Crime, Expectations, and the Deterrence Hypothesis

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ABSTRACT

Tests of the so-called deterrence hypothesis typically rely on estimation of the relationship between current crime rates and current measures of economic conditions, demographics, and enforcement levels. We argue this approach is misguided because both past behavior and future conditions alter the criminal's decision to commit a crime in the present. We develop a model of the aggregate crime rate that takes both past behavior and expectations of future conditions into account. Our model produces short run elasticities roughly in line with previous research, but that long-run elasticities more on the order of 10 to 20 times as large. Our estimates suggest that falling unemployment rates, and changes in enforcement and punishment jointly explain most of the crime drop in the 1990s.

Since Becker's (1967) formal exposition of a theory of crime casting criminals as rational decision-makers, empirical models of the so-called *deterrence hypothesis* have occupied a prominent place in economics. Typically, the researcher estimates a relationship between crime rates and contemporaneous proxies for the costs and benefits of committing crime, such as proxies for the magnitude of punishment and likelihood of apprehension, measures of economic conditions such as unemployment or poverty rates, and demographic variables. The results of such studies are of interest not only as tests of the deterrence hypothesis, but also in the role they play in informing policy. The empirics of the deterrence hypothesis have 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 (Katz, Levitt, and Shustorovich 1996, 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. This is because virtually every empirical model of aggregate crime rates fails to take into account what should be one of the most important aspects of the crime commission decision if criminals are indeed rational decision makers - the decision to commit a crime may have long term consequences. If one expands the rational agent model of the criminal to include this possibility, expectations of *future* enforcement rates and economic conditions should matter in determining crime rates today, as should the decisions the potential criminal made in the past.

Estimates of our model suggest that both future expectations and past behavior are quantitatively important in explaining current crime rates. Our contemporaneous elasticities of crime with respect to proxies of enforcement and punishment are small, (on the order of $-.05$), but long run elasticities are much larger, in the range of $-.5$ to $-.75$. Long-run elasticities become fully operative only after a time lag of about 5 years after a permanent change in an independent variable.

Our findings have important policy implications. If expectations of future conditions are important in driving current crime rates as we find, the policy maker's credibility and ability to commit to a course of action become important. We discuss this and some further implications of our results in greater detail below.

1 Literature

The literature on the deterrence hypothesis is voluminous and has several important branches. Results vary with the time frame examined, the aggregation level of the data, and the specific empirical model employed. Consensus views have evolved over time as the quality of data has improved and econometric techniques have grown more sophisticated. The current consensus view might be stated as follows: 1) economic variables such as poverty rates and unemployment rates have predictive power in explaining crime rates, but exert only small impacts on crime rates; 2) measures of enforcement and apprehension likelihood, such as incarceration rates and the size of the police force have predictive power in explaining crime rates, although there is some variation in beliefs about how large effects are; 3) demographics, measuring, for example, the age distribution or racial composition of the population, are unimportant in explaining crime rates.

In an early survey, Chiricos (1987) summarized the results of 63 studies of crime and unemployment. His finding was that most studies reported a significant and positive relationship between crime and unemployment. In addition to producing his own time-series based evidence, Allen (1996) found that poverty rates are positively correlated with types of crime, although he notes this finding is not universal. Studies based on individual-level data largely corroborate these findings; see, for example, Grogger (1998), Raphael and Wintner-Ebmer (2004), and Machina and Meghar (2004). Kelly (2000), using county level cross sectional data, found that measures of inequality are also important in explaining violent crime. While acknowledging that there is often a statistically significant relationship between unemployment in particular and crime, Levitt (2004) argues that the magnitude of the effect of unemployment on crime is small.

Studies of deterrence tend to be a bit more uniform in their conclusion that punishment and enforcement matter. Usually, incarceration rates are used to proxy punishment severity, while proxies of the likelihood of apprehension and conviction 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), more recent studies have advanced a more promising view, 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. According to his evidence, the typical estimated elasticity is on the order of $-.05$ to $-.20$, but estimates as large as $-.38$ have been obtained.[1]

[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 $-.26$.

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 law 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. Another approach uses a less direct measure of the likelihood of apprehension, such as the relative size of the police force. Research employing probability-style measures 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 variable (number of offenses) appears in the denominator on the right hand side of the model and the numerator of the left hand side variable, strongly biasing results in favor of finding a negative relationship (Spelman, 2000).[2] Typical estimates of elasticities of crime with respect to the relative size of the police force exhibit quite a wide range, but are probably around −.40 (see Levitt 1997, 2004).

In sum, empirical research on the deterrence hypothesis indicates that: 1) crime rates do exhibit some dependence on economic conditions, but the magnitudes of effects seem to be small, and 2) deterrence matters, in that apprehension rates and proxies for punishment severity appear to be inversely related to crime rates. Perhaps another interesting feature of the empirical research on the determinants of crime is that it has, over time, moved away from estimation of models with a specific, explicit theory of criminal behavior in mind.[3] In the next section, we show how thinking about the long run impact of criminal decisions leads

[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 very prominently in Cloninger's (1975) assessment of initial econometric studies of the deterrence hypothesis.

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

to a different sort of econometric model in which past behavior and expectations matter in driving current crime rates. Our estimates obtained from this model are comparable with those from previous research, but the inclusion of terms capturing expectations and past behavior changes dramatically the interpretation of these elasticities. The result is that enforcement and punishment variables, along with economic indicators, have substantially larger effects.

2 Theory

Let the crime rate at time t (in a given jurisdiction) be given by c_t, let Y_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 X_t denote a column vector of variables measuring economic and demographic conditions that impact incentives to commit crime (e.g., unemployment rates, poverty rates, or the age distribution of the population). A general model of crime determination where 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 can be written as:

$$c_t = \gamma c_{t-1} + E_t \left[\sum_{i=0}^{\infty} \rho^i \left(AX_{t+i} + BY_{t+i} \right) \right] \tag{1}$$

The row vectors A and B in (1) capture the impact of policy and economic conditions on crime, and ρ reflects the degree to which potential criminals discount future conditions. E_t denotes the expectations operator with respect to the information set at time t, while the parameter γ captures the degree of persistence in the crime rate - that is, the degree to which past criminal behavior influences current crime.

