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Regions'***

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# **What Drives Crime? Evidence from Russia's Regions**

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## **Abstract**

Using a comprehensive dataset, we examine the economic, social, and demographic determinants of crime in Russia's 88 regional entities over 2000–2005. We consider both violent (murder and robberies) and non-violent crime (thefts, economic crimes), as well as drug crimes. We control for the endogeneity of our independent variables by isolating their exogenous influences on crime rates. We also control for measurement error in crime rates by modeling it as both observed regional effects and random noise. Using dynamic panel system GMM estimation techniques, we find that inequality and income are the most important factors affecting murders, robberies, and thefts. Social and demographic factors are also found to be important but only for certain types of crime. Police deterrence does not tend to reduce any type of crime. There is significant crime inertia in each case. We discuss the implications of the findings for policymakers and the validity of different crime theories.

O1 - Economic Development

J0 - General Labor and Demographic

R11 - Regional Economic Activity: Growth, Development, and Changes

Keywords: crime, inequality, Russia

## I. Introduction

This paper empirically investigates the determinants of crime in Russia. To our best knowledge, this paper provides some initial evidence on the determinants of crime in Russia during the post-transition period.<sup>1</sup> This is surprising because Russia ranks high in international crime statistics: overall, the crime rate is the 31<sup>st</sup> highest in the world (United Nations, 2001), despite likely significant underreporting due to widespread popular suspicion towards the authorities. One potential reason for lack of studies on crime in Russia is data availability. In this study we use a comprehensive dataset, allowing us to estimate the potential determinants of crime in Russia's 88 regions during 2000-2005.<sup>2</sup>

Our paper contributes to the literature in several ways.<sup>3</sup> First, Fajnzylber, Lederman and Loayza (2002a) state that “despite the fact that crime is emerging as a priority in policy agendas worldwide, we know little regarding the economic, social, and institutional factors that make some countries have higher crime rates than others or make a country experience a change in its crime rate” (p. 1324). They also argue the majority of the available studies on the determinants of crime have utilized microeconomic-level data and focused mostly on the U.S and other developed countries. More recent studies provide evidence from cross-country studies.<sup>4</sup> Hence an important shortcoming of the literature is the experience of individual countries.

A small number of individual country studies exist but they mostly focus on developed countries. There is scant evidence from developing, emerging or the former

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<sup>1</sup> We have found an earlier work by Andrienko (2002) who analyzes the determinants of crime in Russia's regions, but the sample period used in this study covers the early transition period (1990-1998) only.

<sup>2</sup> The sample period starts in 2000 as crime data is available starting only in this year.

<sup>3</sup> For a recent review of the literature on the determinants of crime, see Buonanno (2003).

<sup>4</sup> See Fajnzylber et al. (2002a and 2002b) and Lederman, Loayza and Menendez (2002).

transition countries.<sup>5</sup> In this paper, we focus on Russia, an emerging market economy, which has recently completed her transition period from being a former communist country to a market-based economy. Our sample period, covering the more recent post-transition period in Russia, may yield additional insights on the determinants of crime rates in developing and/or emerging market economies.

Second, more recently, there has been a growing interest in the literature to examine the inequality-crime link (see, for example, Fajnzylber et al., 2002a and 2002b and the studies cited therein). By providing further evidence from Russia, our study contributes to this line of literature as well.

Third, although not the main focus of the paper, our estimated model, covering a range of economic and social and demographic variables, may shed some light on the applicability of different theories of crime in developing countries.<sup>6</sup> Kelly (2000) discusses the three theories of crime that stress the link between inequality and crime: Becker's economic theory of crime, the social disorganization theory of Shaw and McKay, and Merton's strain theory. Each theory focuses on a different facet of the link between crime and inequality. In other words, a finding that inequality raises crime rates is consistent with all these theories. Recent studies have also explored this issue. For example, Demombynes and Özler (2005) provide empirical evidence that sociological theories of crime may explain different crime rates in South Africa. Our study extends these growing but scant individual studies attempting to provide evidence on the applicability of different theories of crime.

Fourth, we analyze whether ethnic heterogeneity (i.e., non-Russian population) could be related to crime. The social disorganization theory, which emphasizes the importance of

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<sup>5</sup> Gaviria (2000) analyzes crime in Colombia, while Demombynes and Ozler (2005) focus on South Africa.

<sup>6</sup> For a recent discussion of the theories of crime, see Kelly (2000), Fajnzylber et al. (2002b), and Demombynes and Özler (2005).

informal social controls to prevent crime, regards ethnic heterogeneity as an important identifier in this regard (Kornhauser, 1978). A higher level of ethnic heterogeneity may weaken social controls networks, causing individuals not to be able control exercise over the society's members. This, in turn, encourages individuals to commit crime (Kelly, 2000).

