Factors influencing crime rates:

An econometric analysis approach

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ABSTRACT

The scope of the present study is to research the dynamics that determine the commission of crimes in the US society. Our study is part of a model we are developing to understand urban crime dynamics and to enhance citizens' "perception of security" in large urban environments. The main targets of our research are to highlight dependence of crime rates on certain social and economic factors and basic elements of state anticrime policies. In conducting our research, we use as guides previous relevant studies on crime dependence, that have been performed with similar quantitative analyses in mind, regarding the dependence of crime on certain social and economic factors using statistics and econometric modelling. Our first approach consists of conceptual state space dynamic cross-sectional econometric models that incorporate a feedback loop that describes crime as a feedback process. In order to define dynamically the model variables, we use statistical analysis on crime records and on records about social and economic conditions and policing characteristics (like police force and policing results – crime arrests), to determine their influence as independent variables on crime, as the dependent variable of our model. The econometric models we apply in this first approach are an *exponential log linear model* and a *logit model*. In a second approach, we try to study the evolvement of violent crime through time in the US, independently as an autonomous social phenomenon, using *autoregressive and moving average time-series econometric models*. Our findings show that there are certain social and economic characteristics that affect the formation of crime rates in the US, either positively or negatively. Furthermore, the results of our time-series econometric modelling show that violent crime, viewed solely and independently as a social phenomenon, correlates with previous years crime rates and depends on the social and economic environment's conditions during previous years.

Keywords: crime, urban, dependence, social, economic, factors, statistics, econometrics

1. INTRODUCTION

Crime exists everywhere and is correlated with all types of people. This has led many social scientists to research the various factors that influence the amount of crime and how these factors can be controlled in an effort to reduce crime. Crime is often perceived as a problem amid areas with high poverty levels, unemployment, population density, minority populations, age distribution and school desertion. When government officials know how much these factors affect crime, they can focus their efforts and money spending on facing such phenomena and thus, aiming at the reduction of their consequences in crime committing. Taking into account all these factors and the bibliography from research from other social scientists on the subject of crime dependency on social conditions, we try to focus on some of the factors that appear to play an important role in shaping crime trends in the US, like policing effectiveness, school desertion, immigration, unemployment and poverty.

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Because crime is the result of a combination of factors, it makes no sense to seek to control crime by a single strategy. A mixed set of strategies is always more appropriate and emphasis on particular strategies should vary, according to the nature of the crime problem at hand, the available options for influencing the problem and the urgency with which change is required. Governments who want to control crime rates should seek to influence as many factors as possible, rather than concentrating all their efforts only on one or two factors. The interpretation of our findings may help governing officials to distinct certain crime-prone areas, characterized by these problems and deal with them more systematically, by planning and acting methodically to eliminate opportunities or incentives for crime in particular locations, since these opportunities give rise to gangs and other criminal organizations which further exacerbate crime, both locally and elsewhere.

Reviewing the relevant literature on the subject, one comes across various efforts from many social scientists, to scientifically explain crime evolvement and the various factors and conditions that affect it. A wealth of studies has been produced on the subject in the form of books and research articles. We present some of the most recent and oriented to the association of crime to social and economic conditions by beginning with Eric Baumer *[“An Empirical Assessment of the Contemporary Crime Trends Puzzle: A Modest Step Toward a More Comprehensive Research Agenda”, (2008)]* who highlights the importance of incarceration, policing, gun possession, alcohol and drugs consumption, youth firearm violence, age, cohabitation, teenage motherhood in shaping recent crime trends.

Anthony Braga *[“The Effects of Hot Spots Policing on Crime”, (2001)]* suggests that focused police actions on crime hot spots can prevent crime and disorder. J.W. Shaw *[“Community Policing Against Crime: Violence and Firearms”, (1994)]* stresses the role of efficient policing, like "crime hot-spots" directed patrols with the additional target of firearm - recovery focus, in significantly reducing violent and firearm-related crime. Anthony Braga, David Weisburd, Elin Waring, Loren Green Mazerolle, William Spelman and Francis Gajewski *[“Problem-Oriented Policing in Violent Crime Places: A Randomized Controlled Experiment”, (2006)]* also support the opinion that focused policing can reduce crime and disorder at places with problems of high criminality and prevent the transfer of criminal activities elsewhere.