The typical empirical model of crime only takes into account contemporaneous effects of X_t and Y_t on today's crime rate, which amounts to assuming that $\gamma = \rho = 0$, meaning that criminals are assumed to place no weight on future conditions in decision-making, and that past criminal outcomes have no role in predicting current criminal behavior. Equation (1) allows for a much richer and a more realistic setting where the current crime rate is allowed to be affected by past crime rates and expected future conditions.

One can think of several compelling microeconomic foundations 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).[4] If the implications of committing a crime are long-lasting, one expects that both past behavior and expectations of the future to matter in deciding to engage in a criminal act, because committing a crime alters lifetime returns from legitimate work (particularly if apprehended and punished for a previous offense).

Forward-looking behavior may also be motivated by the fact that punishment for a crime is often not instantaneous. A crime committed today may not be punished until some unspecified time in the future. Furthermore, the structure of the legal system might itself 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.

[4] 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.

Yet another 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 how productive this lifestyle will be in relative terms. Such an assessment involves a joint evaluation of future labor market conditions, the future likelihood of apprehension, and the future severity of punishment. Appendix A presents one example of a micro-founded theoretical model from which a specific structural form of equation (1) can be derived.

How is equation (1) to be estimated? Iterating (1) forward and applying the expectations operator we arrive at the following expression:

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

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 estimating the path of all future benefits and costs of committing crime with the problem of estimating the current expectations of the one period forward crime rate. Fortunately, there are antecedents to dealing with the estimation issues posed by (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 follow these literatures in estimating (2), and we shall describe our estimation approach in detail in 3.2.

Note that Equation (2) has implications for interpretation of estimated coefficients. The contemporaneous effect of a permanent increase in x_i (the i^{th} policy variable) is $\pi_{1,i}$, but its long-run impact equals $\pi_{1,i}/(1-\alpha_0-\alpha_1)$. The more persistent the crime rate (larger α_0, and the more pronounced the current impact of future conditions on criminal behavior (larger α_1, the greater is the impact of the policy measure over time.

We now describe our data, and then discuss our estimation strategy in greater detail.

3 Estimation

3.1 Data

The data set is an expanded version of that used by Spelman (2001). As Spelman (2001) points out, essentially the same data set has also been used by Becsi(1999), Levitt (1996), and Marvell and Moody(1992). We update and expand this data set through basically the present, and also augment it with some additional variables, as described in the data appendix.[5]

The data set is a yearly panel of states (including the District of Columbia) covering the years 1970 though 2006 inclusive. For each state and year, violent and property crime rates, obtained through the uniform crime reports, are matched with a vector of variables measuring economic conditions, demographics, and proxies of enforcement and punishment. Included in the vector of economic conditions are state real income levels, the state unemployment rate, and the poverty rate. All of these are typical variables included in analysis of aggregate crime rates. 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. One variable we include in the vector of variables

[5]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).

measuring economic conditions that is not standard is the growth rate of state per capita income. The logic is that the growth rate may carry some important information about the likely future path of the economy.

For measures of enforcement, we include police per capita (measured as police per 10,000 population) and the imprisonment rate (prisoners per 100,000 population). Sources for data and additional details of the data set are described in detail in appendix B. [6]

Summary statistics of crime rates, and demographic, enforcement, and economic variables appear in table 1. One can see that there is considerable variation in both violent and property crime rates in the sample, and that a large part of the variation occurs between rather than within states. For demographics, while a non-negligible fraction of variation occurs within states, there is more variation between states, rather than within a particular state across time. The opposite is true of basic economic variables - for example, the unemployment rate exhibits more variation within than across states. This comes as no surprise, as macroeconomic measures are likely to be highly correlated across states over time. 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 and between variation.

3.2 Econometric Specification

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

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

[6] Data and **STATA** -do files reproducing all results and tables in this paper are available from the authors.

where $e_{i,t}$ is an error term. The obvious difficulty in estimating (3) is that there is no direct measure of the expectation of future crime rates formed at time t. We construct $E_t c_{it+1}$ by regressing c_{it+1} on information available at time t in the form of past values of exogenous variables and crime rates. Effectively, this amounts to treating the realized value of c_{t+1} as an endogenous variable and using past values of exogenous variables and the dependent variable as instruments. Along these lines, we include second and third order lags of the dependent variable, and first, second, and third order lags of exogenous variables in the instrument set. Our preferred econometric models are estimated in log-differences, and for these models, we include both lagged differences and levels in the instrument set. Assuming that individuals form expectations rationally with respect to the complete information set at time t, the expectations error, i.e., $\varepsilon_{t+1} = c_{it+1} - E_t[c_{it+1}]$, is uncorrelated with any information available at time t, and can be folded into the error term $e_{i,t}$ as measurement error of the expected future crime rate.

Having obtained a way of dealing with future expected crime rates, perhaps the most obvious way to proceed in estimating (3) is by using a fixed effects estimator. However, reliance on fixed effects estimates poses dangers when lags or leads of the dependent variable are present by introducing dynamic panel bias (Bond 2002). It can be shown that reliance on a fixed effects estimator in the presence of lags or leads of the dependent variable may result in overstatement of the parameters attached to the leads and lags. Since an important aspect of our work is obtaining accurate estimates of these parameters, we seek to be especially careful in avoiding this problem. Thus, we choose to estimate (3) in log differences, although we also present some fixed effects estimates.[7] A problem with log differencing the data in

[7] A further benefit of log differencing is that it anticipates potential stationarity problems in the data.

the presence of leads and lags is that this renders both leads and lags of the dependent variable explicitly endogenous. Thus, we instrument for both the leads and lags of the (log-differenced) dependent variable in estimation.