Fifth, many earlier studies have studied the effectiveness of public expenditures to deal with crime.<sup>7</sup> We also contribute to this line of literature by providing some preliminary evidence on the effectiveness of police expenditures in reducing crime in Russia.

Finally, we address the econometric issues raised by Fajnzylber et al. (2002a) in estimating models of crime rates. In particular, we control for the endogeneity of our independent variables such as inequality and income by isolating their exogenous influences on crime rates. We also control for measurement error in crime rates by modeling it as both observed regional effects and random noise. In section III (empirical methodology), we elaborate on these issues.

In the next section, we discuss some theoretical issues regarding the determinants of crime rates to further motivate our empirical methodology presented in Section III. In Section IV, we describe the data set used, while empirical results are presented in Section V. The last section concludes the paper with some policy implications of the findings.

## **II. Theoretical Considerations**

Models of individual criminal behavior are well-documented in the literature. While this study examines crime rates at a regional level, whether or not a crime is committed is an individual decision. Becker (1968) first suggested that individuals make rational decisions to commit crime based upon how the benefits of the act stack up against the costs.

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<sup>7</sup> See Cameron (1998) for an early review of the literature and Buonanno (2003) for recent studies.

We hypothesize, as does Fajnzylber et al. (2002a), that an individual's and a community's past crimes affect whether or not additional crimes are committed. If an individual has been convicted of a crime in the past, as a convict he or she may not be able to obtain certain jobs because of legal constraints or prejudice. As a result of lowered economic well-being and hence income, he or she may be economically motivated to commit additional crimes. The costs of committing additional crimes may also be lowered, since the individual already has "experience" at committing crimes. In addition, initially becoming a convict may be akin to a large fixed cost, and once that fixed cost has been sunk, rehabilitation in the community is difficult, giving the criminal little incentive to try. Also, we consider that aggregate crime levels can influence an individual's decision. The more past crime in an individual's community, the lower the costs of committing a crime oneself, one reason being easier access to other criminals and unsavory people.

We also hypothesize that income and job access are related to crime rates in a number of ways. A higher income would increase the opportunity cost of committing crime. If crime is economically motivated, the higher an individual's income level, the lower the benefit of committing a given crime, as it would increase income by a smaller percentage. If an individual is unemployed, the opportunity cost of committing a crime is lowered. In the aggregate, average income in a region is positively correlated with the level of economic growth, which can provide employment opportunities and increase the opportunity cost of crime. On the other hand, higher average levels of economic growth and income result in wealthier non-criminal members of society, increasing the potential gain to a criminal who wishes to prey upon them. Thus, in the aggregate, we might expect regional income levels to have a negative impact on the regional crime rate and the regional unemployment rate to

have a positive impact on the regional crime rate, but these are empirical questions as theory cannot give us a definitive prediction.

Economic inequality is also expected to affect crime rates, and, as Fajnzylber et al. (2002a) suggest, an individual's relative standing in society will partly determine the likelihood that they commit a crime. For someone at the lower end of the income distribution, an increase in inequality should increase the likelihood that a crime is committed, as long as the absolute difference between their standing and the standing of the richest members of society has increased. This larger gap also increases the potential gain to a criminal who wishes to prey upon the rich. Higher inequality may also induce crime because criminals may view higher inequality as "unjust" or "unfair" and have low expectations of moving up the economic ladder in a legal fashion. For persons at the higher end of the income spectrum, an increase in inequality would probably not increase the likelihood that they commit a crime by much. Thus, in the aggregate, inequality is likely to positively impact crime rates.

Government spending on law enforcement is expected to increase the costs of crime insofar as it increases the probability of being caught. Of course, uncovering this deterrence effect empirically is often problematic, as crime rates are also expected to determine law enforcement spending. Our econometric technique can account for this. While we focus on the economic characteristics of a region discussed thus far, social and demographic variables may also affect the costs and benefits of committing crime and hence the aggregate crime rates. For example, the social disorganization theory, which emphasizes the importance of informal social controls to prevent crime, considers ethnic heterogeneity as an important determinant of crime. We include as many of these as possible in our analysis to test the

relative significance of economic variables over social and demographic variables in explaining crime in Russia.

