Crime, Expectations, and the Deterrence Hypothesis

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ABSTRACT

Empirical tests of the deterrence hypothesis - the idea that crime can be deterred through changes in the costs or benefits derived from committing crime - typically focus on estimation of the relationship between current crime rates and contemporaneous measures of economic conditions, demographics, and enforcement levels. We argue this approach is misguided because both past behavior and future conditions should impact decisions to commit a crime in the present. Accordingly, we develop an econometric model of aggregate crime rates that includes past behavior and expectations of future conditions. Model estimates suggest that expectations of future conditions are important in determining current crime rates. One implication of this finding is that the long run elasticity of crime rates with respect to policy variables may be orders of magnitude larger than short run elasticities, and depend upon whether the change is permanent or transitory. A second implication of this finding is that credibility and the ability of policy makers to commit are important in thinking about policies designed to deter crime.

The *deterrence hypothesis*, first formalized by Becker (1967), states that criminals that are rational agents that weigh the costs and benefits of their actions in deciding whether or not to engage in criminal activity. Since its initial statement, empirical models of the so-called deterrence hypothesis have occupied a prominent place in economics. The standard approach to assessing the deterrence hypothesis is through investigation of the contemporaneous relationship between crime rates and variables that capture as well as possible the costs and benefits of committing crime. Results are of interest not only as tests of the deterrence hypothesis, but also in the role results play in informing policy. Further, the empirical investigation of the deterrence hypothesis has occupied a central position in the study of a variety of controversial issues, such as whether or not capital punishment is a deterrent to crime (Cameron 1994, Katz, Levitt, and Shustorovich 2003, Donohue and Wolfers 2005), the relationship between crime and gun control (Lott and Mustard 1997, Donohue 2004) and the impact of legalized abortion on crime rates (Donohue and Levitt 2001, Joyce 2004).

We argue that the typical econometric model of the deterrence hypothesis is flawed. Our contention is based on the observation that empirical models of aggregate crime rates fail to take into account what should be one of the most important aspects of the crime commission decision if criminals are indeed rational - that decisions to commit a crimes have long term consequences. If one expands the model to include this possibility, expectations of *future* enforcement rates and economic conditions should matter in determining crime rates today, as should past crime commission decisions.

Estimates of our model suggest that both future expectations and past behavior exert an important impact on current crime rates. Our best estimates of contemporaneous elasticities of crime with respect to proxies of enforcement and punishment are small (on the order of $-.05$) but are generally in agreement with previous research. Once expectations of future conditions and past behavior are included in the model, the resulting multiplier effects generate long run elasticities that are much larger than short run elasticities, but elasticities generally depend upon both the nature of the change (i.e., whether transitory or permanent), and also how criminals perceive the change.

Our findings have important policy implications, not only because of the implication that long-run elasticities of crime rates with respect to measures of enforcement are larger than short-run elasticities. If expectations of future conditions are important in driving current crime rates, the policy maker's credibility and ability to commit to a course of action assume central importance in assessing the merits of policy changes.

1 Previous Literature

The literature on the deterrence hypothesis is voluminous and has several branches. Results vary with the time frame examined, the aggregation level of the data, and the econometric model employed. One common econometric approach - the approach followed in this paper - centers on a yearly state level panel of state crime rates, proxies for enforcement, punishment, demographics, and economic conditions running from 1970 to the present. Usually, incarceration rates are used to proxy punishment severity, while proxies of the likelihood of apprehension such as the relative size of the police force are used to measure enforcement.

In contrast to the pessimistic view of the importance of the magnitude of punishment in crime drawn by Cameron (1988), most work has found that apprehension and punishment matter, a result in line with initial work on the deterrence hypothesis by Ehrlich (1973) and others. Spelman (2000) summarizes several recent estimates of the elasticity of crime with respect to incarceration rates, and reports that the typical estimated elasticity is on the order of $-.05$ to $-.20$, but estimates as large as $-.38$ have been obtained.[1]

Estimates of the impact of enforcement are more variable, and some of this variation may perhaps be attributed to reliance on different proxies for the intensity of enforcement. Some researchers rely on direct proxies for apprehension and conviction probabilities (for example, Ehrlich (1974) and Lott and Mustard (1992)). These measures are computed by calculating the number of arrests per offense. Research employing probability-style measures of enforcement typically finds quite large elasticities of crime with respect to apprehension, but are subject to the critique that, when such measures of enforcement are used, the same quantity (number of offenses) appears in the denominator on the right hand side of the model and in the numerator of the left hand side variable, strongly biasing results in favor of finding a negative relationship (Spelman, 2000).[2] The most common alternative approach employs a less direct measure of the likelihood of apprehension which does not depend directly on crime rates, such as the relative size of the police force. Typical estimates of elasticities of crime with respect to the relative size of the police vary, but are probably around $-.40$ (see

[1]The state-level estimates summarized by Spelman, in addition to his own estimates, include Marvell and Moody (1994), Becsi (1999), and Levitt(1996). Marvell and Moody (1994) who find the elasticity of violent crime with respect to the imprisonment rate is -0.06, while the elasticity of the property crime rate is $-.17$. Becsi's (1999) estimates for all types of crime range between -0.05 and -0.09, while Levitt's (1996) estimates are typically larger: his estimates of the violent crime elasticity and property crime elasticity, are, respectively, $-.38$ and $-.26$.

[2]Spelman (2000, p.101-103) notes that this critique appeared in Blumstein, Cohen, and Nagin (1978), which assessed the early literature on deterrence. The critique also figures prominently in Cloninger's (1975) assessment of initial econometric studies of the deterrence hypothesis. Relatedly, Levitt (1998) asks if it is measurement error, deterrence, or incapacitation that drives the negative correlation between arrest rates and crime rates, and Kessler and Levitt (1999) also contrast deterrence and incapacitation.

Levitt 1997, 2004). At any rate, the bulk of empirical research on the deterrence hypothesis indicates that deterrence matters; apprehension rates and proxies for punishment severity appear to be inversely related to aggregate crime rates. Studies based on individual-level data largely corroborate these findings; for example, Grogger (1998) and Machina and Meghar (2004).

The typical empirical study of the deterrence hypothesis also includes measures intended to capture economic conditions and demographics. Logically, economic conditions and demographics matter because they are important determinants of the opportunity costs of committing a crime. Kelly (2000), using county level cross sectional data, found that measures of inequality are important in explaining violent crime. Using a state-level panel, Raphael and Winter-Ebmer (2001) argue that unemployment rates are important determinants of crime rates and that the drop in unemployment in the 1990's explains a large portion of the nation wide crime drop through the 1990s. Gould, Weinberg, and Mustard (2002) study the impact of wages and unemployment rates on crime rates and find that both matter in determining crime rates; they further find that wages have a larger impact on crime rates than unemployment rates. By contrast, Levitt (2004) argues that the magnitude of the effect of unemployment on crime is small and it is unlikely changes in unemployment rates played a large role in the drop in crime through the 1990s.[3]

While most empirical work on crime rates includes demographic control variables, few studies elaborate on the impact of these demographics. An exception is Levitt (1998), who provides both theoretical and empirical support for the position that the age distribution matters in driving crime rates.[4] Thus, results vary as to the importance of demographics, economics, enforcement and apprehension in determining crime rates, inclusion of these things in an empirical model is well-motivated by theory. The fact remains, however, that crime rates appear to be relatively inelastic with respect to demographic variables, economic conditions, enforcement, and punishment.

An interesting feature of the empirical research on the determinants of crime is that it has moved away from estimation of models with a specific, explicit theory of criminal behavior in mind.[5] In the next section, we show how thinking about the long run impact of criminal decisions leads to a different sort of econometric model in which past behavior and expectations of future conditions matter in driving current crime rates. Our estimates obtained

[3]Winter-Ebmer (2001) and Gould, Weinberg, and Mustard (2002) also point out that a large portion of previous literature has found that the impact of unemployment on crime rates is ambiguous.

[4]However, Levitt (1999) suggests that demographic changes are of limited usefulness in understanding movements in aggregate crime rates.

[5]Indeed, a characteristic of Ehrlich's (1973) early work on the subject was his careful specification of a theoretical model that coinciding with his econometric model.

from this model are comparable with those from previous research, but the inclusion of future expectations and past behavior changes interpretation of these elasticities. Estimated elasticities are similar to previous research, however, the inclusion of future expectations changes the interpretation of elasticities.

A further interesting aspect of our results is the possibility that some empirical anomalies may disappear when expectations are built into the econometric model. A common aspect of research on crime is that in crime regressions, estimated coefficients sometimes take on signs opposite those predicted by theory. For example, it is not uncommon to find that the size of the police force and the crime rate are positively correlated.[6] While these anomalies are often attributed to endogeneity problems, our results suggest that the problems may emerge because of a failure to correctly build expectations into the model.