If there is some unexplained common time trend in the data that is not controlled for, the coefficients on leads and lags of the dependent variable will also tend to be overstated. Thus, we also include a set of time dummies D_t in estimating the model. Implementing these adjustments to (3) results in the following specification:

$$\Delta c_{it} = \widehat{\alpha}_0 \Delta c_{it-1} + \widehat{\Pi}_1 \Delta X_{it} + \widehat{\Pi}_2 \Delta Y_{it} + \widehat{\alpha}_1 \Delta c_{it+1} + \widehat{\alpha}_2 \Delta D_t + \Delta e_t \tag{4}$$

A final issue of importance is that of the potential endogeneity of the policy variables, as the size of the current police force, say, might depend upon past crime rates. We use first-order lags of these variables so that they can be considered predetermined. There are also compelling practical reasons for using lags of these enforcement variables. Both imprisonment numbers and police per capita are typically measured at the end of the year (for example, imprisonment data records the number of prisoners in the system in the last week of the year). Thus, the lags of these variables, in addition to being predetermined, may give more accurate measures of their functional values during the following year.

Crime data across states and over time is likely to be heteroskedastic in ways that are difficult to anticipate in the econometric model. We therefore prefer to estimate the model in log differences using GMM, although we also present results for standard instrumental variable estimation.

Indeed, many of the series of interest (for example, the crime rates themselves) fail standard panel stationarity tests.

4 Results

Tables 2 and 3 show the results from estimating property and violent crime rates. The first column on each table presents results from estimating a model with no forward or backward looking terms. The second column on each table presents our preferred estimation approach as described in the previous section.

The OLS results are similar to those summarized by Spelman (2001). Of particular interest are the estimates pertaining to the unemployment rate, the imprisonment rate, and police per capita - all of which are significant in both specifications. Each has an elasticity in the -0.03 to $-.07$ range. Estimation of the equations by GMM with future and past crime rates does not appreciably change these estimated elasticities, but for both property and violent crime, the estimated elasticities of current crime with respect to past crime rates and future expectations are significant and large. For property crimes, the elasticity of the crime rate with respect to the future crime rate is forward crime rate has an estimated elasticity of about .65, while the past crime rate has an elasticity of about .23. These estimates for violent crime are about .53 and .37.

The forward and backward terms change rather profoundly the interpretation of contemporaneous elasticity estimates. To get a sense for the long-run impact of a permanent change in enforcement, we can derive the long-run multiplier for each policy variable, which is given by $\frac{1}{1-\hat{\alpha}_0-\hat{\alpha}_1}$, where $\hat{\alpha}_0$ is the estimated coefficient associated with the lagged crime rate, and $\hat{\alpha}_1$ is the estimated coefficient associated with the forward crime rate. These estimates suggest that the long run multiplier for property crimes is $\frac{1}{1-.651-.233} = 8.62$. For property crimes, the estimates on table 3 suggest an long run multiplier $\frac{1}{1-.627-.35} = 9.80$.

Thus, a contemporaneous elasticity estimate of about .05 becomes a long-run elasticity of about $.05(8.62) = .43$ for property crimes, and $.05(43.478) = .49$ for violent crimes.

Before delving into other aspects of the estimates, it is useful to get a feel for the robustness of the estimates. With this in mind, tables 4 and 5 present estimates for property and violent crime from some alternative models. The first two columns on each table present fixed effects estimators. The columns labelled **FE** present estimates when no attempt is made to control for potential endogeneity of leads and lags of the dependent variable, while the columned labelled **FEIV** uses an instrumental variable approach. One can see from these estimates that the leads and lags of the dependent variable carry coefficients that are significantly larger than those in tables 2 and 3. However, level based fixed effects estimators tend to attribute too much to the leads and lags, and one can see that the estimates are reduced when the model is estimated in differences, as is done in the columns labelled **IV** and **GMM** on tables 4 and 5. One can also see from comparing the IV and GMM estimates (reproduced from tables 2 and 3), there is little appreciable difference in the approaches, although one may argue that the IV estimators may be inefficient.

4.1 Discussion

Table 8 summarizes estimated short and long run elasticities using the specifications presented in tables 2 and 3 (and also the last column of tables 4 and 5). One can see that crime rates appear to be fairly inelastic with respect to contemporaneous elasticities, but are actually fairly large in the long run. In figures 1 and 2, we use standard methods (see Blanchard and Fisher 1989)) for writing expectational difference equations in simple autoregressive form and plot impulse responses. The figures show the response of crime rates to a 1% permanent increase in police per capita and the incarceration rate. The information on the magnitudes of responses figures is the same as that presented in table 8, however, the impulse response graphs allow the reader to get a feel for how long it takes for the crime rate to fully adjust to a permanent change in a policy variable. The figures show that within about five years, most of the long run impact of a permanent change in the variable of interest has worked its way fully into the system. Thus, it takes roughly five years for the impact of a current (permanent) change to fully impact crime rates.

As an additional econometric exercise, tables 7 and 8 present estimates of our preferred model for individual types of crime. On table 9, individual property index crimes are presented, and one can see that in most cases, the basic deterrence model performs quite well with regards to individual index offenses and suggests that expectations of the future are important in driving current crime rates. Enforcement variables are more or less significant across all property crime categories, excepting automobile crimes, which may behave differently due to substantial changes over the time period in the technology of automobile theft deterrence. The unemployment rate appears to be negatively correlated with crime rates for two of the four categories of crime - robbery and larceny.

Turning now to table 8, a different picture emerges. Murder does not appear to fit the model well. The forward term is significant, but has a sign opposite what our theoretical model would predict. Moreover, enforcement variables appear not to matter in driving the murder rate. Alternatively, rape and assault appear to fit the basic economic model better. Our estimates indicate that for both types of crime, expectations and the level of deterrence matter.