Matias Berthelon and Diana Kruger *[“Risky behavior among youth: Incapacitation effects of school on adolescent motherhood and crime in Chile”, (2010)]* analyze the effect of full-day schools, in reducing the chance that teenagers engage in risky behaviors that may lead to youth crime and adolescent motherhood. Lance Lochner and Enrico Moretti *[“The Effects of Education on Crime: Evidence from Prison Inmates, Arrests and Self Reports”, (2001)]* find that completing high school reduces the probability of incarceration for different types of crimes and support the idea that public spending in general education for all, pays back socially in the form of crime reduction. Kimberly Henry, Kelly Knight and Terrence Thornberry *[“School Disengagement as a Predictor of Dropout, Delinquency and Problem Substance Use During Adolescence and Early Adulthood”, (2010)]* prove that school disengagement is a robust warning index related not only to school dropout but also to serious and often illicit problem behaviors of teenagers and young adults.

Blake Taylor *[“Poverty and Crime”, (2006)]* claims that cultural factors that separate minorities from the rest of the population, are associated with social discriminations and social barriers that influence towards violent behaviors and can lead to higher crime rates. Alfred Blumstein and Richard Rosenfeld *[“Factors Contributing to U.S. Crime Trends”, (2008)]* underscore the importance of street gangs, firearm availability, drug markets, policing innovations, incarceration, demographic shifts, childhood socialization, changing economic conditions and social public investments in influencing crime trends. Kristin Butcher and Anne Morrison Piehl *[“Cross-City Evidence on the Relationship Between Immigration and Crime”, (1999)]* find a relationship between immigration into metropolitan areas and high crime rates in that areas. Carl Bankston *[“Youth Gangs and the New Second Generation: A Review Essay”, (1998)]* stresses the role of changes in American immigration law in 1965 in the participation of immigrants’ children in violent youth gangs.

Matthew Melick *[“The relationship between crime and unemployment”, (2003)]* finds that social security subsidies to unemployed prevents them to resort to criminal activities and also that an important role in criminal activity plays not only the motivation of a criminal but also the opportunity of available victims. Isaak Ehrlich *[“Crime, Punishment and the Market of Offenses”, (1996)]* approaches crime with economic terms, building a conceptual market-type model where the dominant role in getting someone to resort to illicit activity is represented by their perception of the relevant profits they might get in relation to the danger of being caught and face legal consequences and punishment. Chester Britt *[“Crime and Unemployment Among Youths in the United States 1958 – 1990 A Time Series Analysis”, (1994)]* finds that youth unemployment is negatively related to violent and property crime. David Cantor and Kenneth Land *[“Unemployment and Crime Rates in the Post WWII United States – A Theoretical and Empirical Analysis”, (1985)]* stress the role of the availability of opportunities during economically harsh times, when for example unemployment is high, in the formation of reduced crime trends. Also, they emphasize about the role of duration in unemployment as they find that long-term unemployed are more prone to resort to criminal activity than the short-term unemployed.

Blake Taylor *[“Poverty and Crime” (2006)]* emphasizes on poverty’s hard consequences playing an important role in turning someone to illicit acts, because they gradually lower their estimated perception of the risk of being caught, as they feel that there is not much to lose and also trap them in a life with very few chances of escaping from poverty. Jens Ludwig, Greg J. Duncan, and Paul Hirschfield *[“Urban Poverty And Juvenile Crime: Evidence From a Randomized Housing-Mobility Experiment” (2000)]* show that high-poverty areas have on average more violent crime and teens are more likely to desert school and get involved in teen gangs when they live in high-poverty areas. Ching-Chi Hsieh and M.D. Pugh *[“Poverty, Income Inequality and Violent Crime: A Meta-Analysis of Recent Aggregate Data Studies”, (1993)]* find that poverty and income inequality are positively associated with crime in most of the relevant studies. E. Britt Patterson *[“Poverty, Income Inequality and Community Crime Rates”, (2006)]* presents his findings indicating that absolute poverty is strongly associated with neighborhood crime rates.

