categories of crime, felonies and misdemeanors are grouped into four main categories as crime against individual (*crind*), crime against property (*crprop*), crime against public (*crpub*) and crime against state and government administration (*crst*). Dependent variables are calculated as rates of total population and as natural logs. Figure 1 shows the graph of crime rates against time. According to the graph, each type of crime dramatically decreases after 1973-1974 and remains relatively stable during 1980s and 1990s. However, after 2000-2001, especially crime against property and crime against public starts to increase.

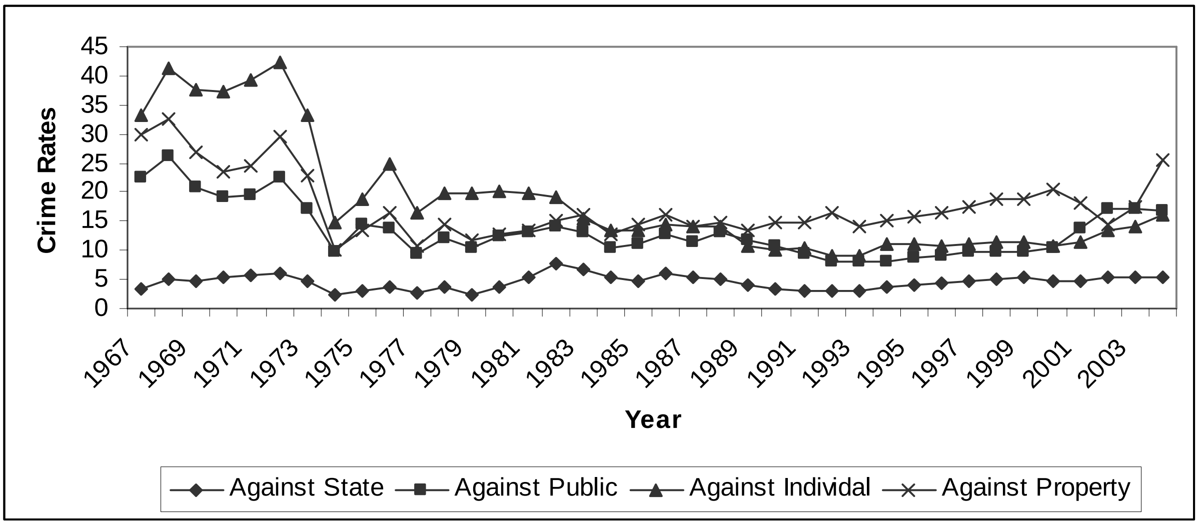

Figure 1. Different types of crime in Turkey as rates of 100000 of population (1967-2004).

Independent Variables

Crime is obviously affected by many variables including, income, unemployment, education level, police force, etc. These variables are grouped as economic variables (income, unemployment, etc.), socioeconomic and demographic variables (education level, age structure, etc.) and deterrent variables (police force, severity of punishment, justice and court systems, etc.).

In the paper, seven independent variables are considered based on previous empirical studies and the availability of Turkish data. Three of them are considered as economic variables: unemployment rate *(unemp)*, private consumption as a rate of GDP *(pcons)* and per capita GDP measured at constant 1987 prices *(pcinc)*. The rates of divorce *(div),* high school graduation *(hsc)* and urbanization *(urb)* are considered as socioeconomic and demographic variables which can have effects on crime. The number of court cases solved per judge as a rate of number of court cases brought per judge is used as deterrent variable *(det)* and it proxies the number of offences solved.

The data is annual and covers 1967-2004 period. Seven independent variables are unfortunately too many for conducting a system approach since the number of observations is only 38. Therefore, the correlations among three economic variables and four dependent variables are computed to select one of those three economic variables. The results in Table 1 show that the correlation coefficients are the highest for per capita GDP (*pcinc*), therefore it will be used as the only economic variable of our model.

All independent variables are expressed as rates of total population except per capita GDP and the deterrent variable. All variables except urbanization and unemployment rates are taken from Turkish Statistical Institute. Urbanization and unemployment rates are obtained from OECD's Labor Force Statistics. All variables are in natural logarithmic form.

Table 1. Correlation coefficients among economic variables and crime rates.