As a final exercise using the estimates, consider now table 9, which presents some rough calculations describing potential contributions of enforcement, imprisonment, and unemployment on the well-publicized crime drop that occurred across the United States through the 1990's(Levitt 2004). On the table, national population weighted average changes for three variables over the period 1990 to 2004 are presented - unemployment rates, police per capita (per 10,000 population), and the incarceration rate (per 100,000 population). Multiplying these changes by the long run elasticities presented in table 6 gives a rough idea as to how much each variable contributed to the 1990s crime drop. Jointly, these three variables appear capable of explaining a sizeable portion of the drop. From these rough calculations, it appears as though increased incarceration is a major factor in explaining the drop in violent crime in particular. While the contribution of falling unemployment rates is small, it is not negligible and the impact of lower unemployment on crime is about the same magnitude as the impact of larger police forces. From this rough picture, one might guess that these three factors alone appear to collectively explain more than half the crime drop for property crime, and come very close to explaining the drop in violent crime over the 1990s (43% versus 47%).

4.2 Conclusion

We have presented and estimated a model of rational criminal actors which takes into account the fact that crime commission decisions should in part depend upon expectations of future economic conditions and levels of enforcement. Our results have important ramifications for understanding the importance of different types of variables in predicting and driving crime rates. Perhaps of greater importance are the policy implications. Due to the twin effects of persistence and expectations, current changes in crime rates play out only over time. Our estimates suggest that the impact of policy changes, or changes in economic conditions for that matter, is only felt after a period of four to five years, and magnify initial changes in the end by a factor of between 8 and 10.

An implication of our results that is just is important as the dynamic impacts of policy is the qualitative result that future conditions and past behavior apparently matter a great deal in describing the behavior of aggregate crime rates. This realization introduces all sorts of possibilities for analysis of policy with respect to crime, as if expectations are important, so are things such as commitment and credibility. As an example, consider a (persistent) increase in the current crime rate, perhaps due to an adverse economic shock. The best policy response one might derive from a static model is that current enforcement levels should be increased in order to bring crime down to an acceptable level. In a dynamic context in which expectations are important, however, policymakers may be able to credibly commit to a strategy beforehand - perhaps one that emphasizes increased effort to fight crime when conditions deteriorate. Rational potential criminals then may realize future enforcement will increase in response to the adverse shock, and therefore revise their expectations of the future crime rate downwards. The lower expected future crime rate partially mitigates the impact of the shock on today's crime rate, which in turn may allows for a less costly initial enforcement surge. Thus, the fact that the policy maker has credibility in this example causes a much smaller current response of the crime rate to the shock.

Indeed, 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 lead theorists towards a fuller consideration of the role of the dynamics of the crime commission decision and the credibility of policy makers within the classic Becker (1967) model.

A Theoretical Appendix

This appendix builds a simple crime model which motivates the inclusion of the lagged and forward-looking terms in equation (2).

A.1 The Individual's Problem

The representative agent derives his or her's utility from consumption *and* crime. Crime is thus not only motivated out of economic gains, but through an inherent satisfaction from committing the action. In particular we specify the representative agent's utility function as follows:

$$U(X_t, C_t) = \alpha X_t + \chi \frac{(C_t - \gamma C_{t-1})^{1-\eta}}{1-\eta} \tag{A.1}$$

The representative agent consumes X_t units of the aggregate consumption good, and supplies C_t units of the aggregate crime production. Furthermore. it is assumed that criminal activity is habit forming. That is, a higher past level of criminal activity reduces an individuals marginal utility of crime today. Finally, the marginal utility of consumption is constant while the marginal utility of crime is diminishing.[8]

The representative agent is given one unit of labor each period which he/she can allocate to either the production of consumption goods (i.e., "honest" labor) or to the production of crime (i.e., criminal activity). Let the probability of getting caught and convicted at time t be denoted by the parameter Φ_t $(0 \leq \Phi \leq 1)$, and the loss of labor endowment if convicted be denoted by J_t . The *effective* labor endowment constraint facing an indiviual can then be written as:

$$N_t^X + N_t^C = 1 - \Phi_t J_t \tag{B.2}$$

where N_t^X and N_t^C represent the labor supply to the production of consumption goods and crime, respectively.

The crime production technology exhibits constant returns to scale and takes the following form:

$$C_t = N_t^C \tag{B.3}$$

Criminal activity also generates a return in terms of the consumption good. However, the total returns from crime in the economy is zero. Thus, the budget constraint facing an individual can be written as:

$$X_t = A_t N_t^X + Q_t N_t^C - Q_t \overline{C_t} \tag{B.4}$$

where, A_t and Q_t are the real marginal returns to labor and crime, respectively. The average crime per capita is represented by $\overline{C}_t$, and thus the average expected loss of income due to crime is $Q_t \overline{C_t}$.

[8]It would be reasonable for the average aggregate crime production, $\overline{C}_t$, to enter in negatively into the utility function. However, since $\overline{C}_t$ is not a choice variable and as long as it enters additively into the utility function, such amendment to (B.1) does not affect the proceeding analysis.