John V. Pepper *[“Forecasting Crime: A City-Level Analysis”, (2008)]* stresses the difficulty of predicting crime rate as a time-series autoregressive variable, because in this case forecasting is independent from causal analysis and a lot on unpredictable and unknown external factors might play an important role.

2. METHODOLOGY

2.1 Datasets

Our research consists of three different approaches regarding the study of crime in the US. The first and second approach involve the analysis of the dependence of urban crime on certain influencing social and economic factors whereas the third approach involves the analysis of the evolvement of violent crime through time in all the US.

For the purpose of our research, we formed two datasets, collecting data from various official data sources like the FBI website, the US National Center for Educational Statistics website, the US Census Bureau website, the US Bureau of Labor Statistics website and the US Bureau of Economic Analysis website.

Regarding our urban crime dependence approaches, we formed a data panel gathering cross-sectional data from 49 US states, for the eleven-year period 2004 – 2014. Due to lack of certain needed data from the databases we searched, about law enforcement personnel and arrests for violent and property crime for some years, we intentionally left out District of Columbia and Hawaii. Because in their primary form some of our collected data were not expressed in the same units of measurement, we had them all expressed in percentage form. So for each state we had as a dependent variable, the percentage of urban crime (violent and property) in the urban area population (reported crimes per one hundred residents in urban areas) and as independent variables influencing urban crime, we had each state’s school dropout percentage, unemployment percentage and below poverty percentages. Also in order to estimate the influence of policing in deterring crime we formed a special police-efficiency indicator per state, involving the size of each state’s law enforcement personnel in relation to police work done as it is depicted in the number of arrests for violent and property crime in each state. The indicator is the law enforcement personnel rate per one hundred arrests for violent and property crime, namely law enforcement personnel to arrests percentage.

Regarding our evolving through time crime approach, we used time series data about the rate of homicides per 100,000 residents in all the US for the time period 1950 – 2012.

2.2 Probabilistic Binary Logit Regression Model

Our first approach involved an effort to find a method for classifying states as being above or below the national mean concerning crime commitment. Towards this direction, we investigated the dependence of urban crime rate across the US with respect to the aforementioned influencing social and economic factors (school dropout rate, unemployment rate,

below poverty rate and law enforcement personnel rate per one hundred arrests), with the use of qualitative data. More specifically, using as a basis our gathered cross-sectional data panel from the 49 US states, for the eleven-year period 2004 – 2014, we researched about the nature (positive or negative) and the size of the dependence of the odds ratio in favor of urban crime in a state being above the national US mean, in a year *t*, on the condition of each one of the influencing factors in a state being above the national US mean in the same year *t* and the previous year *t – 1*.
The above concept required for each year *t* and each pair of successive years *t* and *t-1*, for the period 2004 – 2014, the application of a probabilistic binary logit econometric model, using maximum likelihood methodology for its estimation, where all variables were binary, taking only *1 or 0* values if above or below the national US mean respectively. With this conditionality, for all variables we first had to extract the sample means from each cross-sectional data series, for all years (2004 – 2014) and then subtract the estimated sample mean from each state's respective value, assigning value *1* if above mean and value *0* if below mean. Our model is in the form of the following equation:

$$P_{s\,t} = E\,(\text{urban crime percentage}_{\,s\,t} = 1 \text{ or } 0 \mid \text{school dropout percentage}_{\,s\,t\,/\,t\text{-}1} = 1 \text{ or } 0,\ \text{unemployment percentage}_{\,s\,t\,/\,t\text{-}1} = 1 \text{ or } 0,$$