	CRIND	CRPROP	CRPUB	CRST	PCINC	PCONS	UNEMP
CRIND	1.00						
CRPROP	0.58	1.00					
CRPUB	0.84	0.71	1.00				
CRST	0.19	0.44	0.43	1.00			
PCINC	-0.83	-0.24	-0.58	0.04	1.00		
PCONS	0.64	0.17	0.33	0.07	-0.78	1.00	
UNEMP	0.01	0.04	0.20	-0.22	0.01	-0.11	1.00

4. Empirical Results

The non-stationarity of the data on both dependent and explanatory variables raises estimation difficulties that are not present in ordinary stationary regression models. Consequently, it is extremely important to determine the existence and nature of nonstationarity in the data. We start our empirical analysis with Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests to ascertain the order of integration of the variables. An incorrect decision about the order of differencing would lead to the estimation of a misspecified model and may generate misleading conclusions. We used modified versions of Akaike's Information, Schwarz-Bayesian and Hannan-Quinn criterions to determine the orders of lags in ADF equations.[2] The results are shown in Table 2. Determining the order of integration of the variables in the study was generally straightforward, using ADF and PP tests on the logarithms of the variables. All variables except *urb* (urbanization rate) were found to be I(1). Urbanization rate (*urb*) is integrated of order two. Therefore, this independent variable is excluded from our analysis.

Table 2. Unit Root Tests

	ADF		PP	
	Without Trend	*With Trend*	*Without Trend*	*With Trend*
		Levels		
crind	-1.53 (1)	-2.27 (3)	-1.65 [1]	-1.71 [1]
crprop	-2.45 (0)	-2.43 (2)	-2.08 [2]	-2.78 [0]*
crpub	-1.68 (0)	-2.22 (0)	-1.37 [2]	-2.10 [2]
crst	-2.64 (0)	-2.66 (0)*	-2.74 [1]	-2.66 [0]*
det	-2.39 (3)	-1.82 (3)	-4.44 [1]***	-2.66 [2]*
div	-0.77 (0)	1.68 (0)	-0.28 [3]	2.24 [4]
hsc	-2.77 (0)	-1.14 (0)	-2.77 [0]	-1.04 [4]
pcinc	-3.05 (0)	-0.97 (0)	-3.06 [1]	-0.91 [4]
urb	-2.02 (1)	-1.14 (1)	-0.70 [4]	-1.51 [4]
		First Differences		
crind	-3.96 (2)**	-6.44 (0)***	-9.35 [10]***	-6.58 [2]***
crprop	-7.19 (0)***	-6.82 (0)***	-9.94 [8]***	-7.15 [4]***
crpub	-6.19(1)***	-5.38 (1)***	-8.04 [4]***	-6.87 [2]***
crst	-4.13 (1)**	-4.18 (1)***	-6.72 [8]***	-6.54 [7]***
det	-8.96 (0)***	-9.09 (0)***	-6.29 [5]***	-6.99 [5]***
div	-1.25 (3)	-0.66 (3)	-5.83 [3]***	-5.17 [3]***
hsc	-1.98 (4)	-6.40 (0)***	-6.22 [1]***	-6.39 [1]***
pcinc	-3.83 (1)**	-3.92 (1)***	-6.61 [3]***	-6.71 [3]***
urb	-1.79 (0)	-1.61 (0)	-1.95 [2]	-1.75

Notes: 1- Numbers in parentheses denote the number of lags in the augmented term of ADF regression. They are determined by using modified versions of Akaike's Information, Schwarz Bayesian and Hannan Quinn criterions which are suggested by Ng and Perron (2001).
2- Truncation lags for the Phillips-Perron (PP) test are shown in brackets. They are computed using Barlett Kernel spectral estimation and Newey West bandwidth selection methods.
3- For both ADF and PP tests, the critical values of MacKinnon are used to test the unit root hypothesis. According to MacKinnon's (1991) critical values, *** and ** denotes that the unit root hypothesis is rejected at the 1% and 5% levels respectively.