A.2 Policy Instruments

Policymakers are assumed to be able to control the level of enforcement (e.g., police per capita). If more resources are allocated to enforcement, the probability of apprehending a crimnal is assumed to increase. Denote the level of enforcement by E_t and the probability of incarceration by Φ_t. As dicussed in the main text it is reasonable to assume a one period policy lag. That is, last period's enforcement level determines the current period's probability of getting incarcerated. Assuming a linear relationship between enforcement and Φ, we have:

$$\Phi_t = GE_{t-1} \tag{B.5}$$

A.3 The Effective Labor Endowment and Criminal Activity

The key to the agent's forward-looking behavior in our model is the relationship between past criminal activity and an individual's effective labor endowment today. As discussed in the main text, past criminal activity is likely to affect an individual's current labor market outcomes negatively. It is also reasonable to assume that this impact is less the further back in time the criminal activity occurred. Consequently, we model the potential loss in today's labor endowment, J_t , as the discounted sum of current and past criminal activity. That is,

$$J_t = \Psi \sum_{i=0}^{\infty} \sigma^i C_{t-i} \tag{B.6}$$

were $0 \leq J_t \leq 1$ and σ is the discount rate.[9]

A.4 Crime Dynamics

Given the set-up in the previous section, the maximization problem facing the infinitely lived representative agent can be described as:

$$\max_{X,C} \sum_{i=0}^{\infty} \beta^i U\left(X_{t+i}, C_{t+i}\right) \tag{B.7}$$

subject to

$$s.t\ X_t = A_t\left(1 - \Phi_t J_{,t} - C_t\right) + Q_t\left(C_t - \overline{C_t}\right) \tag{B.8}$$

where β is the discount factor. Using Lagrangian multipliers we can rewrite the optimization problem as:

$$\max_{X,C} \sum_{i=0}^{\infty} \beta^i E_t \left\{U\left(C_{t+i,} X_{t+i}\right) + \varphi_{t+i}\left[A_t\left(1 - \Phi_t J_{,t}\right) + \left(Q_t - A_t\right) C_t - Q_t \overline{C_t} - X_{t+i}\right]\right\}$$

[9] We have simplified the the punsiment mechanism in the sense that it does not matter for the current punishment whether past criminal activity has gone unpunished or not. In a more elaborate model such an assumption may altered.

The first order conditions can then be derived as:

$$\alpha - \varphi_t = 0$$

$$\begin{aligned} 0 = \chi \left(C_t - \gamma C_{t-1}\right)^{-\eta} + \quad & \varphi_t \left[\left(Q_t - A_t\right) - \left(A_t \Phi_t \frac{\partial J_t}{\partial C_t} \right) \right] \\ & + \beta E_t \varphi_{t+1} \left[- \left(A_t \Phi_t \frac{\partial J_{t+1}}{\partial C_t} \right) \right] \\ & + \beta^2 E_t \varphi_{t+2} \left[- \left(A_t \Phi_t \frac{\partial J_{t+2}}{\partial C_t} \right) \right] \\ & + \ldots\ldots\ldots\ldots \end{aligned}$$

From expression (B.6) we have that:

$$\frac{\partial J_{t+i}}{\partial C_t} = \Psi \sigma^i$$

Combining the FOCs we have:

$$\chi \left(C_t - \gamma C_{t-1}\right)^{-\eta} + \alpha \left(Q_t - A_t\right) = \alpha E_t \Psi \sum_{i=0}^{\infty} \left(\beta \sigma\right)^i A_{t+i} \Phi_{t+i} \tag{B.9}$$

Log linearizing (B.9) we have:

$$\begin{aligned} & c_t - \gamma c_{t-1} - \frac{\left(1-\gamma\right)\left(1-\beta\sigma\right)}{\eta\left[A\Phi\Psi - \left(1-\beta\sigma\right)\left(Q-A\right)\right]} \left(Q q_t - A a_t\right) \\ = \quad & -\frac{\left(1-\gamma\right) A\Phi\Psi}{\eta\left[A\Phi\Psi - \left(1-\beta\sigma\right)\left(Q-A\right)\right]} E_t \sum_{i=0}^{\infty} \left(\beta\sigma\right)^i \left(a_{t+i} + \phi_{t+i}\right) \end{aligned} \tag{5}$$

where variables denoted by lower case letters represent the percentage deviation around their steady state levels (denoted by upper case letters). Assume the following notation:

$$\Gamma_q = \frac{\left(1-\gamma\right)\left(1-\beta\sigma\right) Q}{\eta\left[A\Phi\Psi - \left(1-\beta\sigma\right)\left(Q-A\right)\right]}$$

$$\Gamma_a = \frac{\left(1-\gamma\right)\left(1-\beta\sigma\right) A}{\eta\left[A\Phi\Psi - \left(1-\beta\sigma\right)\left(Q-A\right)\right]}$$

$$\lambda = \frac{\left(1-\gamma\right) A\Phi\Psi}{\eta\left[A\Phi\Psi - \left(1-\beta\sigma\right)\left(Q-A\right)\right]}$$

Which gives us:

$$c_t - \gamma c_{t-1} - \Gamma_q q_t + \Gamma_a a_t = -\lambda E_t \sum_{i=0}^{\infty} \left(\beta\sigma\right)^i \left(a_{t+i} + \phi_{t+i}\right) \tag{B.11}$$

Forwarding the expression we have:

$$\beta\sigma E_t\left[c_{t+1}-\gamma c_t-\Gamma_q q_{t+1}+\Gamma_a a_{t+1}\right]=-\lambda E_t\sum_{i=0}^{\infty}(\beta\sigma)^i\left(a_{t+1+i}+\phi_{t+1+i}\right)$$

Thus we have,

$$\begin{aligned} c_t &= \gamma c_{t-1}+\Gamma_q q_t-\Gamma_a a_t-\lambda\left(a_t+\phi_t\right) && (6)\\ &\quad +\beta\sigma E_t\left[c_{t+1}-\gamma c_t-\Gamma_q q_{t+1}+\Gamma_a a_{t+1}\right] && (7)\end{aligned}$$

For simplicity, assume that q_t and a_t are white noise variables. It is then possible to rewrite (B.12) as:[10]

$$(1+\beta\sigma\gamma)\,c_t=\gamma c_{t-1}+\Gamma_q q_t-(\Gamma_a+\lambda)\,a_t-\lambda\phi_t+\beta\sigma E_t c_{t+1}$$

which gives us:

$$\begin{aligned} c_t &= \left(\frac{\gamma}{1+\beta\sigma\gamma}\right)c_{t-1}+\left(\frac{\Gamma_q}{1+\beta\sigma\gamma}\right)q_t-\left(\frac{\Gamma_a+\lambda}{1+\beta\sigma\gamma}\right)a_t && (8)\\ &\quad -\left(\frac{\lambda}{1+\beta\sigma\gamma}\right)\phi_t+\left(\frac{\beta\sigma}{1+\beta\sigma\gamma}\right)E_t c_{t+1}\end{aligned}$$

Equation (B.13) is equivalent to equation (**??**) in the text. It states that the current crime rate is directly related to returns to crime, q_t, and the future expected crime rate. However it is inversely related to economic returns to "honest" labor, a_t, and enforcement (as represented by ϕ_t).