$$\text{below poverty percentage}_{\,s\,t\,/\,t\text{-}1} = 1 \text{ or } 0,\ \text{law enforcement personnel rate per one hundred arrests}_{\,s\,t\,/\,t\text{-}1} = 1 \text{ or } 0)$$

$$= e^{\,z\,s\,t} / (1 + e^{\,z\,s\,t})$$

$$Ln\,(P_{\,s\,t} / 1 - P_{\,s\,t}) = Ln\,(e^{\,s\,t}) = z_{\,s\,t} =$$

$$= b_0 + b_1 * \text{school dropout percentage}_{\,s\,t\,/\,t\text{-}1} + b_2 * \text{unemployment percentage}_{\,s\,t\,/\,t\text{-}1} + b_3 * \text{below poverty percentage}_{\,s\,t\,/\,t\text{-}1}$$

$$+ b_4 * \text{law enforcement personnel rate per one hundred arrests}_{\,s\,t\,/\,t\text{-}1} + u_{\,s\,t\,/\,t\text{-}1}$$

$$s = 1\text{-}49 \qquad t = 2004\text{-}2014$$

2.3 Panel Exponential Log Linear Regression Model

In our second approach, based again on our gathered cross-sectional data panel from the 49 US states, for the eleven-year period 2004 – 2014, we investigated simultaneously cross-sectional urban crime elasticity through time, again with respect to the aforementioned influencing factors (school dropout percentage, unemployment percentage, below poverty percentage and law enforcement personnel to arrests percentage). For this, we employed a fixed effects panel exponential log linear econometric model, using the generalized least squares method for its estimation (in order to treat the autocorrelation and heteroscedasticity problems), where each year's respective slope coefficients represented the percentage change in urban crime for a given percentage change in school dropout percentage, unemployment percentage, below poverty percentage and law enforcement personnel to arrests percentage in that same year. The chosen fixed effects type of panel econometric model is the most appropriate to analyze our panel data because it can take into account each year's individual circumstances shaping urban crime, depicting them on the varying each year's intercept (which was common through states however) while the slope coefficients are held constant across years and states. Our model is in the form of the following equation:

$$\log(\text{ urban crime}_{\,t\,s}) = b_{0\,t} + b_{1\,t} * \log(\text{ school dropout percentage}_{\,t\,s}) + b_{2\,t} * \log(\text{ unemployment percentage}_{\,t\,s})$$

$$+ b_{3\,t} * \log\,(\text{ below poverty percentage}_{\,t\,s}) + b_{4t} * \log(\text{ law enforcement personnel to arrests percentage}_{\,t\,s}) + u_{\,t\,s}$$

$$t = 2004 - 2014 \; s = 1 \ldots 49$$

2.4 Autoregressive Integrated Moving Average Regression Model

In our third approach, our efforts involved the studying of the evolvement of violent crime in the US, as a social phenomenon through time, independently of certain defined influencing social, economic or other factors. In this approach, we analyze the evolvement of violent crime in the US, in a given general social and economic environment, pretty much shaped by exogenous, out of control conditions.
Based on time series data concerning homicides' rate per 100,000 residents, across all the US, for the 1950 – 2012 time period, we proceeded with the deployment of an autoregressive integrated moving average [ARIMA (2,2,2)] time series econometric model, after having our data series checked for stationarity with the usual tests (Augmented Dickey-Fooler, Elliot-Rothenberg-Stock Point-Optimal) and found them to be non-stationary.

More specifically, we analyzed the dependence of the acceleration rate (second differences) of homicides' rate per 100,000 residents, across all the US, for the 1950 – 2012 time period, on its respective values in the two previous time periods, depicted in the model as autoregressive terms and on the changing conditions of the social and economic environment in the two previous time periods, depicted in the model as white noise error terms. Our model is in the form of the following equation

$$d2\ (y_t) = [a_1 * d2\ (y_{t-1})] + [a_2 * d2\ (y_{t-2})] + (m_1 * v_{t-1}) + (m_2 * v_{t-2}),$$

$$[v_{t-1}, v_{t-2} \sim N\ (0, \sigma^2)]$$

3. REGRESSION RESULTS

3.1 Probabilistic Binary Logit Regression Model

The findings of our probabilistic binary logit regression model are presented synoptically in the two following tables:

Table 1. PBLRM results concerning dependence of urban crime in year t, on influencing factors in the same year t

Dependent Variable	*Influencing Variables*			
Urban Crime %	*School Dropout %*	*Unemployment %*	*Below Poverty %*	*Law Enforcement Personnel To Arrests %*
t	*t*	*t*	*t*	*t*
5% Level Of Statistical Significance				
2004				*- 1.86 (0.79)*
2005				*-1.97 (0.79)*
2006	*1.59 (0.74)*		*1.90 (0.81)*	*-2.29 (0.92)*
2007	*1.24 (0.74)*		*1.63 (0.76)*	*-2.08 (0.81)*
2008			*1.46 (0.67)*	
2009				*-1.57 (0.75)*
2010			*1.77 (0.78)*	
2011			*2.65 (0.88)*	
2012			*3.12 (0.90)*	
2013			*2.11 (0.72)*	
2014				
Average	*1.42*		*2.09*	*-1.95*
10% Level Of Statistical Significance				
2004				*- 1.86 (0.79)*
2005				*-1.97 (0.79)*
2006	*1.59 (0.74)*		*1.90 (0.81)*	*-2.29 (0.92)*
2007	*1.24 (0.74)*		*1.63 (0.76)*	*-2.08 (0.81)*
2008			*1.46 (0.67)*	*-1.33 (0.74)*
2009	*1.28 (0.71)*			*-1.57 (0.75)*
2010			*1.77 (0.78)*	
2011			*2.65 (0.88)*	
2012			*3.12 (0.90)*	
2013			*2.11 (0.72)*	
2014			*1.25 (0.69)*	
Average	*1.37*		*1.99*	*-1.85*

Table 2. PBLRM results concerning dependence of urban crime in year t, on influencing factors in the previous year t – 1

Dependent Variable	*Influencing Variables*			
Urban Crime %	*School Dropout %*	*Unemployment %*	*Below Poverty %*	*Law Enforcement Personnel To Arrests %*
t	*t-1*	*t-1*	*t-1*	*t-1*
	5% Level Of Statistical Significance			
2005/2004				*- 2.08 (0.82)*

2006/2005				*-2.03 (0.86)*
2007/2006			*1.66 (0.77)*	*-2.18 (0.87)*
2008/2007			*2.16 (0.81)*	*-2.43 (0.93)*
2009/2008			*1.37 (0.66)*	
2010/2009			*1.44 (0.71)*	*-1.48 (0.75)*
2011/2010			*2.35 (0.81)*	
2012/2011			*2.65 (0.89)*	
2013/2012			*2.62 (0.86)*	
2014/2013			*1.67 (0.70)*	
Average			*1.99*	*-2.04*
10% Level Of Statistical Significance				
2005/2004			*1.45 (0.82)*	*- 2.08 (0.82)*
2006/2005	*1.40 (0.73)*			*-2.03 (0.86)*
2007/2006	*1.19 (0.71)*		*1.66 (0.77)*	*-2.18 (0.87)*
2008/2007	*1.35 (0.80)*		*2.16 (0.81)*	*-2.43 (0.93)*
2009/2008	*1.13 (0.65)*		*1.37 (0.66)*	
2010/2009	*1.26 (0.72)*		*1.44 (0.71)*	*-1.48 (0.75)*
2011/2010			*2.35 (0.81)*	
2012/2011			*2.65 (0.89)*	
2013/2012			*2.62 (0.86)*	
2014/2013			*1.67 (0.70)*	
Average	*1.27*		*1.93*	*-2.04*

Concerning the same year *t* time frame, at a *5%* statistically significant level, the logarithm of the odds ratio in favor of urban crime rate in a state above the national US mean in the period 2004 – 2014, depends

- by *1.42* on average, on school dropout percentage being above the national US mean
- by *2.09* on average, on below poverty percentage being above the national US mean
- by *-1.95* on average, on law enforcement personnel to arrests percentage being above the national US mean

Taking the respective antilogs $(e^{b1} = e^{1.42} = 4.14, e^{b3} = e^{2.09} = 8.09, e^{b4} = e^{1.95} = 7.03)$ suggests that urban crime rate in a state being above the national US mean is

- *4.14* times more likely if school dropout rate in that state is above the national US mean
- *8.09* times more likely if below poverty rate in that state is above the national US mean
- *7.03* times less likely if law enforcement personnel to arrests rate in that state is above the national US mean.