2 Theory

Let the crime rate at time t in a given jurisdiction be given by c_t, let X_t denote a column vector of crime control policy variables (e.g., the relative size of the police force or the incarceration rate), and let Y_t denote a column vector of variables measuring economic and demographic conditions that proxy incentives to commit crime (e.g., unemployment rates, poverty rates, or the age distribution of the population). A model of the aggregate crime rate in which both past crime rates as well as current and future expected values of X_t and Y_t are allowed to affect today's crime rate may be written as follows:

$$c_t = \gamma c_{t-1} + AX_t + BY_t + E_t \left[\sum_{i=1}^{\infty} \rho^i \left(AX_{t+i} + BY_{t+i} \right) \right] \tag{1}$$

The row vectors A and B in (1) capture the impact of exogenous variables on the crime rate, and ρ reflects the degree to which potential criminals discount future conditions in reaching a decision to commit crime in the present. E_t denotes the expectations operator with respect to the information set at time t. The parameter γ captures the degree of persistence in the crime rate - that is, the degree to which past crime rates influence current crime rates.

The usual empirical model of crime only takes into account contemporaneous effects of X_t and Y_t on the current crime rate, which amounts to assuming that $\gamma = \rho = 0$ in equation (1), meaning that criminals are assumed to place no weight on future conditions in deciding whether or not to commit a crime in the current period, and that past criminal outcomes

[6]One prominent example in which this occurs is Levitt (1996), which also discusses various attempts to deal with this problem using instrumental variables with state level data, with limited success (see Levitt, 1996, p. 339.)

have no role in predicting current criminal behavior.[7] Equation (1) allows for a much richer and more realistic setting where the current crime rate is allowed to be affected by past crime rates and expected future conditions.

There are several compelling microeconomic foundations for model (1). For one, crime commission decisions have been observed to have large and persistent effects on labor market outcomes for offenders (see, for example, Lott 1992, Waldfogel 1994, and Waldfogel and Nagin 1996).[8] If the implications of committing a crime are long-lasting, one expects that both past behavior and expectations of the future matter in deciding to engage in a criminal act, because the fact that a current potential criminal has committed a crime in the past alters lifetime returns from legitimate work (particularly if apprehended and punished).

Forward-looking behavior may also be motivated by the fact that punishment for a crime is not instantaneous. A crime committed today may not be immediately discovered, and the criminal may not be apprehended and punished until some unspecified time in the future. Moreover, the structure of the legal system might cause criminals to be forward looking. If a criminal is caught and punished for a crime, this directly increases the costs of committing crime in the future, as in virtually every legal system repeat offenders are punished more vigorously than first time offenders.

A final justification for inclusion of forward-looking terms is that the decision to commit a crime today might lead to more crimes in the future, so the criminal has to make some guess as to the relative productivity of the criminal lifestyle both in the present and in the future. Such an assessment involves a joint evaluation of future labor market conditions, the future likelihood of apprehension, and the future severity of punishment.

If one accepts this motivation for inclusion of expectations for the model in equation (1), how is equation (1) to be estimated? Iterating (1) forward and applying the expectations operator results in the following expression:

$$c_t = \alpha_0 c_{t-1} + \Pi_1 X_t + \Pi_2 Y_t + \alpha_1 E_t[c_{t+1}] \quad (2)$$

where $a_0 = \frac{\gamma}{1+\rho\gamma}$, $a_1 = \frac{\rho}{1+\rho\gamma}$, $\Pi_1 = \frac{1}{1+\rho\gamma}A$, and $\Pi_2 = \frac{1}{1+\rho\gamma}B$. Equation (2) allows us to replace the problem of characterizing future expected values of all right-hand side variables

[7] There are exceptions, one of which is Marvell and Moody (2001), who include past crime rates in their econometric specifications.

[8] It should be mentioned that results are not always what one might expect. For example, Waldfogel and Nagin (1996) find that the impact of conviction on earnings depends upon the age of the offender, and that younger offenders may in fact earn higher wages than their peers. They argue that this may be because offenders are likely to search for different types of jobs than others. For our purposes, there is no need to take a precise position as to *how* future prospects are effected, but only that future prospects are influenced by current decisions, and that agents should consider this when reaching current decisions about whether or not to engage in criminal activity.

with the problem of characterizing current expectations of the one-period-ahead crime rate. There are antecedents to follow in estimating equation (2). Forward-looking terms routinely appear in estimation of the expectations-augmented Phillips curve (Fuhrer 1997)and also in the empirical literature on rational addiction (Becker et. al. 1994), to give two examples.

We briefly note that Equation (2) has implications for interpretation of estimated coefficients. Assessing the impact of changes in X_t or Y_t on crime rates requires first finding a rational expectations solution to (2); one cannot simply read off the values of estimated coefficients in (2) as elasticities. In section 4 of the paper, we will discuss how this can be done and how one might then interpret the estimated coefficients.

3 Model Estimation

3.1 Econometric Specification

From the reduced-form equation (2), our econometric specification can be written as:

$$c_{it} = \widehat{\alpha}_0 c_{it-1} + \widehat{\Pi}_1 X_{it} + \widehat{\Pi}_2 Y_{it} + \widehat{\alpha}_1 E_t c_{it+1} + e_{i,t} \tag{3}$$

where $e_{i,t}$ is an error term. The obvious difficulty in estimating (3) is that there is no available measure of the expectation of future crime rates formed at time t. We therefore construct $E_t c_{it+1}$ by regressing c_{it+1}, the realized one-year-ahead crime rate, on information available at time t - which in this setting includes past values of exogenous variables and crime rates. This amounts to treating the realized value of c_{t+1} as an endogenous variable in specification (3) and estimating the model using standard instrumental variables techniques. The data set provides instruments in the form of past values of exogenous and endogenous variables, and for the time being, we shall rely on this "natural" instrument set in model estimation. Assuming that individuals form expectations rationally, the expectations error, i.e., $\epsilon_{t+1} = c_{it+1} - E_t[c_{it+1}]$, is uncorrelated with information available at time t, and can be folded into the error term $e_{i,t}$.

3.2 Data

The data set is an expanded version of that used by Spelman (2001) and Ayres and Donohue (2003). Spelman (2001) points out that this is essentially the same data have been used by Becsi(1999), Levitt (1996), and Marvell and Moody(1992), among many others. We update and expand this data set to be as current as possible.[9]

The data consist of a yearly panel of states (including the District of Columbia) covering the years 1970 though 2006. For each state and year our primary dependent variables are state violent and property crime rates, defined as the number of index offenses per 100,000 people, deriving from the *Uniform Crime Reports*.[10] We also include a standard collection of exogenous explanatory variables used to characterize economic conditions, demographics, and proxies of the level enforcement and severity of punishment in each jurisdiction. Measures of economic conditions we include are the state unemployment rate and the poverty rate. Demographic variables include the percentage population in the state that is black; the fraction of the population aged 15 to 17, 18 to 24, and 24 to 35; and the fraction of population living in a metropolitan area. For measures of enforcement, we use police per capita (measured as police per 10,000 population) and the imprisonment rate (prisoners per 100,000 population). Sources and additional details of the data set are described in appendix A. This set of variables comprise a base model of aggregate crime rates, upon which we will expand in subsequent sections.

Summary statistics of crime rates and the set of explanatory variables appear in table 4. From the table, one can see that there is considerable variation in both violent and property crime rates, and that a large part of the variation occurs between rather than within states. For demographic variables, while a non-negligible fraction of variation occurs within states, there is greater variation between states, rather than within states across time. The opposite is true of basic economic variables - for example, the unemployment rate exhibits more variation within states over time than it does across states. This comes as no surprise, as macroeconomic measures are likely to be highly correlated across states over time and are known to have changed rather substantially over the past few decades. While it appears that most of the variability in police per capita is between states, it is interesting to note that this is not so true of incarceration rates, which exhibit very similar degrees of within state and between state variation.

3.3 Estimation

We shall first discuss estimation and present results using a standard set of variables, and reserve discussion of more expansive models once some of the issues with model estimation have been developed. Essentially, estimated models are regressions of property and violent

[9]The data set we used as a building block was downloaded of off John Donohue's website (http://islandia.law.yale.edu/donohue/pubsdata.htm). Our data set, along with a **STATA** do-file replicating results, is available by request.

[10]Property index crimes include burglary, larceny, and automobile theft. Violent index crimes include murder, rape, robbery and assault.

crime rates on the set of exogenous variables described in table 1. For comparative purposes, we begin by estimating simple OLS models without any future or past crime rates as explanatory variables, and then estimate models including future and past crime rates without controlling for endogeneity. We then present estimated models obtained using different estimation techniques.

In all estimated models, we employ the lagged values of police per capita and the incarceration rate. This is done for two reasons, one practical, and the other because of the circumstances under which these data were collected. Practically speaking, using lagged values in estimation rather than current values eases potential problems with endogeneity, as we can be certain that they are predetermined relative to crime rates. Using lagged values of incarceration rates and police per capita makes further sense as what should matter during the course of the year is the size of the police force or the incarceration rate - these are stock variables that are being used to explain the flow of crime rates. As these variables are typically measured very close to the end of the year, it would seem that the size at the very beginning of the year would be a better gauge of the level of enforcement and punishment during the year.[11]

Tables 2 and 3 - pertaining to property and violent crime rates, respectively - display results from initial attempts at estimating (3). All models on tables 2 and 3 include fixed effects and yearly time dummy variables.[12] The first column of tables 2 and 3 report OLS estimate models of property and violent crime rates omitting future and past crime rates as explanatory variables. From these results, one can see that while many of the explanatory variables are significant, some of them (such as police per capita and the poverty rate) have signs that are inconsistent with the deterrence hypothesis. The second columns on tables 2 and 3 reports results of OLS estimation, but now including future and past crime rates. This inclusion changes the sign of many coefficients, making the estimates more in line with coefficient signs suggested by the deterrence hypothesis. The estimated coefficients on the future and past crime rates are large in magnitude and significant, although the bulk of other explanatory variables are insignificant. OLS, however, is an inappropriate estimation technique as the model suggests that the expectation of the future crime rate, not actual future crime rates, should be in the model.