A test for cointegration using the Johansen's maximum likelihood method described in the previous section is applied, in order to identify the cointegrating rank r and to provide estimate of the cointegrating matrix. Before determining the number of cointegrating vectors, it is necessary to choose the order of the lags in the VAR. In practice, this is done on the basis of an information criterion such as the Akaike information criterion or the Schwarz Bayesian criterion. However, individual equations of the VAR need to be checked for the presence of autocorrelation and non-normality etc. to ensure that the residuals are indeed uncorrelated and Gaussian. We follow Saikkonen and Lütkepohl (1996) and set the maximum order of VAR to be considered as the integer part of $T^{1/3}=3.36$. Model selection criterions (i.e. Akaike's Information, Schwarz-Bayesian and Hannan-Quinn) selected 1 (one) as the order of VAR. However, the residuals of individual VAR equations show serial correlation and nonnormality

[2] When a process has a unit root but has a negative moving average component, there are steps one can take to minimize size distortions while retaining power in unit root tests. The main ingredient is the use of new modified information criterions to select the autoregressive lag length. See Ng and Perron (2001) for details.

with 1 lag, we therefore select lag length of 2 for all four models. A constant and a trend are included in VAR models for *crind* and *crst*. Only a constant is added to *crprop* and *crpub* models. The inclusion of these deterministic components is confirmed via Likelihood Ratio (LR) tests.

Table 3. Cointegration Rank and Model Selection

	Model 2 (restricted intercept, no trend)		**Model 3 (unrestricted intercept, no trend)**		**Model 4 (unrestricted intercept, restricted trend)**	
Null	**Trace Statistics**	**95% Critical Value**	**Trace Statistics**	**95% Critical Value**	**Trace Statistics**	**95% Critical Value**
Vector Including: Crime Against Individual, Order of VAR=2						
r=0	67.03	76.07	59.43	68.52	94.15	87.31
r<=1	37.66	53.12	31.57	47.21	54.40	62.99
r<=2	23.44	34.91	18.94	29.68	27.48	42.44
r<=3	12.48	19.96	10.21	15.41	16.65	25.32
r<=4	4.02	9.24	1.75	3.76	8.03	12.25
Vector Including: Crime Against Property, Order of VAR=2						
r=0	80.65	76.07	72.54	68.52	93.48	87.31
r<=1*	**42.63**	**53.12**	37.19	47.21	57.93	62.99
r<=2	24.26	34.91	19.19	29.68	34.28	42.44
r<=3	9.47	19.96	6.62	15.41	16.33	25.32
r<=4	3.81	9.24	2.41	3.76	4.12	12.25
Vector Including: Crime Against Public, Order of VAR=2						
r=0	80.98	76.07	73.78	68.52	97.60	87.31
r<=1*	**48.40**	**53.12**	42.33	47.21	56.81	62.99
r<=2	23.83	34.91	18.68	29.68	31.75	42.44
r<=3	11.82	19.96	9.37	15.41	16.17	25.32
r<=4	4.29	9.24	2.08	3.76	7.20	12.25
Vector Including: Crime Against State and Government Administration, Order of VAR=3						
r=0	90.95	76.07	81.41	68.52	104.07	87.31
r<=1	56.91	53.12	48.55	47.21	68.49	62.99
r<=2*	**28.06**	**34.91**	20.54	29.68	38.78	42.44
r<=3	14.57	19.96	8.98	15.41	18.09	25.32
r<=4	6.25	9.24	2.42	3.76	6.53	12.25

Notes: 1- Critical values are taken from Osterwald-Lenum (1992).
2- * shows the number of cointegrating vectors selected by Pantula Principle. In other words, it shows null hypothesis that is accepted for the first time according to Pantula Principle.

The second issue concerns the presence of deterministic components (a constant and a trend) in the cointegration space. The asymptotic distribution of the test for cointegration depends on the assumption we make regarding the deterministic components in a model. The choice between the various models boils down to three realistic cases: Model 2, which assumes no linear trends in the levels of the data, i.e. an intercept which is restricted to the cointegration space; Model 3 which assumes the existence of linear trends in the levels of the data; and Model 4 which allows for trend in the cointegration space. The issue of choosing between the three models can be decided on the basis of the Pantula principle, as noted earlier. The testing strategy begins with choosing the most restrictive model (rank 0, model 2) and comparing the trace test statistic with the critical value.[3] The critical values for Model 2, Model 3 and Model 4 are taken from Osterwald-Lenum (1992). If the model is rejected, we proceed to Model 3 with the rank being kept fixed. This procedure is continued until the null is accepted for the first time.

Following this procedure, we find that Model 2 with rank equal to 1 is the most appropriate model for both *crprop* and *crpub* models (see Table 3). On the other hand, Model 2 with rank equal to 2 is selected for *crst* model. However, there does not seem to be a cointegrating relationship between crime against individual and other independent variables. This means we can carry on with the causality analysis in a VAR-setting using the first differences for *crind* model.