At a *10%* statistically significant level, the logarithm of the odds ratio in favor of urban crime rate in a state above the national US mean in the period 2004 – 2014, depends

- by *1.37* on average, on school dropout percentage being above the national US mean
- by *1.99* on average, on below poverty percentage being above the national US mean
- by *-1.85* on average, on law enforcement personnel to arrests percentage being above the national US mean

Taking the respective antilogs $(e^{b1} = e^{1.37} = 3.94, e^{b3} = e^{1.99} = 7.32, e^{b4} = e^{1.85} = 6.36)$ suggests that urban crime rate in a state being above the national US mean is

- *3.94* times more likely if school dropout rate in that state is above the national US mean
- *7.32* times more likely if below poverty rate in that state is above the national US mean
- *6.36* times less likely if law enforcement personnel to arrests rate in that state is above the national US average.

Concerning the one year lag time frame *t/t-1*, at a *5%* statistically significant level, the logarithm of the odds ratio in favor of urban crime rate in a state above the national US mean in the period 2004 – 2014 depends

- by *1.99* on average, on previous year's below poverty percentage being above the national US mean

- by *-2.04* on average, on previous year's law enforcement personnel to arrests percentage being above the national US mean.

Taking the respective antilogs *($e^{b3} = e^{1.99} = 7.32$, $e^{b4} = e^{2.04} = 7.69$)* suggests that urban crime rate in a state being above the national US mean is

- *7.32* times more likely if previous year's below poverty rate in that state is above the national US mean
- *7.69* times less likely if previous year's law enforcement personnel to arrests rate in that state is above the national US mean

At a *10%* statistically significant level, the logarithm of the odds ratio in favor of urban crime rate in a state being above the national US mean, depends

- by *1.27* on average, on previous year's school dropout percentage being above the national US mean
- by *1.93* on average, on previous year's below poverty percentage being above the national US mean
- by *-2.04* on average, on previous year's law enforcement personnel to arrests percentage being above the national US mean.

Taking the respective antilogs *($e^{b3} = e^{1.99} = 7.32$, $e^{b4} = e^{2.04} = 7.69$)* suggests that urban crime rate in a state being above the national US mean is

- *3.56* times more likely if previous year's school dropout rate in that state is above the national US mean
- *7.32* times more likely if previous year's below poverty rate in that state is above the national US mean
- *7.69* times less likely if previous year's law enforcement personnel to arrests rate in that state is above the national US mean

3.2 Panel Exponential Log Linear Regression Model

The findings of our panel exponential log linear regression model may be summarized in the following table:

Table 3. PELLRM results concerning cross-sectional urban crime elasticity through time with respect to its influencing factors