The next three columns on both tables 2 and 3 are estimated using instrumental variables

[11]The data appendix elaborates further on timing issues in the data. Levitt (1996) also uses the prison population lagged one period in model estimation.

[12]All models are estimated using , and all models are estimated using heteroscedasticity and autocorrelation consistent standard errors. To correct for autocorrelation, we use the Bartlett kernel with a value of 3, which corresponds to a lag order 2 correction. We settled on this value of 3 using the rule of thumb suggested in Baum et. al. (2007) that the kernel length be on the order of $T^{1/3}$.

techniques in which we replace the realized value of the future crime rate with its predicted value. As mentioned previously, this amounts to treating the future crime rate as endogenous and using past values of model variables as instruments. In model III on tables 2 and 3, we use four lags of all exogenous variables and the second-order lag of the dependent variable - the property or violent crime rate - as instruments for the future crime rate. The results are similar to previous results. Model selection statistics indicate that model III on both tables 2 and 3 is not overidentified (the Hansen-Sargan J test statistic suggests the overidentifying restrictions are valid), or underidentified (the Kleinbergen-Paap statistic indicates that the hypothesis the model is underidentified can be rejected).[13] However, the partial F-statistics from first stage estimation reported on tables 2 and 3 indicate that both the property crime and violent crime models may be only weakly identified. The rule of thumb is that first-stage F-statistics should exceed 10 (see Staiger and Stock 1997 and Baum et. al. 2007), and indeed, the models fail to reject the hypothesis of weak identification using more well-developed tests of instrument sets. This is not surprising given the rather large instrument set, and the apparent possibility that some, if not all, of the instruments are weak. As weak instruments can induce bias in instrumental-variables estimates, this potential problem must be treated with care.

Crime data across states and over time is likely to be heteroscedastic in ways that are difficult to anticipate in the econometric model, which suggests that an estimation method more robust to arbitrary error structure be used. Moreover, one might argue that even if some of the left-hand side variables in the model are predetermined, correlation between error terms and the dependent variable may still be present. Under these conditions, an estimation method such as GMM may be preferred, and in column IV on tables 2 and 3, we estimate the model using GMM. While more robust to potential problems with error terms, the models displayed in column IV, tables 2 and 3, have done nothing to deal with weak instrument issues. In fact, some research suggests that GMM and instrumental variables estimates are particularly prone to bias induced by weak instruments, while other estimation methods, such as limited information maximum likelihood (LIML), are less susceptible to weak-instruments bias.[14] The final estimated models on tables 2 and 3 (column V on both tables 2 and 3) repeat the estimation of the model in of column IV using LIML. While this estimation method has the disadvantage in that one must assume that error terms are normally distributed, it has been argued (Baltagi 2008, chapter 8; Stock and Yogo, 2005) that LIML is less prone to bias in the presence of weak intruments. While these models still

[13] This test statistic is perhaps less familiar in that its development is a bit more recent. For details, see Kleinbergen and Paap (2006) and Baum et. al. (2007).

[14] See Stock and Yogo (2005) and Baltagi (2008).

raise some cause for concern, it is encouraging that the LIML estimates are not radically different as the GMM estimates in column IV of tables 2 and 3.

While potentially problematic for a number of reasons, our initial efforts at estimation at least suggest that future and past crime rates are important determinants of current crime rates. There are concerns with these estimated models. First, fixed effects estimates in the presence of leads and/or lags of dependent variables can lead to dynamic panel bias (Baltagi 2008, Chapter 8). While there is some argument about how important this bias is, particularly in panels with a long time dimension, the possibility remains that it may be present. Since an important aspect of our work is obtaining accurate estimates of the these parameters, we should be especially careful in avoiding this possibility. Second, some if not all of our instruments may be weak and the instrument set may be too large. A small amount of experimentation with the instrument set verifies that its weakness has as much to do with the large number of instruments as it does to do with many of them being only weak predictors of future crime rates. We therefore seek to improve the specification by expanding the set of explanatory variables, and also exploring some alternative estimation methods less prone to these potential problems.

3.4 Expanded Model Estimation

As alluded to at the end of the previous section, a potential problem with estimating our model using fixed effects is dynamic panel bias, which may lead to bias in the estimated coefficients on future and past crime rates. A second challenge in estimation is dealing with weak instrument problems. Perhaps the most straightforward way to combat both of these difficulties is through introduction of additional variables into the model. This may aid with potential problems with dynamic panel bias, as additional variables may result in better controlling for persistent shocks at the state level. Additional information may also help in alleviating the weak instruments problem by expanding the potential universe of lagged exogenous variables that may be used as instruments, if not by directly suggesting instruments. We therefore expand the base data set to include some additional variables. Some of these variables are atypical in that they are not customarily part of the discussion of the econometric modeling of aggregate crime rates, and some variables that others have argued are important in understanding crime rates but are more controversial. This expanded set of variables includes: the fraction of state income spent on enforcement, a measure of capital punishment presence (specifically, executions per 1000 prisoners), whether or not states have passed a "shall issue" law, whether or not the state has "strike three" criminal sentencing legislation for repeat offenders. We also include the level of state per capita income, as it is commonly included in models of aggregate crime rates (e.g., Lott and Mustard 1997). We also include in the data set the statewide infant mortality rate, as it may pick up some unobserved component of quality of well-being, or possibly even the prevalence of drug usage.

We introduce three further variables that serve solely as additional instrumental variables. The first variable records whether or not a state had a close gubernatorial election in a given year, where we defined a close election to be one in which the top two candidates were less than 6 % apart in the statewide popular vote. Our logic was that the resolution of a close election would be known only very late in a given year, and therefore may represent a shock occurring to future policy and economic conditions that cannot have any direct bearing on current conditions. We also include the possibility that the close election was won by an independent or republican candidate, as one could argue that this results in different sort of policy shock than an election won by a democratic candidate. Lagged population growth rates may capture beliefs that others have about the future course of the state economy, and therefore may also serve as effective instruments.[15]

While adding data is perhaps the most basic way of improving the fit and performance of a model, a complementary alternative is to employ a different method of estimation. Difference-based estimators, for example, help in circumventing dynamic panel bias (Baltagi, 2008, Ch. 8).[16] The chief problem with working with data in differenced form is that that differencing renders both leads and lags of the dependent variable explicitly endogenous. Thus, when using difference-based estimators, we must treat both the lead and the lag of the dependent variable as endogenous in models estimated in differences.

As a first step towards making these corrections to our estimated models, tables 5 and 6 present expanded models for property and violent crime rates, estimated in levels with fixed effects. These models are estimated in levels using either GMM or LIML with heteroscedasticity and autocorrelation consistent standard errors, including time dummy variables and fixed effects, and using four lags of all exogenous variables, in addition to the second and third order lagged difference of the dependent variable, as instruments. Model II on both tables shows results after pairing down the instrument set by dropping insignificant variables from first-stage instrumental variable regressions.[17] The model selection statistics indicate the model is neither overidentified or underidentified, and the smaller instrument set in-

[15]We experimented with some additional instruments, for example, dummy variables capturing the electoral cycle in each state. Because Levitt (1996) also found these variables did not prove to be useful as instruments for policy changes, we do not discuss these results.

[16]A further benefit of working with differences is that it anticipates potential stationarity problems in the data. Indeed, many of the series of interest (for example, the crime rates themselves) fail standard panel stationarity tests.

[17]Appendix B provides a description of the ultimate instrument sets used in various estimated models.

creases the first-stage partial F statistic substantially. Model III on both tables 5 and 6 shows the results of estimating the model with the paired down instrument set using LIML. As before, the aim in estimating models with LIML is to provide some verification that model estimates are not too sensitive to weak instrument bias. In terms of the estimated coefficients on the models, the coefficients for the future and past crime rates are significant, and some enforcement variables and some other explanatory variables - for example, the unemployment rate - are significant and are nearing levels suggested by prior research.

While these estimates suggest that expectations and past behavior are important in explaining current crime rates, they still do not completely address the potential problem of dynamic panel bias. An alternative is to use an alternative estimator such as a difference-based estimator, and tables 7 and 8 present several such estimates. The progression as one moves left to right across tables 7 and 8 is roughly the same as that on tables 5 and 6. Initial model estimates are presented, the instrument set is reduced by excluding variables insignificant in the first stage regression and the model is estimated again, and then a final set of estimates are presented using LIML to check that estimates are stable under an estimation method more robust to weak identification.

