How to Catch Capone:
The Optimal Punishment of Interrelated Crimes

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Abstract

This paper characterizes optimal criminal punishments when there are multiple interrelated crimes. Optimal punishments are functions of the extent to which related crimes are complements or substitutes weighted by their relative harms to society. This insight applies more generally to Pigouvian taxation with costly administration: in a second-best setting, the optimal Pigouvian tax is partly a function of spillovers to other externality-generating activities. The available empirical evidence on the relationship between index crimes in the United States suggests that tailoring criminal punishments properly to incorporate relationships between crime could reduce the aggregate harm to victims by 3%, or about $8 billion dollars annually, for a given level of enforcement resources. The actual harm reduction of a marginal increase in arrests for an index crime is about 1.5-3 times greater than the harm reduction calculated without these effects.

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I Introduction

Crime places a heavy burden on society. A partial list of costs includes the direct harm from crime, decreased property values, policing, arresting, trying, convicting, sentencing, and incarcerating criminals, the lost contributions of those incarcerated, and the onus of wrongful convictions. Governments in the United States spent more than $260 billion in 2010 to administer criminal justice,\(^1\) and Anderson (1999) estimates the total burden of crime to be $1.7 trillion. Sentencing crimes optimally should decrease these burdens.

Most crimes are not committed in isolation. Al Capone headed a criminal organization that profited from bootlegging, prostitution, racketeering, and murder. He was tried and served a prison term, but his convictions were not for any of these crimes. He served time for tax evasion and contempt of court. In Capone’s case, the rules underlying the criminal justice system were certainly stretched (and possibly broken) to ensure that he ended up behind bars. Nonetheless his experience illustrates that (1) criminals often undertake many criminal actions; (2) the returns to these actions are a function of other criminal acts; (3) these actions vary in their social harm; and (4) these actions also vary in how costly they are to detect and punish.\(^2\) Thanks to the relationship between Capone’s more socially harmful crimes and tax evasion, it was probably optimal to convict him for tax evasion and give him the most severe sentence possible. More generally, basing part of the enforcement of crimes on related criminal activities can reduce the social burden of criminal activities.

A criminal may commit several different crimes contemporaneously, the same crime serially, or different crimes non-contemporaneously. This is not random chance; in many cases criminals can increase the profit of a crime by committing other crimes in conjunction or in series. Previous work has touched on this, suggesting for example that economies of scale or learning as a mechanism might increase the payoff from serial repetition (Aizer and

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\(^1\)U.S. Bureau of Justice Statistics.

\(^2\)A cost may be monetary but need not be. It may have been possible to convict Capone for his more socially harmful crimes, but doing so would have required an infringement on his rights that was socially too costly to bear.
Doyle, 2013). While both of these models suggest specialization, surveys of prisoners and records of criminals re-arrested for different crimes demonstrate that many criminals are generalists (Beck and Shipley, 1989). Empirical work supports this claim, finding that changing the punishment for one crime may have large and significant effects on the commission of other crimes (Levitt, 1998b; Kuziemko and Levitt, 2004; Benson et al., 1998; Shepherd, 2002).

It follows that if increasing the punishment of a crime leads to decreased commission of other crimes, then there is additional motivation to increase that punishment. If increasing the punishment of a crime leads to increased commission of other crimes, then there is cause to doubt that the punishment should be increased. Taking these cross-crime effects into consideration could reduce the total burden of crime. Our preliminary estimates suggest that re-allocating existing enforcement resources could reduce the harm to victims of index crimes by about $8 billion annually, which is about 3% of the total annual harm to victims of index crimes.\footnote{The FBI designates certain crimes as index crimes and uses these crimes to produce its annual report. These crimes have a standardized definition across states. In this paper, we consider the following index crimes: murder and non-negligent manslaughter; forcible rape; robbery, assault; burglary; larceny; and auto-theft.}

Our paper analyzes interrelated crimes. However, our model’s implications extend beyond criminal justice in two important ways. First, there is no need for the actions analyzed to be socially harmful acts. Second, there is no need for the punishment to be administered through the criminal justice system.