### III. Methodological Considerations

The use of panel data to investigate the effect of unemployment, inequality, income, and other economic variables on crime rates is advantageous for a number of reasons. First, we can account for any region-specific unobserved heterogeneity, or portion of the error term that varies by region but not over time. Inability to account for this leads to inconsistency and bias in the estimated coefficients. Such unobserved heterogeneity could include measurement error, institutional characteristics, and cultural characteristics. Second, we can account for any inertia in crime rates by including lags of the dependent variable as an explanatory variable. Third, we can account for joint determination (reverse causality) of the dependent variable and explanatory variables by including the lags of these explanatory variables as instruments. Reverse causality will exist if inequality or unemployment is determined by crime rates. Fajnzylber et al. (2002b) point out, if crimes occur mostly among low-income individuals, then crime may positively affect inequality. Or, crime may negatively affect average income in the country if it discourages investments.

Specifically, we use the system generalized method of moments (GMM) estimator for dynamic panel data, developed by Holtz-Eakin et al. (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). Consider the following model,

$$y_{i,t} = \delta y_{i,t-1} + X_{it}\beta + \alpha_i + u_{i,t} \quad (1)$$

$$E(\alpha_i) = E(u_{it}) = E(\alpha_i u_{it}) = 0$$

where  $y$  is the reported crime rate of region  $i$  in year  $t$ ,  $X$  includes all other explanatory variables,  $\alpha_i$  is the region-specific unobserved heterogeneity that varies across regions but not over time for each region, and  $u_{i,t}$  is the idiosyncratic error term, varying by region and over time. The region-specific unobserved heterogeneity is allowed to be correlated with the explanatory variables. The idiosyncratic error term may also be correlated with some of the explanatory variables.

One problem with estimating equation (1) via OLS is the endogeneity of the lag of the crime rate. If a region in Russia experiences a large positive crime shock for a reason not modeled, the shock is subsumed into the error term. The region-specific unobserved heterogeneity will appear larger over the time span of the data (since it does not vary by year), and in the following year the lag of the crime rate will also be large and positive. This positive correlation between the error term and the lag of the crime rate would yield inconsistent and biased OLS results, results that are in this case biased upwards.

An initial attempt to purge the fixed effects might be panel data fixed effects estimation or least squared dummy variable regression (entering a dummy variable for each region). Roodman (2006) shows that this will not entirely remove “dynamic panel bias” and in fact would result in downward bias on the lag of the crime rate in our previous example. Thus, the magnitude of the estimated coefficient on the lag of the crime rate resulting from an improved estimation strategy should fall between those of the OLS and fixed effects.

One strategy to purge the unobserved heterogeneity is to difference the data. Equation 1, when first-differenced, yields the following:

$$y_{i,t} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (X_{it} - X_{i,t-1})\beta + (u_{i,t} - u_{i,t-1}) \quad (2)$$

or

$$\Delta y_{i,t} = \delta \Delta y_{i,t-1} + \Delta X_{it} \beta + \Delta u_{i,t}$$

The differencing eliminates the region-specific unobserved heterogeneity. However, the lag of the crime rate remains endogenous because  $y_{i,t-1}$  is correlated with  $u_{i,t-1}$ . Other explanatory variables may also be correlated with the lag of the error term if they are not strictly exogenous and only contemporaneously exogenous in the non-differenced equation. Fortunately, deeper lags of the explanatory variables are exogenous and can be used as instruments.

As Roodman (2006) explains, the first-differenced transformation is best used for strongly balanced panels. In an unbalanced panel, if  $y_{i,t}$  is missing, then  $\Delta y_{i,t}$  and  $\Delta y_{i,t+1}$  will be missing. Since our data are unbalanced (in a given year, a number of regions have missing data), we use a second option for purging the unobserved heterogeneity. This method, called “orthogonal deviation” (Arellano and Bover, 1995), subtracts from  $y_{i,t}$  the mean of all future available values. This method mitigates data loss and makes all lagged variables available as instruments. We will denote data transformed by orthogonal deviation as:

$$\tilde{y}_{i,t} = \delta \tilde{y}_{i,t-1} + \tilde{X}_{it} \beta + \tilde{u}_{i,t} \quad (3)$$

One estimation strategy is the 2SLS Anderson-Hsiao (1981) “levels” estimator, but using  $y_{i,t-2}$  and deeper lags as instruments for  $\tilde{y}_{i,t-1}$  (as opposed to just  $y_{i,t-2}$ ) to improve

efficiency. The same can be done for the other endogenous explanatory variables. Roodman (2006) points out that this will yield consistent estimates, but the more lags that are used as instruments, the smaller the sample size, as observations will be dropped when lags are not available. Holtz-Eakin et al. (1988) were able to bypass this problem by developing a set of instruments that generate the following moment conditions:

$$E[y_{i,t-s}\tilde{u}_{i,t}] = 0 \text{ for } s \geq 2, t = 3, 4, \dots, T \quad (4)$$

$$E[X_{i,t-s}\tilde{u}_{i,t}] = 0 \text{ for } s \geq 2, t = 3, 4, \dots, T \quad (5)$$

To implement the dynamic panel GMM estimator, the variance covariance matrix must be estimated, assuming that the  $u_{i,t}$  are correlated within regions but not across regions. As a result, Roodman (2006) suggests including time dummy variables in the regression model.