The first three columns on both tables present models in which lagged differences of exogenous variables, and the second-order lagged difference of the dependent variable, are used as instruments. The last three columns on both tables present models in which lagged levels of exogenous variables are used as instruments instead of lagged differences, as some have argued that using level-based instruments for differenced based estimators is useful because of the additional information brought to bear by levels (Baltagi, 2008, Ch. 8).

Model V on tables 7 and 8 appears to exhibit the best all around performance. These models appear not to suffer from identification problems (either over- or underidentification), and have relatively large first-stage partial F statistics. Moreover, the estimation method (GMM) is flexible in terms of the assumption on the permitted structure of error terms, and standard errors are adjusted to be robust to heteroscedasticity and autocorrelation consistent. The estimation of the model in logged differences mitigates concerns about dynamic panel bias. As a final robustness check, model VI on tables 7 and 8 estimates the model using LIML, with similar results.

If we take model V of both tables 7 and 8 as our best specification, we see that a small collection of the usual variables are significant. The estimated coefficient of police per capita in the property crime rate regression (table 7, column V) is -0.05, and the estimated coefficient on prisoners per capita is -0.033. Among other significant variables, unemployment rates, infant mortality rates, and the percent population living in a metropolitan area are significant in the property crime specification with estimated coefficients of 0.032, 0.039, and

0.006, respectively. The estimated coefficient on the one-period-ahead crime rate is .773, and the coefficient on the past crime rate is .213. The estimation results for violent crime yield similar results. The coefficient of the police per capita in the violent crime regression (table 8, column V) is −0.088, while the estimated coefficient of imprisonment rate is −0.070. The unemployment rate has a significant coefficient of 0.037 and the infant mortality rate a coefficient of 0.085. The estimated coefficient of the level of income is .377 in the violent crime regression; this is an anomalous result that has occurred in other research. The coefficient on the one-period ahead violent crime rate is 0.661, while the coefficient on the lagged crime rate is .299. We now turn to discussing interpretation of these estimates.

4 Interpretation of Estimation Results

Estimation results suggest that expectations of future conditions play an important role in determining crime rates. In light of this observation, interpretation of the estimated coefficients of exogenous variables is no longer straightforward. Consider an increase in the level of enforcement. This change has an immediate impact on the crime rate, but has an indirect impact on current crime rates by altering expectations of future crime rates. This is true even if this change is completely transitory in that it only applies in the current period, because future crime rates depend upon past values of the crime rate. This example highlights two critical aspects of assessing the importance of policy or other changes. First, one must consider that expectations are changed by current changes in exogenous variables. Second, one must know the exact nature of a change, and how this change is perceived by potential criminals to correctly assess its impact.

To make these ideas concrete, consider the expectational difference equation (2) that we set out to estimate:

$$c_t = \alpha_0 c_{t-1} + \Pi_1 X_t + \Pi_2 Y_t + \alpha_1 E_t c_{t+1}, \tag{4}$$

Where X_t is a vector of policy variables, Y_t is a vector of control variables, and Π_1, Π_2 are row vectors of (estimated) coefficients. α_1 is the weight placed on future expectations of exogenous variables in driving current crime rates, and α_0 captures the dependence of current crime rates on past crime rates.

Equation (4) can be solved in a way that facilitates interpretation.[18] Consider a simple case in which the vector X_t is equal to a given constant plus some transitory component, so that $X_t = \overline{X} + x_t$, where x_t is a vector of randomly distributed terms with mean zero. Similarly, suppose that other exogenous variables are simply given by their mean values with

[18]The solution method is that described in Blanchard and Fisher (1985, p. 261-5

error terms added: $Y(t) = \overline{Y} + y_t$. Then, $E_t X_{t+1} = \overline{X}$, and $E_t Y_{t+1} = \overline{Y}$.[19]

We wish to describe the current crime rate c_t as a function of information available at time t - that is, as a function of past crime rates, exogenous variables, and policy variables. This solution will have the form:

$$c_t = a_0 c_{t-1} + P_1 \overline{X} + P_2 \overline{Y} + Q_1 x_t + Q_2 y_t, \tag{5}$$

Where the values for P, Q, and a_0 are to be determined from model estimates. The values of P will describe the impact of *permanent* changes in exogenous variables on the current crime rate, while the values of Q will capture the impact of *transitory* changes in exogenous variables on the current crime rate. Once we have determined the value of a_0, we will be able to assess the impact of permanent changes in exogenous variables on the steady-state, long run crime rate. From equation (5), the long run, steady-state crime rate can be written as:

$$\overline{c} = \frac{P_1 \overline{X} + P_2 \overline{Y}}{1 - a_0} \tag{6}$$

From (6), one can see that the long-run impact on $\overline{c}$ of a unit change in the mean of a given policy measure or exogenous variable is $\frac{P_{ij}}{1-a_2}; i = 1, 2$. To find the coefficients of (5), iterate equation (5) forward one period and apply the expectations operator E_t. This gives the following expression:

$$E_t c_{t+1} = a_0 c_t + P_1 \overline{X} + P_2 \overline{Y} \tag{7}$$

Inserting (7) into (4) gives:

$$c_t = \alpha_0 + \alpha_1 \left[a_0 c_t + P_1 \overline{X} + P_2 \overline{Y} \right] + \Pi_1 X_t + \Pi_2 Y_t \tag{8}$$

Using the specifications $X_t = \overline{X} + x_t$, and $Y_t = \overline{Y} + y_t$ in (8) and rearranging gives:

$$c_t = \frac{\alpha_0}{1 - \alpha_1 a_0} c_{t-1} + \frac{(\alpha_1 P_1 + \Pi_1)\overline{X}}{1 - \alpha_1 a_0} + \frac{(\alpha_1 P_2 + \Pi_2)\overline{Y}}{1 - \alpha_1 a_0} + \frac{\Pi_1 x_t}{1 - \alpha_1 a_0} + \frac{\Pi_2 y_t}{1 - \alpha_1 a_0} \tag{9}$$

Matching coefficients between (9) to (5) results in a series of equations that map estimates of (4) into the coefficients of (5). Evidently, the autoregressive component of (5) is described by the equation:

$$a_0 = \frac{\alpha_0}{1 - \alpha_1 a_0} \tag{10}$$

[19] This is the simplest possible way of framing our discussion of the implications of estimation results for assessing changes in policy or other variables. We elaborate on more complex specifications below.

Equation (10) is a quadratic equation in the estimated lead and lag terms, which can be solved accordingly:

$$\alpha_1 a_0^2 - a_0 + \alpha_0 = 0, \quad \text{or} \quad a_0 = \frac{1}{2}\frac{1 \pm \sqrt{1 - 4\alpha_0\alpha_1}}{\alpha_1}. \tag{11}$$

An implication of (11) is that there will exist more than one solution to (4). This is not an uncommon occurrence in rational expectations models, and we follow the custom of selecting the stable root. This is generally the negative component of the quadratic in (11).[20]

Given a solution for a_0, we have the following equations describing the coefficients of other terms in equation (5):

$$P_{ij} = \frac{\alpha_1 P_{ij} + \Pi_{ij}}{1 - \alpha_1 a_0}, \quad i = 1, 2; \qquad Q_{ij} = \frac{\Pi_{ij}}{1 - \alpha_1 a_0}, \quad i = 1, 2. \tag{12}$$

The solutions to these equations are estimated coefficients augmented to take into account that changes also influence expectations of future crime rates. The coefficients of P_{ij} describe the impact of a *permanent* change in policy or in an exogenous variable on the current crime rate. The coefficients of Q_{ij}, alternatively, tell us the impact of a *transitory* change in a policy or exogenous variable on the current crime rate, taking into account the impact of a change on expectations.

If we wish to find the ultimate long run impact of these policy changes, we must first solve the respective equation in (12) to get P_{ij}, and then compute $\frac{P_{ij}}{1-a_0}$ as described in equation (6). Performing these calculations and simplifying yields:

$$LRM_{ij} = \frac{P_{ij}}{1 - a_0} = \frac{\Pi_{ij}}{1 - \alpha_0 - \alpha_1} \tag{13}$$

We now have three different ways of thinking about our coefficient estimates. Given coefficient estimates, we can describe the impact of a permanent shock on the current crime rate, a permanent shock on the long-run crime rate, or of a transitory shock on the current crime rate.[21] As described in the previous section, our belief is that our most reliable estimated models are those in column V of tables 7 and 8. The coefficients on the future and past crime rates for the property crime rate are .77 and .21, respectively; solving (11) gives $a_0 = .26$. For the violent crime rate, the estimated coefficients of future and past crime rates are .66

[20] It bears mentioning that equation (11) results in some restrictions that estimated coefficients must satisfy if the equation is to be stable or even generate reasonable solutions. For example, it cannot be the case that $\alpha_0\alpha_1 > \frac{1}{4}$, as then no solution exists.