B 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.

[10] Alternatively, the return to crime and the return to honest labor (i.e., q_t and a_t) can be modeled as autoregressive processes. This would allow the possibility to model persistent shifts in these variables.

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. 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/).

6. 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.

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Table 1 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
Growth rate of real per cap. state. inc.	1.67	28.36	-17.14		2.83	1938
				within=	2.82	$\bar{T}$=38
				between=	0.27	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 - Base Property Crime Model

	OLS	GMM
Property crime rate $(t+1)$		0.651***
		(0.130)
Property crime rate $(t-1)$		0.233**
		(0.110)
Unemployment rate	0.026**	0.033***
	(0.011)	(0.012)
Growth rate of real per cap. state. inc.	-0.001	-0.001
	(0.001)	(0.001)
Poverty rate	0.012	0.021
	(0.012)	(0.013)
Percent pop. 15 to 17 years old	-0.016	0.060
	(0.092)	(0.090)
Percent pop. 18 to 24 years old	0.078	0.023
	(0.069)	(0.091)
Percent pop. 25 to 34 years old	0.009	-0.079
	(0.063)	(0.083)
Percent pop. black	-0.095**	-0.059
	(0.042)	(0.065)
Percent pop. in metro area	0.003**	0.005**
	(0.001)	(0.003)
Police per capita $(t-1)$	-0.032**	-0.054***
	(0.014)	(0.014)
Prisoners per capita $(t-1)$	-0.039**	-0.039**
	(0.017)	(0.018)
N	1655	1593
Adjusted R2	0.525	0.359
Hansen J		14.691
Hansen p-value		0.994

Notes: The dependent variable is the state annual property crime rate (property crimes per 100,000). All models are estimated in logged differences. For the GMM estimates, the instrument list includes 1st and 2nd order lagged log-differences and log levels of independent variables, and 2nd and 3rd order lagged log-differences, and the 2nd order lagged level of the dependent variable. All estimates include dummy variables for each time period. The GMM equation was estimated using **STATA**'s `ivreg2`.

Table 3 - Base Violent Crime Model

	OLS	GMM
Violent crime rate $(t+1)$		0.533***
		(0.132)
Violent crime rate $(t-1)$		0.365***
		(0.128)
Unemployment rate	-0.018	0.034*
	(0.021)	(0.020)
Growth rate of real per cap. state. inc.	0.001	0.001
	(0.002)	(0.001)
Poverty rate	-0.013	0.023
	(0.020)	(0.020)
Percent pop. 15 to 17 years old	-0.155	-0.091
	(0.167)	(0.161)
Percent pop. 18 to 24 years old	0.060	-0.088
	(0.075)	(0.119)
Percent pop. 25 to 34 years old	-0.071	-0.189
	(0.185)	(0.167)
Percent pop. black	0.096	0.051
	(0.101)	(0.093)
Percent pop. in metro area	-0.001	-0.010
	(0.004)	(0.007)
Police per capita $(t-1)$	-0.070***	-0.078***
	(0.024)	(0.022)
Prisoners per capita $(t-1)$	-0.101***	-0.078**
	(0.032)	(0.031)
N	1705	1599
Adjusted R2	0.259	-0.032
Hansen J		26.657
Hansen p-value		0.689

Notes: Dependent variable is the state annual violent crime rate (violent crimes per 100,000.) See table 2 notes for further explanation.

Table 4 Additional Specifications: Property Crime Rate

	FE	FEIV	IV	GMM
Property crime rate $(t+1)$	0.507***	0.610***	0.650***	0.651***
	(0.013)	(0.083)	(0.144)	(0.130)
Property crime rate $(t-1)$	0.490***	0.410***	0.232*	0.233**
	(0.013)	(0.067)	(0.130)	(0.110)
Unemployment rate	0.006	0.007	0.032**	0.033***
	(0.005)	(0.005)	(0.013)	(0.012)
Growth rate of real per cap. state. inc.	-0.001*	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Poverty rate	0.007	0.013	0.022*	0.021
	(0.008)	(0.010)	(0.013)	(0.013)
Percent pop. 15 to 17 years old	0.003	-0.008	0.027	0.060
	(0.023)	(0.024)	(0.086)	(0.090)
Percent pop. 18 to 24 years old	0.020	0.009	0.008	0.023
	(0.018)	(0.019)	(0.065)	(0.091)
Percent pop. 25 to 34 years old	0.015	0.001	-0.084	-0.079
	(0.020)	(0.021)	(0.078)	(0.083)
Percent pop. black	-0.002	0.005	-0.079*	-0.059
	(0.006)	(0.008)	(0.044)	(0.065)
Percent pop. in metro area	0.002	0.002	0.005	0.005**
	(0.003)	(0.003)	(0.004)	(0.003)
Police per capita $(t-1)$	-0.016	-0.017	-0.049**	-0.054***
	(0.012)	(0.012)	(0.021)	(0.014)
Prisoners per capita $(t-1)$	-0.005	-0.001	-0.038**	-0.039**
	(0.005)	(0.005)	(0.017)	(0.018)
N	1756	1648	1593	1593
Adjusted R2	0.964		0.361	0.359
Sargan			15.896	
Sargan P-value			0.989	
Hansen J			15.896	14.691
Hansen p-value			0.989	0.994

Notes: Dependent variable is the state annual property crime rate (property crimes per 100,000.) All estimates include time period dummy variables. Columns **FE** and **FEIV** are estimated in levels. Column **FEIV** is estimated using 1st and 2nd order logged levels of the independent variables and 2nd and 3rd order logged levels of the dependent variable used as instruments. See table 2 notes for further explanation of the estimation of columns **IV** and **GMM**.