The dynamic panel *system* GMM estimator employed here incorporates equation (1) in “orthogonal deviations” (what has been discussed this far) *and* in levels as a system to increase efficiency. For the level regression, since the unobserved heterogeneity is not purged, instruments must be used. The instruments are the lagged differences of the endogenous explanatory variables. This is based on the assumption that, while the unobserved heterogeneity may be correlated with the levels of the explanatory variables, it will not be correlated with their differences. The following moment conditions are satisfied for the second part of the system (the regression in levels):

$$E[(y_{i,t-1} - y_{i,t-2})(\alpha_i + u_{i,t})] = 0 \quad (6)$$

$$E[(X_{i,t-1} - X_{i,t-2})(\alpha_i + u_{i,t})] = 0 \quad (7)$$

The four moment conditions (equations 4-7) are used to implement dynamic panel system GMM estimation, producing consistent parameters. We also implement the Windmeijer (2005) finite-sample standard error correction, as the system GMM standard errors are biased downward.

#### **IV. Data**

The dataset comprises annual observations for Russia's 88 regional entities over 2000–2005. All data are from various editions of Rosstat's yearbook *Regions of Russia* unless mentioned otherwise. Table 1 gives variable definitions and descriptive statistics. In the first block of variables are various crime indicators, while the rest of the table contains the explanatory variables. These include demographic indicators, education levels, and economic performance measures.

While most series are directly obtained from the Rosstat yearbook, some of the variables merit additional discussion. The unemployment rate is calculated as the number of unemployed in percent of the working age population. In the absence of sufficient data to calculate Gini coefficients, income inequality is proxied by the standard deviation of the percentages of households in 8 income brackets (less than 1000 rubles, 1000-1500, 1500-2000, 2000-3000, 3000-4000, 4000-5000, 5000-7000, greater than 7000 rubles). To adjust for the vast differences in regional price levels, as well as inflation, per capita income is deflated by the price level, which is proxied by the minimal food basket that was the only measure available until 2003 and the more adequate standardized consumption basket available since 2004.

Table 2 presents the means for some variables of interest (income, inequality, unemployment rate, and law enforcement expenditures) when the various crime rates are above and below their median levels. For all types of crime rates, income levels are higher when crime rates are below their median levels. This could suggest the poor economic circumstances lower the opportunity cost of committing crimes, or it could simply suggest that fewer crimes occur in high-income areas because they are geographically separated from low-income areas. Both inequality and law enforcement expenditures are higher when all types of crime rates are above their median levels. The latter result suggests that law enforcement expenditures are targeted to high-crime areas, but the question remains whether they reduce crime rates. Unemployment rates tend to be higher when crime is above median levels, but this is not the case for robberies, which is somewhat surprising given it is the case for murders.

## **V. Empirical Results**

Table 3 presents the results of dynamic panel regressions in which various all and subsets of crime rates (reported number of crimes per 100,000 of the population) are the dependent variables. For each regression, we report the Windmeijer (2005) standard errors corrections.

### **V.1. Results for All Crime Rates**

First we consider the results of the dynamic panel data estimation for *all crimes*. Population density (density), males per 1,000 females (male), tertiary students per 10,000 population (tertiary), secondary students per 10,000 population (secondary), and the year dummy variables are all considered exogenous, while the remaining explanatory variables

are allowed to be endogenous. The results indicate that the one-year lag of the crime rate, the percentage of the working age population, the number of secondary students per 10,000 population, income inequality, and income level are the only explanatory variables whose coefficients are significantly different from zero at the 10% level or less, apart from the year dummy variables. Past crime has a positive impact on current crime, as expected, and the magnitude of the coefficient indicates that an increase in one crime per 100,000 people last year results in an increase of .86 of a crime per 100,000 in the current year. Thus, there is significant inertia with respect to crime. Moreover, robustness checks indicate that the magnitude of this coefficient falls between that of the OLS coefficient (.975) and that of the fixed effects coefficient (.343), as expected and as discussed above<sup>8</sup>. As the midage population increases by one percentage point (holding constant the young population, but allowing the elderly population to decrease by one percentage point) the crime rate increases by over 5 crimes per 100,000 people. An increase of one secondary student per 10,000, controlling for the number of tertiary students, increases the crime rate by about .7. Secondary students are usually 10-16 years old. The result that more secondary students increase crime likely reflects that these are in the critical age group for much of the petty crime (often drug related).<sup>9</sup> Income has a negative impact on the crime rate, with an increase of 1,000 rubles resulting in a decrease of approximately .74 crimes per 100,000. This indicates the individual and aggregate income levels impact the costs of committing crimes more than the benefits of committing crimes. Controlling for income level, income

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<sup>8</sup> This general result holds for regressions for all crime rates types.