[21] Of course, the impact of a transitory shock on the long run crime rate is by definition zero.

and .30, respectively, resulting in $a_0 = .39$. Solving for P_{ij} in equation (12) gives:

$$P_{ij} = \frac{\Pi_{ij}}{1 - \alpha_1(1 + a_0)}.$$

Thus, estimated coefficients must be inflated by a factor of $(1 - \alpha_1(1 + a_0))^{-1}$ to assess the impact of an anticipated permanent change in an exogenous or policy variable on the current crime rate. For the property crime rate, $(1-\alpha_1(1+a_0))^{-1} = 14.6$, while for the violent crime rate, $(1-\alpha_1(1+a_0))^{-1} = 7.0$. From equation (12), transitory changes influence current crime rates according to the adjusted coefficients:

$$Q_{ij} = \frac{\Pi_{ij}}{1 - \alpha_1 a_0}.$$

To assess the impact of transitory changes on current crime rates, estimated coefficients must be inflated by a factor of $(1-\alpha_1 a_0)^{-1}$. For the property crime rate, $(1-\alpha_1 a_0)^{-1} = 1.19$, while for the violent crime rate, $(1-\alpha_1 a_0)^{-1} = 1.24$. These results indicate that permanent changes in exogenous variables have impacts on current crime rates that are orders of magnitude larger than transitory changes.

Using our expression for long run multipliers in equation (13), apparently estimated coefficients in the property crime model must be inflated by a factor of 50, and in the violent crime model by a factor of 25. In table 9, the various multipliers are applied to estimated coefficients to give a sense as to how elasticities change with the nature of the change in the exogenous variable and the time frame.

4.1 Discussion

The results displayed on table 9 must be considered with care for several reasons. There are some anomalous results in model estimation (for example, the positive sign attached to real per capita income in violent crime specifications). Estimates from models designed to avoid potential problems such as dynamic panel bias may suffer from weak identification. Since the estimated coefficients on future and past crime rates work their way into the denominators of multipliers, very small changes in model estimates may provoke rather large changes in long run elasticities. For example, if we applied the estimates from table 7, column I, in computing long run multipliers instead of those from table 7, column V, the long run multiplier changes dramatically, taking on a value closer to 2.3 rather than a value of 50! Some estimated models produce estimates of lead and lag terms that sum to greater than one, implying that the long run multiplier in response to permanent changes in exogenous variables cannot be computed.

On the other hand, the fact remains that in virtually any model we estimated, lead and lag terms appear to be significant and large, suggesting that past conditions and expectations of the future are of some importance in understanding current crime rates. Qualitatitively, this result implies that the exact nature of a change in a given exogenous variable - something heretofore ignored in the econometric literature on crime rates - is critical in understanding its current and eventual impact. A key aspect of our results is that not only does the nature of the change matter, but also the way it is perceived by potential criminals. The estimates on table 9 of the impact of changes on the current crime rate of a permanent change, for example, only apply if agents believe the change to be permanent, and the policy maker can credibly commit to a permanent change. Therefore, one must view the results on table 9 through a lens which includes an assessment of criminal perceptions and policy maker credibility.

5 Conclusions

In this paper we have estimated a model of aggregate crime rates that explicitly takes into account that if crimes are committed by rational agents, crime commission decisions should in part depend upon expectations of future economic conditions, enforcement, and punishment. While none of our estimated models are immune from criticism, virtually all of our estimation results imply that future expectations are important in explaining current crime rates, and that expectations are important in understanding the dynamics of aggregate crime rates. Even if one questions the quantitative results we have presented, their qualitative meaning is important.

Our finding that expectations matter presents both challenges and opportunities for policy makers. On the one hand, it becomes harder to predict the exact effect of planned policy measures on the crime rate because this will depend upon whether the change is perceived to be temporary or long-lasting. On the other hand, if policymakers can commit to a pre-specified and credible course of action, then it may be possible to effectively manage expectations and thus make crime-reducing policies more efficient. For instance, suppose governments are somehow committed to increasing enforcement for a prolonged period of time as soon as economic conditions deteriorate. If such a policy is credible, the impact of a contemporaneous increase in the unemployment rate on today's crime rate would be lessened because of the expectations of increased crime fighting effort in subsequent periods. Such a commitment, if practically feasible, would actually reduce the need for a contemporaneous increase in enforcement and make crime fighting less costly. Of course, to gain the needed credibility may take time and require significant resources in the short-run.

The implication that past behavior and expectations of the future are important in driving crime rate has rich and interesting implications for policy. We hope that our approach and results will invite fuller consideration of the role of expectations and credibility in the classic Becker (1967) model.

A Data Appendix

The data we used in this study basically derives from a version of the data set used in Spelman (2001), made available by John J. Donohue on his website (http://islandia.law.yale.edu /donohue/pubsdata.htm). We checked all the data against historical sources and updated the data set so that it is as recent as possible. The data sources for individual items are as follows:

1. All crime data comes from the uniform crime reports, available from the bureau of justice statistics (http://bjsdata.ojp.usdoj.gov/dataonline/Search/Crime/State /statebystatelist.cfm). This data is also available online in historical editions of the Statistical Abstract of the United States available at (http://www.census.gov/compendia /statab/).

2. Early poverty rates comes from the Statistical Abstract. We added in data for the District of Columbia to that already in the Spelman's (2000) data. Data from 1970-1974 and 1976 were missing for the District of Columbia, so we interpolated these values. More recent information on poverty rates comes from the Small Area Survey of Income and Poverty Estimates produced by the United States Census (http://www.census.gov /hhes/www/saipe/). From this source we took poverty information for 1993 and from 1996-2005.

3. Age distribution data also derives from the Statistical Abstract, but do to format changes in the reporting of this information, more recent data (from 2001 on) was calculated by hand from Census bureau estimates (http://www.census.gov/popest /estimates.php).

4. There is in fact detailed information on incarceration rates going back for some time. The chief problem with this data is that there is a comparability problem. In practice, this problem appears to have a negligible impact on the data. In years prior to 1971 prison population data also includes persons jailed for some states. We took our data from the Statistical Abstract. We also relied upon some data from Bureau of Justice Statistics sources (http://www.ojp.usdoj.gov/bjs/prisons.htm). As mentioned in the text, the prison population is typically measured on the last day of the year. The District of Columbia drops out of the sample in 2001 because jurisdiction of its prisoners was transferred to the federal government at this time. Some early values are missing; we interpolated values in Delaware and North Carolina in 1968, and Rhode Island and Arkansas over the time period 1968-1970.

5. Police data and expenditures data were taken from the Statistical Abstract. These data were checked against data appearing in the early versions of the Justice Expenditure and Employment Abstracts (JEEA). Since the Statistical Abstract had no data from 1980-1 on expenditure, we took this data from the JEEA. For similar reasons, police employment data from 1980-2 also derives from the JEEA. Missing values which had to be interpolated were 1973, 1984, 1989, 1990, and 1996 for police employment data, and 1973, 1984, 1989, 1990, and 2003 for the expenditure data.

6. Coding of three strikes legislation was developed following Marvel and Moody (2001), while coding of "shall issue" gun permit laws was developed following Donohue (2004). Donohue describes several controversies in the coding of gun control laws, and his data includes several alternative means of codifying this information. We relied upon the coding which Donohue and Ayres (2003) refer to as the "Vernick" coding. We experimented with some of the other ways in which this information was coded but this had no perceptible impact on results.

7. All data on state income come from the Bureau of Economic Analysis's Local Area Personal Income Reports (http://www.bea.gov/bea/regional/reis/). This source also gives population data for each state. The growth rate of state income was calculated as the log difference in income. All income data was deflated using the CPI available from the St. Louis Federal Reserve (base 1982-4, available at http://research.stlouisfed.org /fred2/).

8. Data on the infant mortality rate derives from the Statistical Abstract.

9. Data on state gubernatorial elections cam from the *Congressional Quarterly.*

B Instrument Sets

This section describes the instrument sets used for the various instrumental variables regressions in the paper.

1. Table 2, Model III: Second order lag of the property crime rate, and first, second, third, and fourth order lags of all exogenous variables.

2. Table 2, Model IV: Second order lag of the property crime rate, and first, second, third, and fourth order lags of all exogenous variables.

3. Table 2, Model V: Second order lag of the property crime rate, and first, second, third, and fourth order lags of all exogenous variables.

4. Table 3, Model III: Second order lag of the violent crime rate, and first, second, third, and fourth order lags of all exogenous variables.

5. Table 3, Model IV: Second order lag of the violent crime rate, and first, second, third, and fourth order lags of all exogenous variables.

6. Table 3, Model V: Second order lag of the violent crime rate, and first, second, third, and fourth order lags of all exogenous variables.

7. Table 5, Model I: Second order lag of the property crime rate, whether or not there was a close gubernatorial election, whether or not there was a close gubernatorial election won by a republican or independent, and first, second, third and fourth order lags of the fraction of income spent on enforcement, the population growth rate, and all exogenous variables.

8. Table 5, Model II: The lagged fraction of income spent on enforcement, the lagged unemployment rate, the lagged poverty rate, the second order lag of the imprisonment rate, the third order lag of the percentage of population 25 to 34, and the fourth order lag of the percentage population black.

9. Table 5, Model III: Same as Table 4, model II.

10. Table 6, Model I: Second order lag of the violent crime rate, whether or not there was a close gubernatorial election, whether or not there was a close gubernatorial election won by a republican or independent, and first, second, third and fourth order lags of the fraction of income spent on enforcement, the population growth rate, and all exogenous variables.