Dependent Variable	*Influencing Variables*			
Log(Urban Crime %)	*Log(School Dropout %)*	*Log(Unemployment %)*	*Log(Below Poverty %)*	*Log(Law Enforcement Personnel To Arrests %)*
$R^2 = 0.47$ $R^2_{adj} = 0.41$ S.E = 0.88 DW = 2.06				
5% Level Of Statistical Significance				
2004			*0.20 (0.09)*	*-0.07 (0.03)*
2005			*0.18 (0.09)*	*-0.10 (0.03)*
2006			*0.20 (0.08)*	*-0.14 (0.02)*
2007		*0.28 (0.11)*		*-0.15 (0.06)*
2008			*0.14 (0.07)*	*-0.08 (0.03)*
2009			*0.15 (0.07)*	*-0.08 (0.03)*
2010			*0.14 (0.06)*	*-0.06 (0.01)*
2011			*0.19 (0.06)*	
2012	*0.05 (0.03)*		*0.17 (0.05)*	
2013	*0.10 (0.03)*	*-0.13 (0.05)*	*0.11 (0.06)*	
2014	*0.08 (0.03)*	*-0.18 (0.08)*	*0.13 (0.06)*	
Average	*0.08*	*-0.01*	*0.16*	*-0.10*
10% Level Of Statistical Significance				
2004			*0.20 (0.09)*	*-0.07 (0.03)*
2005			*0.18 (0.09)*	*-0.10 (0.03)*
2006			*0.20 (0.08)*	*-0.14 (0.02)*
2007		*0.28 (0.11)*		*-0.15 (0.06)*
2008			*0.14 (0.07)*	*-0.08 (0.03)*
2009			*0.15 (0.07)*	*-0.08 (0.03)*
2010	*0.04 (0.02)*		*0.14 (0.06)*	*-0.06 (0.01)*
2011			*0.19 (0.06)*	

2012	*0.05 (0.03)*		*0.17 (0.05)*	
2013	*0.10 (0.03)*	*-0.13 (0.05)*	*0.11 (0.06)*	
2014	*0.08 (0.03)*	*-0.18 (0.08)*	*0.13 (0.06)*	
Average	*0.07*	*-0.01*	*0.16*	*-0.10*

As it concerns the cross-sectional elasticity of urban crime through time with respect to its influencing factors as we had defined them, our findings indicate that at 5% statistically significant level, school dropout affected positively the commitment of urban crime in three (2012, 2013, 2014) out of the eleven years of the searched time period (2004 – 2014) by *0.08%* on average, unemployment affects positively the commitment of urban crime in one (2007) and negatively in two (2013, 2014) out of the eleven years of the searched time period (2004 – 2014) by -0.01% on average, below poverty level affects positively the commitment of urban crime in ten (2004, 2005, 2006, 2008, 2009, 2010, 2011, 2012, 2013, 2014) out of the eleven years of the searched time period (2004 – 2014) by *0.16%* on average and the rate of law enforcement personnel to arrests affects negatively the commitment of urban crime in seven (2004, 2005, 2006, 2007, 2008, 2009, 2010) out of the eleven years of the searched time period (2004 – 2014) by *-0.10%* on average.

At 10% statistically significant level, results are similar to those at 5% statistically significant level, except that school dropout affects positively the commitment of urban crime in four (2010, 2012, 2013, 2014) out of the eleven years of the searched time period (2004 – 2014) by *0.07%* on average.

3.3 Autoregressive Integrated Moving Average Regression Model

The findings of our autoregressive integrated moving average regression model are presented synoptically in the following table:

Table 4. ARIMA results concerning the evolvement of the acceleration rate of violent crime across all the US through time

Dependent Variable	*Influencing Variables*			
$d2y$	$d2y_{t-1}$	$d2y_{t-2}$	v_{t-1}	v_{t-2}
$R^2_{adj} = 0.55$ $S.E = 0.28$ $DW = 1.92$				
5% Level of Statistical Significance				
	-0.32 (0.12)	*0.40 (0.10)*		*-1.40 (0.10)*

US violent crime's acceleration rate, as it is depicted by the second differences of the homicides' rate per 100,000 residents time series, across all the US, for the 1950 – 2012 time period, was found to have a negative dependence by *-0.32* on its respective value one year before, a positive dependence by *0.40* on its respective value two years before and a negative dependence by *-1.40* on the general conditions prevailing two years before, seemingly giving a quadratic stochastic trend in the original time series. One possible explanation for this behavior may be that the social and economic changing environment in the US, in which violent crime evolves, affects the evolution of violent crime not immediately, but within a two time lag.