Table 4. Coefficients of Cointegrating Vectors

Vector Including	Vector 1	Vector 2
Crime Against Individual		
hsc	-	-
div	-	-
det	-	-
pcinc	-	-
Crime Against Property		
hsc	-2.14 [7.93]***	-
div	1.88 [15.8]***	-
det	7.28 [5.25]**	-
pcinc	0.44 [0.07]	-
Crime Against Public		
hsc	-0.86 [2.86]*	-
div	0.62 [1.62]	-
det	-4.04 [7.27]***	-
pcinc	0.66 [2.08]	-
Crime Against State and Government Administration		
hsc	-0.11	0.19
div	-1.41	0.71
det	-15.53	0.67
pcinc	4.81	-1.64

Notes: 1- Vectors are normalized on crime variables (made italic).
2- Numbers in brackets are Chi-square statistics for testing the null of exclusion of the variables. ***, ** and * show significance at 1%, 5% and 10% respectively.

Estimated coefficients of cointegrating vectors are reported in Table 4. There is no cointegrating vector for *crind* model, because there is no evidence of long run relationship between *crind* and independent variables. In addition, we interpret only Vector 1 of the *crst* model, because, Vector 2 of this model does not have expected signs and it is hard to interpret the coefficients of the vector.[4]

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[3] The Monte Carlo experiments reported in Cheung and Lai (1993) suggest that the trace test shows more robustness to both skewness and excess kurtosis in the residuals than the maximal eigenvalue test. In addition, Lütkepohl et. al. (2001) also suggest trace test in favor of maximum eigenvalue. Therefore, while selecting the appropriate model and the cointegration rank, we are guided by the trace statistic.

[4] In the case of multiple cointegrating vectors, where there is no longer a unique long-run relationship towards which the VECM is adjusting, a single equation cointegrating regression will only estimate the linear combination of the existent vectors. Researchers generally regard this problem as an identification problem for single equation cointegrating regression, and it was solved by choosing the particular cointegrating vector where

Vector 1's coefficients have generally expected signs and magnitudes. They reflect long-run elasticity measures as the variables are in logarithms. There is a positive relationship between per-capita income and crime. A 1% increase in per-capita income increases crime against property, crime against public and crime against state and government administration by 0.44%, 0.66% and 4.84% respectively. However, likelihood ratio (LR) tests can not reject the restriction of zero *pcinc* coefficients. Socio-economic and demographic variables, namely education level and divorce rate, have expected effects on crime against property and crime against public. Education helps reducing all three types of crime. Rise in divorce rate on the other hand stimulates crime against public and property. Divorce rate has an unexpected effect on crime against state and government administration. According to the Vector 1 of *crst* model, an increase in divorce rate decreases crime against state and government administration. Another unexpected sign belongs to the deterrent variable in crime against property model. It surprisingly takes a positive sign.

The next step involves testing Granger-causality among the variables. Tests for either or both short run or long run causality can be determined from VECM. For a VAR first-differences system with cointegrated variables, the Granger-causality test must be conducted in the environment of VECM. The relevant error-correction term must be included to avoid misspecification and omission of important constraints.

Table 5 gives the Granger-causality results based on VECM with uniform lag structure. As stated in section two, the F-test of the explanatory variables (in first differences) indicates the short-run causal effect, while the long-run causal relationship is implied through the significance of the lagged ECT. Short-run Granger causality results are derived from the VECM regressions for the *crprop, crpub* and *crst* models, and from the VAR regression in first-differences for the *crind* model.

Obviously, since the tests above did not indicate a cointegrated relationship for crime against individual, no tests of long-run causality are performed. In addition, in the short run, explanatory variables do not significantly Granger cause crime against individual. From this model, we can only see that crime is a Granger cause of deterrent variable while high school graduation rate is a Granger cause of per-capita income.

Results based on the VECM indicate that in the short run, individually only divorce rate significantly Granger causes the property crime rates (as reflected in the significance of the *F*-tests of the lags of *div* variable). The proportion by which the property crime rate adjusted endogenously in the short run to its long-term equilibrium relationship with other cointegrating variables is nevertheless significant (as evidenced in the significance of the t-test of the lagged ECT). In other words, the short-run disequilibrium in the long-run cointegration relationship Granger causes crime against property.