<sup>9</sup> Finding a positive link between education and crime is not uncommon in the literature [see Ehrlich (1973) and Fajnzylber et al. (2002b)]. The latter study argues that the impact of education on crime is, a priori, ambiguous. In particular, they argue that education may raise the loot from crime and the presence of profitable criminal activities in countries like Russia is larger than others, hence the net effect of education on crime can be positive (higher crime).

inequality has a large positive impact on the crime rate. A one unit increase in the standard deviation of the percentage of households in eight income brackets results in an increase of 65 crimes per 100,000 people.

While the existence of a non-Russian majority in the population (ethnic) is only statistically significant from zero at the 16.5% level, the crime rate is larger in these regions by over 70 crimes per 100,000 people. The ethnic regions are those in the Northern Caucasus, where much of the civil unrest in Russia is concentrated (including Chechnya). While the unemployment rate and population density both have a positive effect on the crime rate, as is expected, neither of the coefficients is statistically significant. In addition, fiscal spending on law enforcement as a percentage of the income of the population has a negative but insignificant effect on crime rates.

We also test to see if the idiosyncratic error term  $u_{i,t}$  is serially correlated using an Arellano-Bond test applied to the residuals in differences. If first order serial correlation exists, then  $y_{i,t-2}$  is not a valid instrument. In order to test for first-order serial correlation in levels, the test attempts to detect second-order serial correlation in differences. First order serial correlation in differences is expected, since  $\Delta u_{i,t}$  is related to  $\Delta u_{i,t-1}$  through the  $u_{i,t-1}$  term. However, testing for second-order serial correlation will detect any relationship between  $u_{i,t-1}$  in  $\Delta u_{i,t}$  and the  $u_{i,t-2}$  in  $\Delta u_{i,t-2}$ . The p-value for the Arellano-Bond test statistic in our estimated model is .608, so we can fail to reject the null hypothesis of no second-order serial correlation in differences, thus avoiding a problem with using the second lag of the crime rate as an instrument. In addition, we can carry out a test of overidentification, where the null is that the instruments are jointly valid. The Hansen test produces a p-value of .793, so we can fail to reject the null hypothesis. However, it should be noted that the test is

weakened by the use of many instruments, where “many” is not well defined, so our result may not be reliable<sup>10</sup>.

## **V.2 Results for Subsets of Crime Rates**

The results for junior crimes, a subset of all crimes, are reported next in Table 3. There is slightly less inertia for the junior crime rate, and the effect of inequality is smaller in magnitude, though still very statistically significant. The effect of income, however, is not statistically significant and much smaller in magnitude as compared to all crimes. Moreover, the effect of law enforcement expenditures is positive, though only significant at the 14% level. Having an ethnic majority is also now statistically significant, with a positive impact on the junior crime rate.

Next we present results for specific types of crimes. First we consider the murder rate, which varies considerably across regions, from .11 to 519 per 100,000 people. The results show that the coefficients on the lag of the murder rate, the number of secondary students, and inequality are different from zero at the 5% level or less. While the magnitude of the marginal effect on the lag of the murder rate is similar to that of the lag of the overall crime rate in the previous model, the effect of inequality has a much smaller negative impact on murder rates. So, murder rates also exhibit strong inertia, but inequality only has a small impact. Other economic characteristics of the region do not impact the murder rate. This is perhaps not entirely surprising since murder is less likely to be economically motivated than certain other types of crimes.

We next consider robbery rates, which vary from .02 to 657 per 100,000 people, and theft rates, which vary from .04 to 8,975 per 100,000 people. The lag of robbery rates, the

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<sup>10</sup> We also fail to reject both the null hypothesis for serial correlation of the idiosyncratic error and the joint validity of the instruments for all the regressions for the varying types of crime rates.

percentage of the working age population, inequality, and income all have coefficients that are significantly different from zero at the 5% level or less. Again, we see quite a bit of inertia in robbery rates. Interestingly, the percentage of the working age population has a small but positive impact on robbery rates (holding constant the young population but allowing the elderly population to decrease). A likely reason for the positive impact is that the working age population also includes people in their late teens and early twenties. In fact, the very young and the elderly are unlikely to be criminal. Inequality has a positive impact on robbery rates, with a one-unit increase in the measure of inequality increasing robbery rates by approximately 4 per 100,000 people. Income level has a small but negative impact on robbery rates. Overall, it seems that economic factors have more of an impact on robbery rates than on murder rates, which is to be expected.