We illustrate the first point with the example of money laundering. In isolation, money laundering is not socially harmful—the launderer is simply obscuring her source of income. The benefit, however, of obscuring the source of income is high when that income is criminally derived or deployed, and this is why money laundering is criminalized. Stated differently, the punishment of money laundering is aimed at decreasing the commission of other acts, not money laundering itself. Similar logic applies to many other activities including many possessory and conspiratorial crimes.
The second extension of the model is to sanctions outside of the criminal justice system. The two most obvious bodies under which sanctions are issued are civil law courts and government regulatory agencies. Tort law affects the propensity to commit litigable acts, but it surely encourages and discourages other acts too. Government regulation, for example through corrective taxation, is also governed by our model. Although it is not the main focus of the paper, the additional insights regarding corrective taxation are significant because they suggest applications of this work to a variety of other settings such as the control of pollution, taxation of unhealthy foods, or subsidies for public health projects. Our model has purchase even outside of government structures—parents may set curfews (and corresponding punishments) for several reasons and likely not only because they object to their children being out late. Curfews may increase children’s sleep and homework completed or decrease their drug-use and hooliganism.

Legislatures, judiciaries, and prosecutors already informally take into consideration crime interdependence. Famously, Al Capone was convicted of tax evasion because enforcement agencies were unable to convict him for any of his other, more socially harmful, criminal acts. When statutory punishments are enacted, legislative records suggest that interrelation is sometimes taken into consideration. For example, legislatures have made claims about the effect of illegal immigration on criminal activity in support of a particular sanction on illegal immigration, and similar arguments are made concerning illegal drug use. The legislators’ analysis underlying these claims, however, may not be rigorous. We aim to provide machinery to improve this analysis.

In the following section we present a model of criminal activity and characterize the social planner’s optimal policy response. Sections II.2 and II.3 explain the difference between this result and other analyses of criminal activity. Section II.4 relates this result to an abstract Pigouvian tax setting. Section III relates insights about the optimal policy to observations of the criminal justice system. Section IV discusses prior estimates of the own-price elasticity of crime and the few studies which attempt to measure some type of cross price elasticity. Section IV.1 through IV.4 convert existing estimates into a welfare measure of the relative importance of our paper’s contribution.
Section V concludes.

II A Model of Interrelated Crimes

Our model considers individuals who allocate their time to various activities under a temporal budget constraint. These activities generate utility either directly or by generating income that can be used for consumption thus indirectly increasing utility. Some activities are socially harmful and some are socially harmless. We call the socially harmful activities crimes. This is in contrast to the common definition of crime as an activity which the law criminalizes—a definition we cannot use since punishment is endogenously determined.

A social planner may choose to punish activities. A punishment is an additional cost, borne by the criminal, of committing a crime. An obvious intuitive interpretation of punishment is an additional expected time cost of committing a crime, equal to the probability of conviction multiplied by the length of prison sentence or community service for an activity. Formally, these are the punishments in the model, but the insights are valid for other sanctions. For example, rehabilitation, fines, or a job training program could each be prescribed responses to conviction. We model the behavior of the individual as responding to a time cost, but the model could be extended to explicitly analyze more complex inputs into the individual’s decision making process.

II.1 Representative Agent Model

Becker (1968) models the decision to commit crime as the result of the maximization of a Von Neuman Morgenstern utility function $EU = pU(Y - f) + (1 - p)U(Y)$.

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4Heineke (1978); Ehrlich (1973) also uses this approach to individual behavior
5A more general version of the model would allow socially beneficial activities and describe the optimal policies governing them. The intuition of such a model is the same, but some activities would be subsidized.
6In a footnote, Becker recognizes that the payoffs for a given crime may depend on other aspects of the criminal justice system, particularly the punishments for other crimes because of substitution, but his
psychic gain, $f$ is the fine, and $p$ is the probability of punishment. Becker’s contribution focuses on the insight that criminals respond to incentives in the form of the probability $p$ and severity $f$ of punishment.