The significance of the t-tests of the error-correction terms in *crpub* model indicate that the burden of short-run adjustment appears to have fallen mostly on deterrent variable and per-capita GDP rather than on crime (*crpub*) which remains relatively exogenous. In the short run, deterrent variable is the only Granger cause of crime against public at 10% significance level.

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its long-run estimate corresponds closely (in both magnitude and sign) to those predicted by economic theory or other long-run estimation techniques.

The results also imply that crime against state and government administration is Granger-caused partly by high school graduation rate and partly by short-run adjustment to long-term equilibrium trend (as evidenced in the significant F-test for *hsc* and significant t-test of an error correction terms).

Table 5. Granger Causality Tests

	Δcr	Δhsc	Δdiv	Δdet	Δpcinc	ect1	ect2
Dependent Variable			**F-Statistics**			**t-statistics**	
			Crime Against Individual				
Δcr(ind)	-	0.02	1.18	0.10	1.06	-	-
Δhsc	1.33	-	0.10	0.03	0.75	-	-
Δdiv	0.23	0.01	-	0.08	0.26	-	-
Δdet	4.27**	2.20	0.06	-	0.02	-	-
Δpcinc	0.23	3.11*	0.01	0.01	-	-	-
			Crime Against Property				
Δcr(prop)	-	1.42	3.57*	0.08	0.39	-2.11**	-
Δhsc	0.17	-	4.27**	1.12	0.01	-3.56***	-
Δdiv	0.31	0.01	-	0.01	0.01	-1.34	-
Δdet	6.97***	2.43	1.15	-	0.28	1.52	-
Δpcinc	2.55	3.98**	1.22	0.63	-	-2.35**	-
			Crime Against Public				
Δcr(pub)	-	0.02	0.01	3.05*	0.66	-0.61	-
Δhsc	3.41*	-	0.14	0.06	0.66	0.62	-
Δdiv	0.89	0.32	-	0.15	0.02	1.40	-
Δdet	0.26	0.08	0.71	-	0.29	-3.10***	-
Δpcinc	0.93	0.72	0.01	1.17	-	2.00**	-
			Crime Against State and Government Administration				
Δcr(st)	-	3.02*	2.06	0.31	0.37	-2.60***	3.01***
Δhsc	4.49***	-	1.03	0.34	0.65	-0.17	1.38
Δdiv	2.25	0.03	-	0.07	0.03	1.25	-0.66
Δdet	0.86	0.57	1.75	-	0.01	-0.90	-1.73
Δpcinc	0.10	2.54	1.54	4.39**	-	2.20**	0.76

Notes: 1- The order of the lag length is determined by Schwarz Bayesian criterion and it is consistent with the preferred VAR-models, so that a VAR(2) is transformed to a VECM(1).
2- The ECTs are derived by normalizing cointegrating vector(s) on *cr*, resulting in *r* number of residuals.
3- *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Detecting Granger causality is restricted to essentially within-sample tests, which are useful in discerning the plausible Granger exogeneity or endogeneity of the dependent variable in the sample period, but are unable to deduce the degree of exogeneity of the variables beyond the sample period. To examine this issue, the variance decompositions are considered, which measure the percentage of a variable's forecast error variance that occurs as the result of a shock from a variable in the system. If a variable is truly exogenous with respect to the other variables in the system, own innovations are expected to explain almost all of the variables' forecast error variance (Sims, 1982).

The variance decompositions results are summarized in Table 6 over a 10-year period. Evidence of both short-run and long-run Granger noncausality for *crind* model is further supported by VDCs. A high proportion (86.10%) of the variance of forecast error of this crime is still explained by its own shocks even after ten years.

Table 6. Variance Decompositions

	Percentage of forecast variance explained by innovations in:				
	crime rate	high school graduation	divorce	deterrent	per-capita income
Years			*Crime Against Individual*		
1	100.00	0.00	0.00	0.00	0.00
2	89.20	6.41	1.98	2.24	0.15
3	86.52	8.64	1.97	2.57	0.27
4	86.17	8.92	1.99	2.57	0.32
5	86.12	8.93	2.02	2.57	0.34
10	86.10	8.93	2.03	2.57	0.34
			Crime Against Property		
1	100.00	0.00	0.00	0.00	0.00
2	88.74	0.43	6.70	1.22	2.88
3	88.99	0.95	5.40	1.81	2.81
4	90.06	0.77	4.44	2.20	2.50
5	90.11	0.80	3.76	2.84	2.47
10	88.87	0.62	3.25	5.25	1.98
			Crime Against Public		
1	100.00	0.00	0.00	0.00	0.00
2	97.36	0.05	0.94	0.40	1.23
3	93.61	2.68	1.35	1.37	0.95
4	90.96	4.35	1.07	2.42	1.17
5	88.44	6.26	0.89	3.19	1.19
10	79.19	12.17	0.48	6.79	1.35
			Crime Against State and Government Administration		
1	100.00	0.00	0.00	0.00	0.00
2	87.08	8.25	0.55	0.85	3.24
3	82.40	8.75	2.76	2.42	3.63
4	76.72	9.26	2.80	7.18	4.02
5	72.60	9.10	3.23	10.69	4.36
10	58.64	7.89	11.55	15.99	5.90