Income levels also negatively impact theft rates, while inequality also positively impacts theft rates, though the magnitudes of the coefficients are larger. Again, strong and significant inertia is present, though not as strong as for other types of crime. This is reasonable since thefts may come with lesser penalties than other crimes, or an individual may be less likely to be caught, and thus their economic and social standing in the community may not be as affected. In addition, in regions with a non-Russian majority, on average 100 more theft are committed per 100,000 people, and this coefficient is significant at the 5% level. Other demographic factors that have a significant impact on theft rates are the percentage of the population below working age and the number of secondary students per 10,000 people. All else equal, the more young people there are (holding constant the working age population but allowing the elderly population to decrease), the lower the theft rate, but the more students in secondary school, the higher the theft rate. The result that more

young people reduce the theft rate is likely due to the fact that people below working-age (15 in Russia) are actually unlikely to be criminals already.

For economic and drug crimes, there is slightly less inertia than with other types of crimes. As with other types of crimes, the unemployment rate is insignificant for both types of crimes. For drug crimes, inequality is significant at the very marginal 11% level, but it is not significant for economic crimes. As with thefts and junior crimes, the existence of a non-Russian majority has a significant and fairly large impact on drug crimes and economic crimes. Income, however, does not. Interestingly, the effect of law enforcement expenditures is not only significantly different from zero at about the 10% level or less for both economic and drug crimes, but it also indicates a positive relationship between expenditures and crime rates.<sup>11</sup>

## **VI. Conclusions**

To our best knowledge, this study is the first investigating the determinants of crime in Russia covering the post-transition recent period. We control for the endogeneity of our independent variables such as inequality by isolating their exogenous influences on crime rates. We also control for measurement error in crime rates by modeling it as both observed regional effects and random noise.

Our findings can be summarized as follows: First, all crimes have significant inertia. This is consistent with earlier studies. An important policy implication of this finding is that policymakers need to act quickly to design early prevention policies to reduce crime

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<sup>11</sup> This unexpected result may be due that the instruments did not do a good job and we are picking up some reverse causality.

(Fajnzylber et al., 2002a). An important related finding is that the degree of inertia varies across different types of crimes. This is an interesting finding and requires further research.

Second, inequality tends to increase all crime rates significantly and drug crimes marginally. Inequality does not seem to have a significant impact on economic crimes. One reason for this finding may be that because economic crime definition includes mostly corporate activities such as the obstruction of legal business activity, establishment of illegal business, money laundering and other illegal activities that are more affected by corruption than inequality.

Third, when income level rises, some crime rates (robberies and thefts) drop. Combining these two results for inequality and income, which together determine the poverty level of a country, we may conclude that reducing poverty level is necessary to successfully reduce most crime rates in Russia. Russian policymakers can have economies of scale effects in their crime-reducing effects by focusing on poverty reduction policies that would reduce inequality and increase income level at the same time.

Fourth, regarding the social and demographic determinants of crime, we have found that both young and ethnic (non-Russians) variables are significant for thefts as well as economic and drug crime rates. Middle age variable is significant but only for robberies and the overall crime rate. Male variable has no significant impact on crime rates except economic crimes. Education has a significant and positive effect on all types of crime rates except robberies. A positive finding for education is not uncommon as reported in many previous studies.

Although it is not the main focus of this paper, our results suggest that all the theories of crime may have some relevance in the case of Russia, as they all emphasize the link between inequality and crime. Although economic theory is more applicable to property crime (thefts and robberies), our finding that inequality is also a significant determinant of murder rates (violent crime) suggests that the observed link between murder rates and inequality may be working through some non-economic or social channels, supporting the non-economic theories of crime. Our evidence is consistent with Demombynes and Özler (2005) who report that local inequality is highly correlated with violent crimes in a larger geographical area in South Africa. Income variable is significant, validating the Becker's theory, while the significance of some social and demographic variables further supports the social theories of crime. Also, our ethnic variable is significant for thefts as well as economic and drug crime rates, which is consistent with the implications of the social disorganization theory. An important implication of the findings is that understanding crime rates in may require an interdisciplinary approach. Future studies explaining why crime takes place should employ a synthesis of different economic, social and other theories of crime.