11. Table 6, Model II: The lagged infant mortality rate, the lagged poverty rate, and the lagged percentage population living in a metropolitan area, the second order lags of the unemployment rate and the percentage population living in a metropolitan area, the third order lag of the unemployment rate, and the fourth order lag of the percentage population living in a metropolitan area.

12. Table 6, Model III: Same as Table 5, model II.

13. Table 7, Model I: Second order lag of the property crime rate, whether or not there was a close gubernatorial election, whether or not there was a close gubernatorial election won by a republican or independent, and first, second, third and fourth order lags of the fraction of income spent on enforcement, the population growth rate, and all exogenous variables. All instruments are in differences.

14. Table 7, Model II: First order lags of the population growth rate, the unemployment rate, the poverty rate, the percentage population aged 25 to 34, and the percentage population living in a metropolitan area; second order lags of the incarceration rate and the fraction of population 25 to 34; third order lags of the percentage population 25 to 34 and the percentage population living in a metropolitan area, fourth order lags of the percentage population 18 to 24, and fifth order lags of the incarceration rate and the fraction of state income spent on law enforcement. Note that fifth order lags of the last two variables enter into the instrument set as these variables were lagged once to begin with. All instruments are in differences.

15. Table 7, Model III: Same as Table 7, Model II.

16. Table 7, Model IV: Second order lag of the property crime rate, whether or not there was a close gubernatorial election, whether or not there was a close gubernatorial election won by a republican or independent, and first, second, third and fourth order lags of the fraction of income spent on enforcement, the population growth rate, and all exogenous variables. All instruments are in levels.

17. Table 7, Model V: Second order lag of the property crime rate, first order lags of the population growth rate, the level of real per capita income, the unemployment rate, the fraction population aged 25 to 34, the percentage population living in a metropolitan

area; second order lags of the population growth rate, the unemployment rate, the incarceration rate, and the percentage population living in a metropolitan area; third order lags of the the percentage population 25 to 34, the percentage population living a metropolitan area, the incarceration rate, and police per capita, fourth order lags of the incarceration rate, the fraction of income spent on enforcement, and the percentage population living in a metropolitan area. All instruments are in levels.

18. Table 7, Model VI: Same as Table 7, Model V.

19. Table 8, Model I: Second order lag of the violent crime rate, whether or not there was a close gubernatorial election, whether or not there was a close gubernatorial election won by a republican or independent, and first, second, third and fourth order lags of the fraction of income spent on enforcement, the population growth rate, and all exogenous variables. All instruments are in differences.

20. Table 8, Model II: First order lag of the fraction of state income spent on enforcement, population growth rate, infant mortality rate, unemployment rate, fraction population aged 18 to 24, fraction population living in a metropolitan area, presence of a shall issue law; second order lag of the incarceration rate, the infant mortality rate, fraction population aged 25 to 34, fractionc population living in a metropolitan area, the fraction population black, and the presence of a three strikes law; third order lags of the population growth rate, the unemployment rate, the percentage population living in a metropolitan area, the percentage population black, fourth order lags of the population growth rate, the fraction population aged 18 to 24, and the fifth order lag of the fraction state income spent on enforcement. All instruments are in differences.

21. Table 8, Model III: Same as Table 8, Model II.

22. Table 8, Model IV: Second order lag of the violent crime rate, whether or not there was a close gubernatorial election, whether or not there was a close gubernatorial election won by a republican or independent, and first, second, third and fourth order lags of the fraction of income spent on enforcement, the population growth rate, and all exogenous variables. All instruments are in levels.

23. Table 8 Model V: Second order lag of the violent crime rate; first order lags of the population growth rate, the unemployment rate, the percentage population 18 to 24, the percentage population living in a metropolitan area, and the percentage population black, second order lags of the population growth rate, the unemployment rate, the percentage population living in a metropolitan area, the percentage population black; third order lags of police per capita, the percentage population 18 to 24, and the percentage population black, and fourth order lags of the population growth rate, the unemployment rate, and the percentage population living in a metropolitan area. All instruments are in levels.

24. Table 8, Model VI: Same as Table 8, Model V.

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Table 1 - Base Model Summary Statistics

Variable	Mean	Max	Min		Std. Dev.	Obs.
Property crime rate	4163.74	9512.1	942.20		1303.72	1937
				within=	787.23	$\bar{T}$=38
				between=	1049.01	n=51
Violent crime rate	450.6	2921.8	27.7		314.71	1938
				within=	130.58	$\bar{T}$=38
				between=	289.11	n=51
Unemployment rate	5.89	18	1.9		2.04	1887
				within=	1.71	$\bar{T}$=38
				between=	1.11	n=51
Poverty rate	13.04	35.4	3.7		4.18	1887
				within=	1.94	$\bar{T}$=38
				between=	3.74	n=51
Percent pop. 15 to 17 years old	4.83	6.91	2.5		0.84	1836
				within=	0.79	$\bar{T}$=36
				between=	0.29	n=51
Percent pop. 18 to 24 years old	11.4	16.11	7.56		1.7	1836
				within=	1.59	$\bar{T}$=36
				between=	0.63	n=51
Percent pop. 25 to 34 years old	15.2	23.58	10.13		2.16	1836
				within=	1.87	$\bar{T}$=36
				between=	1.1	n=51
Percent pop. black	10.68	71.05	0.17		12.06	1835
				within=	1.11	$\bar{T}$=36
				between=	12.19	n=51
Percent pop. metro	64.01	100	0		22.97	1824
				within=	6.86	$\bar{T}$=36
				between=	22.13	n=51
Prisoners per capita	226.89	1821.77	20.34		187.42	1930
				within=	149.37	$\bar{T}$=38
				between=	118.28	n=51
Police per capita	2.62	8.85	0.59		0.9	1836
				within=	0.36	$\bar{T}$=36
				between=	0.83	n=51

Table 2 - Property Crime Models

	I	II	III	IV	V
Property crime rate $(t+1)$		0.507***	0.598***	0.584***	0.658***
		(45.445)	(12.247)	(13.395)	(8.179)
Property crime rate $(t-1)$		0.490***	0.417***	0.426***	0.368***
		(44.219)	(10.524)	(11.852)	(5.659)
Police per capita $(t-1)$	0.355***	-0.016	-0.015	-0.009	-0.015
	(3.259)	(-1.614)	(-1.461)	(-0.969)	(-1.451)
Prisoners per capita $(t-1)$	-0.074***	-0.005	-0.005	-0.005	-0.003
	(-3.036)	(-1.372)	(-1.310)	(-1.382)	(-0.832)
Unemployment rate	0.144***	0.008**	0.011**	0.011***	0.012**
	(6.064)	(2.215)	(2.473)	(2.731)	(2.478)
Poverty rate	-0.252***	0.007	0.011	0.008	0.015
	(-6.040)	(0.937)	(1.288)	(0.963)	(1.510)
Percent pop. 15 to 17 years old	0.087	0.001	-0.017	-0.018	-0.021
	(0.812)	(0.045)	(-0.987)	(-1.158)	(-1.160)
Percent pop. 18 to 24 years old	0.519***	0.018	0.015	0.020	0.011
	(6.775)	(1.180)	(0.874)	(1.451)	(0.624)
Percent pop. 25 to 34 years old	0.064	0.016	0.004	0.003	0.001
	(0.688)	(1.008)	(0.274)	(0.237)	(0.078)
Percent pop. black	-0.200***	-0.002	0.003	0.002	0.006
	(-6.555)	(-0.488)	(0.477)	(0.442)	(0.811)
Percent pop. in metro area	0.019**	0.002	0.004*	0.004**	0.004
	(2.039)	(0.684)	(1.695)	(2.063)	(1.632)
N	1758	1756	1542	1542	1542
Hansen J	0.000	0.000	33.082	33.082	31.214
p-value			0.608	0.608	0.696
Kleinbergen-Paap rk LM stat.			70.396	70.396	70.396
p-value			0.001	0.001	0.001
Partial F, cr$(t+1)$			2.598	2.598	2.598
p-value			0.000	0.000	0.000
Estimation Method	OLS	OLS	IV	GMM	LIML

Notes: All models are estimated in levels using logs, with yearly time dummy variables and state level fixed effects. Standard errors are heteroscedasticity and autocorrelation consistent.
$***$ denotes significance at 99 % $**$ denotes significance at 95 % $*$ denotes significance at 90 %.