According to Becker’s famous result, high sanctions that completely deter are costless and optimal. As previous research has shown, this result does not hold when complete deterrence is infeasible. Since some crime will occur, high or maximal sanctions are not optimal because they must still be administered. This result also does not hold if threatening sanctions is costly. This is a realistic assumption for a variety of reasons, the most obvious being that both criminals and the criminal justice system are not completely deterministic. Mistakes, a lack of information, or criminal behavior that is not influenced by sanctions could all result in the threats being carried out, even if only infrequently. Even if complete deterrence is feasible, severe punishments may have additional costs to administer or monitor. Crimes that have severe punishments, and crimes that might be mistaken for a crime with a severe punishment (e.g. manslaughter may be difficult to distinguish from murder), should be more carefully investigated and more intensely litigated. As long as threats themselves have a potential cost, complete deterrence of offenders who are responsive to sanctions may be possible but not optimal.

We extend Becker’s work by modeling a representative agent who chooses how much of each of $n$ different activities to engage in. The individual is restricted by a temporal budget constraint with total time $T$. The activities are indexed $\{1, 2, \ldots, n\}$. The individual is a utility maximizer with preferences represented by a strictly quasi-concave, differentiable utility function. For each activity, $j$, she faces a time cost of $t_j$ and must decide what quantity of activity, $x_j$, to undertake. In addition to the time cost $t_j$, the government may impose sanctions for some of the activities. Following Becker, the punishments chosen by the government are described by two parameters for each activity $j$. $s_j$ is the sanction per unit of crime that the government detects, and $p_j$ is the probability of detection for activity $j$. The individual is risk neutral and thus responds only to changes in the expected time cost, including analysis considers only one crime.
punishment, of each activity. The individual’s problem can be written:

$$\max_{x_j \geq 0} U(x_1, ..., x_n) \text{ subject to } \sum_j (p_j s_j + t_j) x_j \leq T$$

The solution to the individual’s problem can be characterized by a set of demand functions $\mathbf{x}^* = \{x_1^*, x_2^*, ... x_n^*\}'$. Each demand function depends on the total time the individual has and the time prices she faces: $x_j^*(\sigma_1, ..., \sigma_n, T)$ where $\sigma_k = p_k s_k + t_k$. We omit $T$ from the demand function because we assume that it is constant.

The government, too, must solve an optimization problem. Its problem is to select a set of $2n$ parameters such that total social cost is minimized. The government faces three varieties of cost that combine to generate a cost function, $C$: (1) the direct cost of crime; (2) the cost associated with the vector of sanctions; and (3) the cost associated with detection. $C$ is increasing in all of its arguments. The government’s problem is:

$$\min_{p_j, s_j \geq 0} C(\mathbf{x}^*(\sigma_1, ..., \sigma_n), \mathbf{p}, \mathbf{s})$$

We assume that the cost function has second order conditions such that the local optimum is the unique global optimum. The government’s optimal policy is fully characterized by the first order conditions. The first order conditions are:

$$0 = \frac{\partial C}{\partial p_k} + \sum_j \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} \frac{\partial \sigma_k}{\partial p_k}$$

$$0 = \frac{\partial C}{\partial s_k} + \sum_j \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} \frac{\partial \sigma_k}{\partial s_k}$$

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7Because we model a representative agent and mean sanctions, the representative activity choices will not violate the budget constraint. Any given individual may violate her budget constraint depending on how often her criminal activity is detected. This is analogous to models of lifetime consumption decisions under uncertainty, in which a person could die with unspent wealth or unpaid debts.