## References

Anderson, T.W., and C. Hsiao. 1982. "Formulation and Estimation of Dynamic Models Using Panel Data," *Journal of Econometrics*, 18: 47–82.

Andrienko, Yury. 2002. "What Determines crime in Russian Regions?" Economics Education and Research Consortium Russia Research project #99-2521.

Arellano, M., and S. Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies* 58: 277–97.

Arellano, M., and O. Bover. 1995. "Another Look at the Instrumental Variables Estimation of Error Components Models," *Journal of Econometrics* 68: 29–51.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach," *Journal of Political Economy* 76: 169-217.

Blundell, R., and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics* 87: 11–143.

Buonanno, Paolo. 2003. The Socioeconomic Determinants of Crime: A Review of Literature, Working Paper 65, University of Milano-Bicocca, Department of Economics.

Cameron, Samuel. 1988. "The Economics of Crime Deterrence: A Survey of Theory and Evidence," *Kyklos* 2: 301-23.

Demombynes, Gabriel and Berk Özler. 2005. "Crime and Local Inequality in South Africa," *Journal of Development Economics* 76: 265-92.

Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation," *Journal of Political Economy* 81: 521-65.

Fajnzylber, Pablo, Daniel Lederman, and Norman Loayza. 2002a. "What Causes Violent Crime?" *European Economic Review* 46: 1323-1357.

Fajnzylber, Pablo, Daniel Lederman, and Norman Loayza. 2002b. "Inequality and Violent Crime?" *Journal of Law and Economics* XLV: 1-40.

Gaviria, Alejandro. 2000. "Increasing Returns and the Evolution of Violent Crime: The Case of Colombia," *Journal of Development Economics* 61: 1-25.

Holtz-Eakin, D., W. Newey, and H.S. Rosen. 1988. "Estimating Vector Autoregressions with Panel Data," *Econometrica* 56: 1371–95.

Kelly, Morgan. 2000. "Inequality and Crime," *Review of Economics and Statistics* 82: 530-39.

Kornhauser, R.R. 1978. *Social Sources of Delinquency*. Chicago, IL: University of Chicago Press.

Lederman, Daniel, Norman Loayza and Ana Maria Menendez. 2002. Violent Crime: Does Social Capital Matter?" *Economic Development and Cultural Change* 50: 509-539.

Roodman, D. 2006. "How to Do xtabond2: An Introduction to "Difference" and "System" GMM in Stata," Working Paper 103. Center for Global Development, Washington.

United Nations Office on Drugs and Crime. 2001. Seventh United Nations Survey of Crime Trends and Operations of Criminal Justice Systems, covering the period 1998 – 2000.

Windmeijer, F. 2005. "A Finite Sample Correction for the Variance of Linear Efficient Two-step GMM Estimators," *Journal of Econometrics* 126: 25–51.

**Table 1**  
**Variable Definitions and Descriptive Statistics**

<i>Variable Name</i>	<i>No. Obs.</i>	<i>Mean</i>	<i>St. Dev.</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Definition</i>
Crimerate	1,344	475	1,525	3	20,506	Registered crimes per 100,000 population
Juniornrate	1,339	44.23	162.03	0.09	2,006	Crimes committed by juniors per 100,000 population
Murderrate	816	10.28	42.03	0.11	519	Murders per 100,000 population
Robberyrate	816	21.05	53.62	0.02	657	Robberies per 100,000 population
Thefrate	816	243.23	770.38	0.04	8,975	Thefts per 100,000 population
Ecocrimerate	748	47.31	146.68	0.06	1,645	Economic crimes per 100,000 population
Drugrate	810	20.76	50.05	0.04	772	Drug crimes per 100,000 population
Population	1,404	16.91	15.30	0.17	104	Population per 100,000
Male	1,404	1,112	73	901	1,247	Males per 1,000 females
Tertiary	1,282	235.13	148.45	2.00	1,255	Tertiary students per 10,000 population
Secondary	1,392	143.35	43.26	12.00	246	Secondary students per 10,000 population
Young	1,404	22.42	4.97	12.40	39.90	% of below-working age population
Midage	1,405	59.37	4.20	49.30	72.10	% of working-age population
Elderly	1,404	18.20	5.53	2.40	27.40	% of above-working-age population
Unempl	1,185	7.86	4.98	0.00	51.71	Unemployment rate (percent)
Inequality	522	0.77	0.37	0.32	2.46	Standard deviation of the % of households in 8 income brackets
Ethnic	1,408	0.17	0.38	0.00	1.00	Dummy for non-Russian majority in the population
Density	1,276	37	55	0.10	365	Population per square kilometer
Income	707	165	78	28	669	Monetary income of population (1,000 rubles)
Law Exp	478	10.09	5.50	0.83	51.86	Fiscal spending on law enforcement as % of income of the population