Table 3 - Violent Crime Models

	I	II	III	IV	V
Violent crime rate $(t+1)$		0.501***	0.533***	0.526***	0.553***
		(31.048)	(11.763)	(14.115)	(6.637)
Violent crime rate $(t-1)$		0.499***	0.473***	0.477***	0.459***
		(34.065)	(13.646)	(16.647)	(7.455)
Police per capita $(t-1)$	0.287***	-0.032*	-0.014	-0.005	-0.014
	(2.771)	(-1.869)	(-0.617)	(-0.306)	(-0.612)
Prisoners per capita $(t-1)$	-0.014	-0.013**	-0.012**	-0.009*	-0.012*
	(-0.454)	(-2.205)	(-1.975)	(-1.681)	(-1.845)
Unemployment rate	-0.097***	-0.004	0.001	-0.003	0.001
	(-2.939)	(-0.501)	(0.145)	(-0.464)	(0.167)
Poverty rate	-0.055	-0.006	-0.009	0.002	-0.007
	(-1.069)	(-0.475)	(-0.597)	(0.185)	(-0.402)
Percent pop. 15 to 17 years old	-0.056	-0.018	-0.011	0.007	-0.013
	(-0.372)	(-0.585)	(-0.363)	(0.245)	(-0.388)
Percent pop. 18 to 24 years old	0.548***	0.018	0.003	0.013	-0.001
	(4.586)	(0.725)	(0.116)	(0.557)	(-0.044)
Percent pop. 25 to 34 years old	0.082	-0.000	-0.004	0.021	-0.004
	(0.529)	(-0.016)	(-0.122)	(0.834)	(-0.113)
Percent pop. black	0.035	0.001	-0.007	-0.009	-0.007
	(0.710)	(0.088)	(-0.767)	(-1.271)	(-0.795)
Percent pop. in metro area	0.021	-0.001	0.003	0.001	0.004
	(1.438)	(-0.164)	(0.450)	(0.171)	(0.488)
N	1759	1759	1546	1546	1546
Hansen J	0.000	0.000	39.541	39.541	39.376
p-value			0.315	0.315	0.321
Kleinbergen-Paap rk LM stat.			68.310	68.310	68.310
p-value			0.001	0.001	0.001
Partial F, cr$(t+1)$			3.030	3.030	3.030
p-value			0.000	0.000	0.000
Estimation Method	OLS	OLS	IV	GMM	LIML

Notes: All models are estimated in levels using logs, with yearly time dummy variables and state level fixed effects. Standard errors are heteroscedasticity and autocorrelation consistent.

$***$ denotes significance at 99 % $**$ denotes significance at 95 % $*$ denotes significance at 90 %.

Table 4 - Summary Statistics for Expanded Models

Variable	**Mean**	**Max**	**Min**		**Std. Dev.**	**Obs.**
Percent state inc. spent on enforcement	0.59	2.06	0.22		0.2	1887
				within=	0.08	$\bar{T}$=38
				between=	0.18	n=51
Executions per 1000 prisoners	0.02	1.21	0		0.08	1930
				within=	0.08	$\bar{T}$=38
				between=	0.03	n=51
Shall-Issue Law	0.27	1	0		0.44	1938
				within=	0.34	$\bar{T}$=38
				between=	0.29	n=51
Three Strike Law	0.14	1	0		0.35	1938
				within=	0.32	$\bar{T}$=38
				between=	0.15	n=51
Real Per Capita Income	13449.52	28842.29	6261.49		3068.26	1938
				within=	2329.68	$\bar{T}$=38
				between=	2016.05	n=51
Infant Mortality Rate	11.82	35.5	3.8		4.96	1836
				within=	4.55	$\bar{T}$=36
				between=	1.99	n=51
Close Gubernatorial Election	0.05	1	0		0.23	1938
				within=	0.22	$\bar{T}$=38
				between=	0.03	n=51
Close Election won by Republican	0.03	1	0		0.16	1938
				within=	0.16	$\bar{T}$=38
				between=	0.03	n=51
Population Growth Rate	0.01	0.08	-0.04		0.01	1887
				within=	0.01	$\bar{T}$=38
				between=	0.01	n=51

Table 5 - Expanded Property Crime Models

	I	II	III
Property crime rate $(t+1)$	0.571***	0.584***	0.633***
	(15.684)	(9.197)	(8.309)
Property crime rate $(t-1)$	0.437***	0.423***	0.387***
	(15.080)	(8.420)	(6.459)
Police per capita $(t-1)$	-0.015*	-0.017*	-0.019*
	(-1.763)	(-1.728)	(-1.953)
Prisoners per capita $(t-1)$	-0.006*	-0.005	-0.004
	(-1.790)	(-1.266)	(-0.877)
Executions per 1000 prisoners $(t-1)$	-0.006	-0.007	-0.013
	(-0.515)	(-0.565)	(-0.983)
Shall Issue Law - Vernick Coding	-0.001	-0.002	-0.003
	(-0.576)	(-0.565)	(-1.020)
Three Strikes Legislation	-0.001	-0.001	-0.000
	(-0.266)	(-0.449)	(-0.157)
Unemployment rate	0.011**	0.010**	0.011**
	(2.513)	(2.076)	(2.246)
Poverty rate	0.008	0.010	0.014
	(1.118)	(1.021)	(1.382)
Real Per Capita Income	-0.008	-0.009	-0.005
	(-0.436)	(-0.456)	(-0.221)
Infant Mortality Rate	0.018*	0.016	0.015
	(1.959)	(1.282)	(1.104)
Percent pop. 15 to 17 years old	-0.020	-0.014	-0.015
	(-1.278)	(-0.719)	(-0.786)
Percent pop. 18 to 24 years old	0.022	0.020	0.018
	(1.602)	(1.093)	(0.968)
Percent pop. 25 to 34 years old	0.008	0.003	-0.001
	(0.493)	(0.156)	(-0.042)
Percent pop. black	0.001	-0.002	0.000
	(0.148)	(-0.347)	(0.059)
Percent pop. in metro area	0.004**	0.003	0.003
	(2.191)	(1.013)	(1.238)
N	1496	1509	1509
Hansen J	56.645	9.217	9.036
p-value	0.812	0.101	0.108
Kleinbergen-Paap rk LM stat.	94.258	44.500	44.500
p-value	0.019	0.000	0.000
Partial F, cr$(t+1)$	2.124	8.185	8.185
p-value	0.000	0.000	0.000
Estimation Method	GMM	GMM	LIML

Notes: All models are estimated in levels using logs, with yearly time dummy variables and state level fixed effects. Standard errors are heteroscedasticity and autocorrelation consistent.
$***$ denotes significance at 99 % $**$ denotes significance at 95 % $*$ denotes significance at 90 %.

Table 6 - Expanded Violent Crime Models

	I	II	III
Violent crime rate $(t+1)$	0.517***	0.513***	0.472***
	(15.622)	(10.058)	(7.116)
Violent crime rate $(t-1)$	0.488***	0.489***	0.517***
	(19.849)	(13.768)	(11.314)
Police per capita $(t-1)$	-0.012	-0.018	-0.022
	(-0.701)	(-0.779)	(-0.914)
Prisoners per capita $(t-1)$	-0.010*	-0.012*	-0.014**
	(-1.710)	(-1.777)	(-1.982)
Executions per 1000 prisoners $(t-1)$	0.007	0.004	0.006
	(0.371)	(0.189)	(0.244)
Shall Issue Law - Vernick Coding	-0.003	-0.003	-0.003
	(-0.786)	(-0.717)	(-0.631)
Three Strikes Legislation	-0.003	-0.002	-0.002
	(-0.704)	(-0.506)	(-0.473)
Unemployment rate	0.002	0.007	0.004
	(0.268)	(0.830)	(0.441)
Poverty rate	0.005	-0.002	-0.007
	(0.421)	(-0.126)	(-0.404)
Real Per Capita Income	0.055	0.077	0.047
	(1.418)	(1.506)	(0.880)
Infant Mortality Rate	0.015	0.021	0.034
	(0.929)	(1.084)	(1.490)
Percent pop. 15 to 17 years old	0.028	-0.008	-0.004
	(0.912)	(-0.233)	(-0.119)
Percent pop. 18 to 24 years old	0.005	0.009	0.019
	(0.194)	(0.284)	(0.587)
Percent pop. 25 to 34 years old	0.007	-0.044	-0.018
	(0.261)	(-1.060)	(-0.407)
Percent pop. black	-0.009	-0.005	-0.004
	(-1.069)	(-0.453)	(-0.328)
Percent pop. in metro area	0.001	0.003	0.002
	(0.261)	(0.430)	(0.314)
N	1500	1504	1504
Hansen J	68.642	8.074	8.081
p-value	0.421	0.233	0.232
Kleinbergen-Paap rk LM stat.	96.930	37.874	37.874
p-value	0.012	0.000	0.000
Partial F, cr$(t+1)$	2.697	10.205	10.205
p-value	0.000	0.000	0.000
Estimation Method	GMM	GMM	LIML

Notes: All models are estimated in levels using logs, with yearly time dummy variables and state level fixed effects. Standard errors are heteroscedasticity and autocorrelation consistent.
$***$ denotes significance at 99 % $**$ denotes significance at 95 % $*$ denotes significance at 90 %.