4. DISCUSSION OF FINDINGS

The results of both our probabilistic binary logit regression model and our panel exponential log linear regression model regarding the dependence of urban crime on certain social and economic influencing factors that we have defined, **show the importance of school dropout and poverty in the commitment of crime in urban areas**, confirming the findings of Berthelon-Kruger, Lochner-Moretti and Henry-Knight-Thornberry about the positive effect of school desertion in crime commitment and Taylor, Ehrlich, Ludwig-Duncan-Hirschfield, Hsieh-Pugh and Patterson about the positive relation between poverty and crime.

It is a common phenomenon that a large percentage of children and juveniles who desert school have increased possibilities to participate in teen or adult gangs that engage in various types of illicit criminal activities. The state should provide second chances to young teenagers who desert school to find their way back to the academic community or alternatively to professional education, so as to have a chance again to live their lives normally, away from gangs and illicit activities.

Regarding poverty, it is the causal effect of many bad conditions and situations that can lead a person to illicit activities and crime commitment. Poverty can actually make someone economically and socially “default” since he or she cannot have a decent level of life in terms of economic and social presence and activity or even in terms of being unable to cover basic needs for themselves and their family. This sets an oversize psychological burden to someone and may lead them to think that profitable illicit action may worth the risk, since after all they don’t have to lose a lot more than a misery life they already live. Legal consequences concerning crime commitment are not thought as much more bad or fearful to someone, in comparison with their poverty situation and no longer pose a deterrent enough factor against criminal activity.

The results from our two first approaches also **stress the deterrent effect of effective policing on urban crime**, corroborating with the claims of Braga, Shaw and Braga-Weisburd-Waring-Mazerolle-Spelman- Gajewski. Even by the use of our general meta-index concerning the analogy of law enforcement personnel to police work, our model shows the negative effect that policing generally has on crime. Much more so, effective policing as a result of innovative actions, based on technology assistance and integration of technological solutions into police work regarding surveillance and crime prevention, can be a major deterrence for a percentage of possible criminals, since it makes them assess more carefully the risk of getting caught for illicit activities and so not easily take that risk.

Lastly, concerning our first and second approaches, **the controversial results about the effect of unemployment on urban crime commitment come to terms with the findings of other researchers**, such as Melick, Britt and Cantor-Land. The negative effect of unemployment to crime may seem counter-intuitive but it can be explained since unemployment means reductions in income or no income at all, so it affects consumption by reducing it too, so there are less available material goods or money to be stolen. During rough economic periods people become less suitable victims for robbery too, because they do not go out but prefer staying home, in order to save money but also because they guard this less personal property of theirs more carefully. Therefore, a negative relationship between unemployment and crime may well be explained. Of course in the long run, as long-term unemployment gradually leads to poverty thus reversing to a positive contribution to crime commitment for all the reasons presented above.

In our third approach about the evolvement of violent crime through time in the US, **our autoregressive integrated moving average regression model’s results demonstrate the difficulties of forecasting crime rates** due to the existence of external factors that cannot be always defined with clarity and modelled adequately, while playing an important role in crime formation by shaping its stochastic patterns and affecting the speed with it expands and outspreads. According to Green, a basic characteristic of time series is that each included observation contains to a smaller or larger degree some unique information, hence the difficulties in adequately modelling it. As he states *“it is very optimistic to expect to know precisely the correct form of the appropriate model for the disturbance in any given situation”*. Despite these, he claims that time series econometric models with autoregressive and moving average terms have been proved much more effective in applied research for their explaining and forecasting abilities since many time series processes can be modelled as regressions on lagged variables with additive error terms depicting innovations and changes of the environment in which they evolve through time.

Our econometric analysis about the dependence of crime commitment in the US on certain social and economic factors, needs to deepen even more, estimating the results of the relative contributions of other explanatory variables to observed crime rates as well. Changes in crime in relation to the changes in the values of other corresponding explanatory variables, except those we analyzed in the present paper, could serve as useful indicators for widening anticrime policies that are currently followed, with additional measures that need to be considered. This will provide useful tools for completing their mission successfully to authorities that are designated with the formation of the anticrime policies.

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