**Table 2**  
**Means of Variables of Interest by Crime Rate Level**

	<i>Income</i>	<i>Inequality</i>	<i>Unemployment Rate</i>	<i>Law Enforcement Expenditures</i>
Crime Rate Below Median Level	177.93	0.69	7.55	9.76
Crime Rate Above Median Level	155.31	0.83	8.33	10.40
Junior Crime Rate Below Median Level	177.04	0.68	7.88	9.65
Junior Crime Rate Above Median Level	155.06	0.85	8.09	10.59
Murder Rate Below Median Level	180.80	0.70	8.28	8.98
Murder Rate Above Median Level	148.50	0.83	10.16	11.22
Robbery Rate Below Median Level	172.00	0.69	9.60	10.06
Robbery Rate Above Median Level	156.61	0.82	8.81	10.12
Theft Rate Below Median Level	175.40	0.71	9.19	10.02
Theft Rate Above Median Level	152.93	0.82	9.23	10.18
Economic Crime Rate Below Median Level	172.11	0.71	8.91	9.81
Economic Crime Rate Above Median Level	154.87	0.83	9.53	10.44
Drug Crime Rate Below Median Level	176.34	0.68	8.26	9.19
Drug Crime Rate Above Median Level	150.95	0.84	10.21	10.97

**Table 3**  
**Dynamic Panel GMM System Estimates**  
*Dependent Variables: Crime Rates*

Variable	All Crimes		Junior Crimes		Murders		Robberies		Thefts		Economic Crimes		Drug Crimes	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Lag of crime rate	0.863	0.000	0.602	0.000	0.892	0.000	0.975	0.000	0.740	0.000	0.347	0.000	0.518	0.003
Unempl	1.943	0.400	0.565	0.454	0.044	0.159	0.055	0.674	1.796	0.318	0.694	0.370	0.919	0.133
Inequality	65.303	0.047	11.014	0.032	1.144	0.050	3.979	0.046	51.297	0.028	14.787	0.204	9.314	0.111
Income	-0.744	0.008	-0.082	0.222	-0.006	0.200	-0.045	0.045	-0.596	0.012	-0.103	0.335	-0.062	0.322
Lawexp	-0.619	0.547	0.366	0.140	-0.014	0.465	0.082	0.333	0.681	0.359	0.798	0.109	0.481	0.048
Ethnic	76.812	0.165	36.491	0.017	1.706	0.156	3.693	0.529	100.752	0.045	56.701	0.053	30.896	0.006
Young	-5.319	0.309	-2.988	0.014	-0.103	0.356	-0.366	0.471	-9.138	0.019	-5.074	0.050	-2.551	0.009
Midage	5.053	0.077	0.633	0.289	-0.014	0.818	0.390	0.051	3.152	0.301	0.947	0.414	0.343	0.639
Male	-0.091	0.492	-0.052	0.076	-0.003	0.303	0.003	0.774	-0.137	0.302	-0.108	0.055	-0.055	0.134
Secondary	0.705	0.013	0.173	0.033	0.013	0.047	0.031	0.389	0.611	0.045	0.213	0.054	0.155	0.070
Tertiary	-0.002	0.984	-0.012	0.416	-0.001	0.447	0.004	0.266	-0.020	0.773	-0.013	0.549	-0.008	0.572
Density	0.173	0.423	0.015	0.636	0.002	0.318	0.003	0.723	0.144	0.375	0.004	0.917	0.017	0.462
Year 2000	-49.774	0.006	4.080	0.417	-0.220	0.543	-3.211	0.007	-18.866	0.234	0.425	0.970	7.832	0.049
Year 2001	-40.142	0.012	4.442	0.348	-0.122	0.691	-2.247	0.018	-13.278	0.351	12.205	0.174	3.405	0.256
Year 2002	-71.525	0.000	-1.014	0.765	-0.280	0.247	-3.645	0.000	-39.782	0.000	4.015	0.556	0.272	0.912
Year 2003	-11.940	0.174	4.392	0.053	0.141	0.391	-1.938	0.004	8.897	0.307	5.259	0.294	2.150	0.206
Year 2004	-22.141	0.003	4.137	0.047	0.124	0.372	-0.173	0.759	-0.352	0.958	3.470	0.388	1.786	0.316
Intercept	-131.303	0.687	42.649	0.531	4.598	0.527	-21.171	0.324	73.689	0.826	116.319	0.371	53.290	0.503