Table 7 - Expanded Property Crime Models - Estimated in Differences

	I	II	III	IV	V	VI
Property crime rate $(t+1)$	0.492***	0.560***	0.628	0.675***	0.773***	0.807***
	(4.950)	(2.892)	(1.541)	(8.715)	(6.533)	(4.293)
Property crime rate $(t-1)$	0.076	0.186*	0.249	0.294***	0.213*	0.182
	(1.026)	(1.729)	(1.597)	(4.342)	(1.896)	(1.119)
Police per capita $(t-1)$	-0.031***	-0.037***	-0.040**	-0.047***	-0.050***	-0.046***
	(-2.663)	(-2.707)	(-2.543)	(-4.061)	(-3.738)	(-3.207)
Prisoners per capita $(t-1)$	-0.049***	-0.041**	-0.038*	-0.033**	-0.033*	-0.038*
	(-3.500)	(-2.496)	(-1.701)	(-2.337)	(-1.944)	(-1.823)
Shall Issue Law	0.000	-0.016	-0.018	-0.007	-0.016	-0.021
	(0.043)	(-1.081)	(-0.847)	(-0.631)	(-0.891)	(-1.001)
Three Strikes Legislation	-0.003	-0.002	0.003	-0.003	0.002	0.004
	(-0.294)	(-0.209)	(0.240)	(-0.306)	(0.144)	(0.272)
Executions per 1000 pris. $(t-1)$	-0.007	-0.010	-0.016	-0.005	-0.019	-0.020
	(-0.469)	(-0.577)	(-0.778)	(-0.261)	(-0.938)	(-0.916)
Unemployment rate	0.030***	0.030**	0.025*	0.027***	0.032**	0.029**
	(3.179)	(2.495)	(1.798)	(2.636)	(2.483)	(2.005)
Poverty rate	0.011	0.006	0.020	0.013	0.020	0.023
	(1.000)	(0.474)	(1.187)	(1.010)	(1.250)	(1.336)
Real Per Capita Income	-0.171**	-0.132	-0.134	-0.113	-0.106	-0.120
	(-2.388)	(-1.551)	(-1.159)	(-1.509)	(-1.065)	(-1.032)
Infant Mortality Rate	0.028*	0.042**	0.037	0.034**	0.039*	0.035
	(1.912)	(2.214)	(1.619)	(2.048)	(1.743)	(1.411)
Percent pop. 15 to 17 years old	-0.043	-0.026	0.024	-0.013	0.046	0.027
	(-0.639)	(-0.276)	(0.222)	(-0.186)	(0.457)	(0.240)
Percent pop. 18 to 24 years old	0.032	-0.034	0.005	0.025	0.056	0.039
	(0.502)	(-0.405)	(0.049)	(0.401)	(0.645)	(0.378)
Percent pop. 25 to 34 years old	-0.037	-0.068	-0.085	-0.042	-0.063	-0.099
	(-0.555)	(-0.777)	(-0.707)	(-0.634)	(-0.750)	(-1.047)
Percent pop. black	-0.079*	-0.093*	-0.082	-0.034	-0.050	-0.087
	(-1.800)	(-1.706)	(-1.281)	(-0.833)	(-0.899)	(-1.254)
Percent pop. in metro area	0.005***	0.005**	0.005*	0.006**	0.006**	0.005**
	(2.594)	(2.155)	(1.812)	(2.549)	(2.476)	(2.060)
N	1444	1447	1447	1496	1498	1498
Hansen J	58.705	10.311	9.230	44.119	7.672	7.136
p-value	0.726	0.503	0.601	0.983	0.936	0.954
Kleinbergen-Paap rk LM stat.	63.298	21.430	21.430	74.790	38.743	38.743
p-value	0.606	0.044	0.044	0.240	0.001	0.001
Partial F, cr$(t+1)$	1.987	5.009	5.009	2.630	8.203	8.203
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Partial F, cr$(t-1)$	2.599	6.956	6.956	3.685	8.763	8.763
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Estimation Method	GMM	GMM	LIML	GMM	GMM	LIML

Notes: All models are estimated in differences using logs, with yearly time dummy variables and state level fixed effects. Standard errors are heteroscedasticity and autocorrelation consistent.
$***$ denotes significance at 99 % $**$ denotes significance at 95 % $*$ denotes significance at 90 %.

Table 8 - Expanded Violent Crime Models - Estimated in Differences

	I	II	III	IV	V	VI
Violent crime rate $(t+1)$	0.369***	0.448***	0.481***	0.564***	0.661***	0.807***
	(4.352)	(3.736)	(3.099)	(7.524)	(5.931)	(4.687)
Violent crime rate $(t-1)$	0.224***	0.279***	0.249**	0.338***	0.299***	0.262**
	(3.424)	(3.141)	(2.122)	(5.462)	(3.300)	(2.017)
Police per capita $(t-1)$	-0.061***	-0.086***	-0.081***	-0.083***	-0.088***	-0.098***
	(-2.669)	(-3.295)	(-2.909)	(-3.987)	(-3.554)	(-3.499)
Prisoners per capita $(t-1)$	-0.065***	-0.055**	-0.070**	-0.059**	-0.070**	-0.069*
	(-2.743)	(-1.997)	(-2.097)	(-2.417)	(-2.025)	(-1.795)
Shall Issue Law	-0.016	-0.020	-0.017	-0.019	-0.018	-0.014
	(-1.174)	(-1.209)	(-0.881)	(-1.276)	(-0.917)	(-0.615)
Three Strikes Legislation	-0.009	-0.002	-0.006	-0.006	-0.009	-0.010
	(-0.604)	(-0.137)	(-0.336)	(-0.364)	(-0.522)	(-0.520)
Executions per 1000 pris. $(t-1)$	0.008	0.013	0.008	0.002	0.009	0.005
	(0.272)	(0.405)	(0.232)	(0.076)	(0.242)	(0.120)
Unemployment rate	0.014	0.017	0.023	0.032*	0.037*	0.052*
	(0.814)	(0.840)	(1.018)	(1.756)	(1.692)	(1.960)
Poverty rate	-0.001	0.012	0.009	0.012	0.019	0.018
	(-0.040)	(0.550)	(0.403)	(0.590)	(0.780)	(0.663)
Real Per Capita Income	0.481***	0.430**	0.374*	0.334**	0.377**	0.315
	(3.224)	(2.197)	(1.729)	(2.126)	(1.971)	(1.359)
Infant Mortality Rate	0.057**	0.040	0.057*	0.065**	0.085**	0.076*
	(2.300)	(1.343)	(1.688)	(2.382)	(2.323)	(1.768)
Percent pop. 15 to 17 years old	0.005	-0.139	-0.107	-0.005	-0.063	-0.173
	(0.040)	(-0.910)	(-0.633)	(-0.040)	(-0.389)	(-0.917)
Percent pop. 18 to 24 years old	-0.053	-0.128	-0.149	-0.087	-0.147	-0.204
	(-0.546)	(-1.150)	(-1.097)	(-0.976)	(-1.308)	(-1.427)
Percent pop. 25 to 34 years old	-0.157	-0.332**	-0.260	-0.171	-0.132	-0.353*
	(-1.185)	(-1.986)	(-1.255)	(-1.240)	(-0.756)	(-1.803)
Percent pop. black	0.007	0.142	0.102	0.045	0.003	0.150
	(0.116)	(1.643)	(1.000)	(0.728)	(0.041)	(1.378)
Percent pop. in metro area	-0.008	-0.008	-0.006	-0.010*	-0.006	-0.007
	(-1.279)	(-1.288)	(-0.895)	(-1.819)	(-0.848)	(-0.950)
N	1449	1452	1452	1500	1504	1504
Hansen J	75.677	8.454	8.221	59.261	9.730	8.438
p-value	0.194	0.981	0.984	0.709	0.782	0.865
Kleinbergen-Paap rk LM stat.	72.307	43.432	43.432	77.470	46.807	46.807
p-value	0.307	0.002	0.002	0.179	0.000	0.000
Partial F, cr$(t+1)$	1.861	3.752	3.752	2.379	4.878	4.878
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Partial F, cr$(t-1)$	2.669	5.292	5.292	3.136	6.773	6.773
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Estimation Method	GMM	GMM	LIML	GMM	GMM	LIML

Notes: All models are estimated in differences using logs, with yearly time dummy variables and state level fixed effects. Standard errors are heteroscedasticity and autocorrelation consistent.
$***$ denotes significance at 99 % $**$ denotes significance at 95 % $*$ denotes significance at 90 %.

Table 9 - Short and long run elasticities

	Coefficient	Current crime rates Elasticity w.r.t.: Transitory change	Current crime rates Elasticity w.r.t.: Permanent change	Long-run crime rates Elasticity w.r.t.: Permanent change
Property Crime:				
Police Per Capita	-0.050	-0.060	-0.730	-2.5
Imprisonment Rate	-0.033	-0.039	-0.482	-1.65
Unemployment Rate	0.032	0.038	0.467	1.6
Infant Mortality Rate	0.039	0.046	0.569	1.95
Percent pop. Metro Area	0.006	0.007	0.088	0.30
Violent Crime:				
Police Per Capita	-0.088	-0.110	-0.616	-2.2
Imprisonment Rate	-0.070	-0.087	-0.490	-1.75
Unemployment Rate	0.037	0.046	0.259	0.93
Infant Mortality Rate	0.085	0.105	0.595	2.13
Real Per Capita Income	0.377	0.467	2.639	9.43

Notes: Elasticities are computed using GMM estimates from tables 7 and 8, column V using the methods described in the text.