Table 5 Additional Specifications : Violent Crime Rate

	FE	FEIV	IV	GMM
Violent crime rate $(t+1)$	0.499***	0.456***	0.366***	0.533***
	(0.014)	(0.066)	(0.128)	(0.132)
Violent crime rate $(t-1)$	0.501***	0.543***	0.460***	0.365***
	(0.014)	(0.055)	(0.118)	(0.128)
Unemployment rate	-0.000	0.005	0.020	0.034*
	(0.009)	(0.009)	(0.020)	(0.020)
Growth rate of real per cap. state. inc.	0.001	0.002**	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Poverty rate	-0.006	-0.012	0.003	0.023
	(0.014)	(0.015)	(0.022)	(0.020)
Percent pop. 15 to 17 years old	-0.021	-0.030	-0.195	-0.091
	(0.040)	(0.040)	(0.140)	(0.161)
Percent pop. 18 to 24 years old	0.015	0.008	-0.124	-0.088
	(0.031)	(0.035)	(0.113)	(0.119)
Percent pop. 25 to 34 years old	0.001	-0.019	-0.264**	-0.189
	(0.035)	(0.036)	(0.130)	(0.167)
Percent pop. black	0.000	0.003	0.125*	0.051
	(0.011)	(0.011)	(0.072)	(0.093)
Percent pop. in metro area	-0.001	-0.003	-0.010	-0.010
	(0.005)	(0.006)	(0.007)	(0.007)
Police per capita $(t-1)$	-0.033*	-0.033	-0.102***	-0.078***
	(0.020)	(0.021)	(0.036)	(0.022)
Prisoners per capita $(t-1)$	-0.013*	-0.012	-0.079***	-0.078**
	(0.008)	(0.008)	(0.028)	(0.031)
N	1759	1651	1599	1599
Adjusted R2	0.939		0.022	-0.032
Sargan			48.965	
Sargan P-value			0.021	
Hansen J			48.965	26.657
Hansen p-value			0.021	0.689

Notes: Dependent variable is the state annual violent crime rate (violent crimes per 100,000.) See table 4 notes for further explanation of estimation procedures.

Table 6 - Short and long run elasticities

	Short Run Elasticities	Long Run Elasticities
Property Crime:		
Police Per Capita	-0.054	-0.466
Imprisonment Rate	-0.039	-0.336
Unemployment Rate	0.033	0.284
Violent Crime:		
Police Per Capita	-0.078	-0.765
Imprisonment Rate	-0.078	-0.765
Unemployment Rate	0.034	0.333

Notes: Elasticities are computed using GMM estimates from tables 6 and 7.

Table 7 - Property Index Crimes

	Robbery	Larceny	Burglary	Automobile
Index Crime$(t+1)$	0.590***	0.620***	0.280**	0.587***
	(0.176)	(0.138)	(0.127)	(0.156)
Index Crime$(t-1)$	0.235*	0.279**	0.322***	0.309*
	(0.134)	(0.111)	(0.118)	(0.167)
Unemployment rate	0.071**	0.030***	0.026*	0.008
	(0.031)	(0.012)	(0.015)	(0.029)
Growth rate state inc.	0.003	0.000	-0.002**	0.000
	(0.003)	(0.001)	(0.001)	(0.001)
Poverty rate	0.006	0.031**	-0.001	0.006
	(0.033)	(0.014)	(0.016)	(0.026)
Percent 15 to 17	0.016	0.045	0.018	0.026
	(0.217)	(0.092)	(0.119)	(0.173)
Percent 18 to 24	-0.014	0.060	-0.101	0.086
	(0.167)	(0.097)	(0.084)	(0.157)
Percent 25 to 34	-0.332	-0.078	0.001	-0.062
	(0.224)	(0.084)	(0.111)	(0.205)
Percent black	0.112	-0.063	-0.108	-0.165
	(0.157)	(0.067)	(0.080)	(0.132)
Percent metro	0.001	0.007***	0.002	-0.001
	(0.006)	(0.003)	(0.003)	(0.003)
Police per capita $(t-1)$	-0.064**	-0.063***	-0.046**	-0.029
	(0.032)	(0.015)	(0.019)	(0.030)
Prisoners per capita $(t-1)$	-0.105*	-0.031	-0.060***	-0.069*
	(0.053)	(0.019)	(0.021)	(0.039)
D.yr37	-0.042*	0.011	0.023	-0.056***
	(0.023)	(0.009)	(0.015)	(0.019)
Constant	-0.051***	0.005	0.005	-0.040***
	(0.017)	(0.007)	(0.011)	(0.014)
N	1599	1599	1599	1599
Adjusted R2	-0.111	0.321	0.387	-0.029
Hansen J	21.436	19.480	29.165	22.329
Hansen p-value	0.900	0.946	0.561	0.872