Notes: 1- Variance decomposition of crime against individual is constructed based on VAR of differences of the variables.
2- The innovations are orthogonalized in the following order: (*cr*, *hsc*, *div*, *det*, *pcinc*) through Choleski decomposition. Several alternative orderings are tried do not alter the results to any substantial degree.

Post-sample VDCs for crime against property show that in the short-run (e.g. two years), the contribution of divorce rate is relatively high (6.70%) in explaining the variations in *crprop*. This result is consistent with the Granger causality results which indicate the short-run causal relationship between *div* and *crind*. Although temporal causality results indicate a long-run endogeneity of *crprop* by the significant t-value, this result can not be supported with dynamic causality results of VDCs. Own shocks of *crprop* is the major (88%) source of its forecast error variance at ten-year horizon.

VDCs of *crpub* give no evidence of short-run causality. At two-year horizon, only 2.64% of the shocks is explained by the independent variables. This proportion rises to 20.81% after ten years, which is still small to indicate endogeneity of *crpub*.

Post-sample VDCs confirms within-sample Granger causality results for crime against state and government administration. High school graduation rate is the main source of variation in forecast error of *crst* in the short-run. In the long-run, 41.36% of the variance is explained by the independent variables.

As a general result, VDCs can not support the long-run causal relationships found by within-sample Granger causality tests. All variables seem to remain exogenous in the long-run. Crime against state and government administration (*crst*) is the most endogenous type of crime (i.e. a substantial portion of the variation of this crime is explained by the independent variables).

5. Concluding Remarks

This paper explores the interactions among four different subcategories of crime defined by Turkish Criminal Law (crime against state or government administration, crime against public, crime against individual and crime against property), percent of offences solved, per capita income, rates of divorce and higher education for Turkey. Empirical investigation is made by the use of a temporal Granger-causal framework through a multivariate cointegrated analysis.

Empirical results indicate the existence of a long run relationship between all types of crime except crime against individual. The results show that increases in per-capita income increase crime against property, crime against public and crime against state and government administration although the likelihood ratio (LR) tests can not reject the restriction of zero coefficients. As expected, increases in education reduce all three types of crime. Rise in divorce rate stimulates crime against public and property but decreases crime against state and government administration. The deterrent variable affects crime against public and crime against state and government administration negatively but unexpectedly affects crime against property positively. The long-run cointegrating relationships found by Johansen's methodology are also confirmed by the significant error correction terms in VECM models.

As for the short run causality, again no evidence is found for crime against individual. Property crime rates are found to be caused by the divorce rate, while the deterrent variable is the only Granger cause of crime against public and high school graduation rate is the only short run cause of crime against state and government administration.

Finally, the variance decompositions (VDCs) computed to search for the degree of exogeneity of the variables support that crime against individual is exogenous. However, VDCs for the other three types of crimes do not support the long-run causal relationships. Crime against state and government administration is found to be the most endogenous type of crime.

The conflicting results have to be interpreted carefully before using them for policy purposes. It should be noted foreword that the extent of the available data for this study is very limited especially for a time-series analysis. In addition, the content of the dependent variables used to explain different types of crime is also crucial. The deterrent variable (the number of court cases solved per judge as a rate of number of court cases brought per judge) used in this study was the only available variable for the sample period. Other variables such as police force, severity of punishment could have been better proxies for deterrent variable. Also, the urbanization rate had to be left out of the analysis due to its time-series properties. All taken together, being the first to examine the economics of crime for Turkey as to the knowledge of the authors, this study provides an important contribution to the field. Further investigation is undoubtlessly necessary for overcoming the drawbacks of the study.

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