Notes: Estimation method is the same as the GMM estimates from table 6

Table 8 - Violent Index Crimes

	Murder	Rape	Assault
Index Crime($t+1$)	-0.390**	0.440**	0.466***
	(0.160)	(0.172)	(0.134)
Index Crime($t-1$)	0.011	0.082	0.536***
	(0.061)	(0.092)	(0.143)
Unemployment rate	-0.055	0.048	0.019
	(0.043)	(0.034)	(0.028)
Growth rate state inc.	0.007**	-0.001	0.002
	(0.003)	(0.002)	(0.002)
Poverty rate	0.043	0.001	0.028
	(0.051)	(0.034)	(0.027)
Percent 15 to 17	-0.435	-0.548**	-0.036
	(0.365)	(0.234)	(0.222)
Percent 18 to 24	0.602**	0.072	-0.190
	(0.305)	(0.165)	(0.153)
Percent 25 to 34	-0.289	-0.034	-0.279
	(0.310)	(0.190)	(0.217)
Percent black	-0.446*	0.235*	0.066
	(0.243)	(0.133)	(0.132)
Percent metro	-0.005	0.007	-0.020**
	(0.009)	(0.008)	(0.009)
Police per capita ($t-1$)	0.003	-0.091**	-0.169***
	(0.063)	(0.042)	(0.033)
Prisoners per capita ($t-1$)	-0.044	-0.068	-0.061
	(0.067)	(0.044)	(0.043)
D.yr37	-0.038	0.060**	0.004
	(0.037)	(0.025)	(0.020)
Constant	-0.034	0.019	-0.009
	(0.026)	(0.017)	(0.015)
N	1599	1599	1599
Adjusted R2	0.240	-0.272	-0.255
Hansen J	34.299	41.927	19.549
Hansen p-value	0.312	0.091	0.945

Notes: Estimation method is the same as that used for the GMM estimates from table 6.

Table 9 - The Crime Drop 1991-2004

	1991	2004	% Change	Property Crime Drop	Violent Crime Drop
Crime					
Property Crime	5140	3517	-37%		
Violent Crime	758	465	-47%	Potential Contribution to:	
Enforcement				Property Crime Drop	Violent Crime Drop
Police per capita	2.79	3.07	+10%	5%	8%
Incarceration Rate	298	435	+37%	12%	28%
Economics					
Unemployment Rate	5%	4%	-22%	6%	7%
			Total:	21%	43%

Notes: All values are computed by computing a population-weighted average across states. Police per capita is per 10,000 population. Both crime rates and the incarceration rate are measured per 100,000 population. Infant mortality rates and police per capita is through 2003.

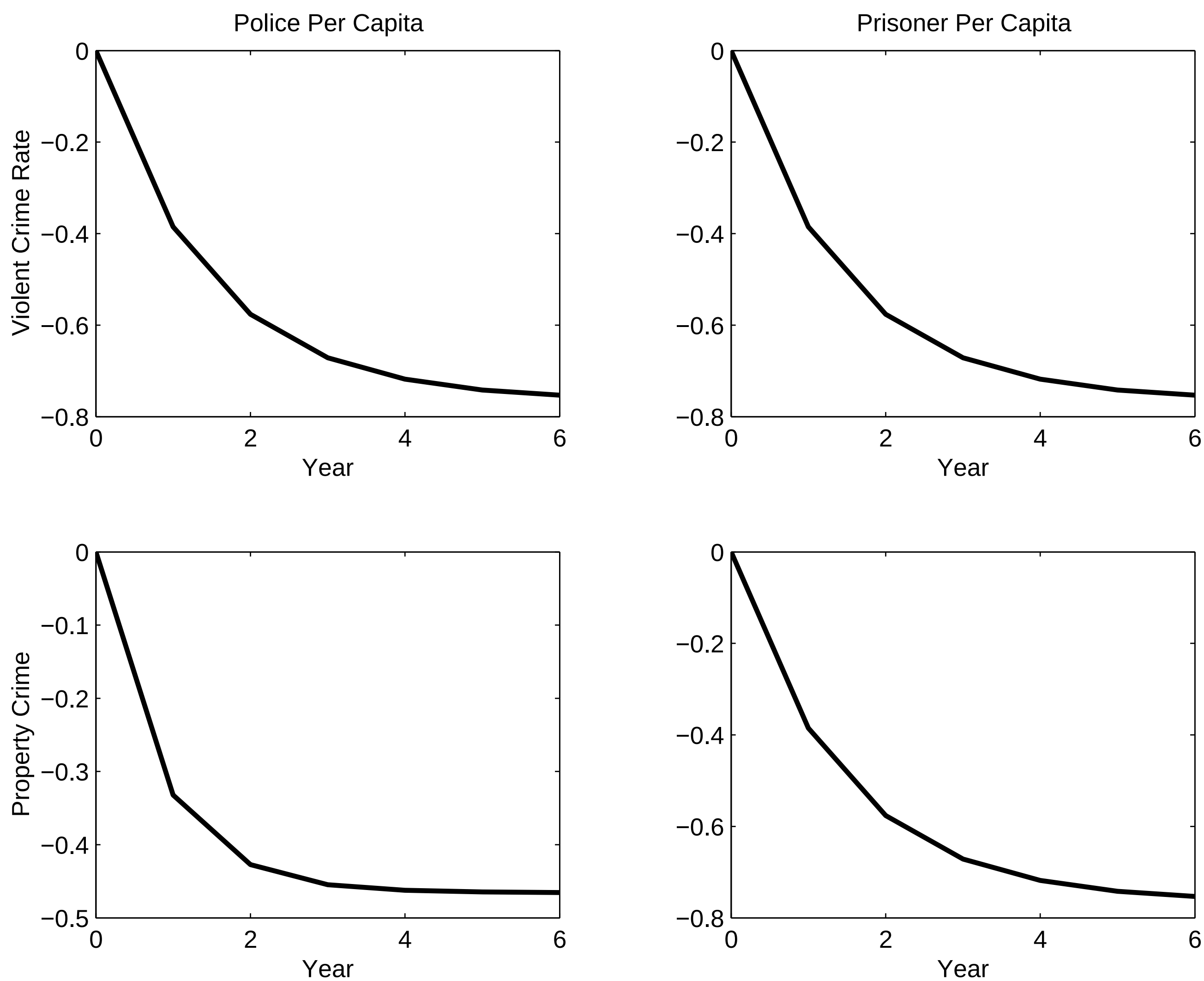

Figure 1 - Property crime rate response to a 1% change in police per capita and imprisonment rate per capita, using estimated coefficients from table 8