8We write $\frac{\partial C}{\partial p_k}$ to denote the partial derivative of $C$ with respect to the second argument; we write $\frac{\partial C}{\partial x_j}$ to denote the partial derivative of $C$ with respect to the third argument.
The first order conditions carry the intuition that that the ‘cost’ of increasing $s_k$ or $p_k$ must equal the ‘benefit’ which is the fall in costs due to the decrease in all crime. The conditions can be used to solve for the optimal $s_k$ and $p_k$ as follows.\(^9\)

\[
    s_k = -\frac{\partial C}{\partial p_k} \sum_j \frac{\partial C}{\partial x_j} \frac{\partial x_j}{\partial \sigma_k} \\
    p_k = -\frac{\partial C}{\partial s_k} \sum_j \frac{\partial C}{\partial x_j} \frac{\partial x_j}{\partial \sigma_k}
\]

We define the elasticity of a crime rate with respect to enforcement against that crime as an own price elasticity and the elasticity of a crime with respect to another crime’s enforcement as a cross price elasticity.

**II.2 Complements and Substitutes**

We can distinguish activities that are complements, $\frac{\partial x_j^*}{\partial \sigma_k} < 0$, and substitutes, $\frac{\partial x_j^*}{\partial \sigma_k} > 0$, with activity $k$ and separate the above summand. We use the notation $\sum_+\!\!$ to refer to the sum over all activities $j$ that are gross substitutes with activity $k$, that is $\sum\!\!_+\!\! \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} = \sum\!\!_+ \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k}$. The notation $\sum_-$ refers to the analogous sum over all of the activities that are gross complements with activity $k$.

\[
    \sum\!\!_j \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} = \sum\!\!_+ \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} + \sum\!\!_- \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} + \frac{\partial C}{\partial x_k^*} \frac{\partial x_k^*}{\partial \sigma_k}
\]

\(^9\)This holds if the solution is interior. Otherwise:

\[
    s_k = \max \left\{ 0, -\frac{\partial C}{\partial p_k} \sum_j \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} \right\} \\
    p_k = \max \left\{ 0, -\frac{\partial C}{\partial s_k} \sum_j \frac{\partial C}{\partial x_j^*} \frac{\partial x_j^*}{\partial \sigma_k} \right\}
\]
Activity $k$ should be punished whenever:

$$
\sum_{-} \frac{\partial C}{\partial x_j} \frac{\partial x^*_j}{\partial \sigma_k} + \frac{\partial C}{\partial x_k} \frac{\partial x^*_k}{\partial \sigma_k} < - \sum_{+} \frac{\partial C}{\partial x_j} \frac{\partial x^*_j}{\partial \sigma_k}
$$

even if $k$ has no social cost (i.e. $\frac{\partial C}{\partial x_k} \leq 0$). Similarly, the optimal punishments sometimes leave socially harmful activities unpunished. Activity $k$ should go unpunished whenever:

$$
\sum_{-} \frac{\partial C}{\partial x_j} \frac{\partial x^*_j}{\partial \sigma_k} + \frac{\partial C}{\partial x_k} \frac{\partial x^*_k}{\partial \sigma_k} > - \sum_{+} \frac{\partial C}{\partial x_j} \frac{\partial x^*_j}{\partial \sigma_k}
$$

even if $k$ is socially harmful (i.e. $\frac{\partial C}{\partial x_k} > 0$). In fact, when the model is modified to allow for subsidies, the optimal sanctions may suggest a subsidy for certain criminal activities.

II.3 Comparison to the Naive Social Planner

The difference between our model and prior literature is the harm weighted sum of the response of related crimes:

$$
\sum_{+} \frac{\partial C}{\partial x_j} \frac{\partial x^*_j}{\partial \sigma_k} + \sum_{-} \frac{\partial C}{\partial x_k} \frac{\partial x^*_k}{\partial \sigma_k}
$$

We refer to this term as the correction for related crimes. When this term is positive (negative), activity $k$ is a harm weighted gross substitute (complement) to other activities. When an activity has a positive (negative) correction for related crimes, the optimal punishment is less (more) harsh than the naive punishment. Consider the behavior of a policymaker who does not recognize that crimes are interrelated. This ‘naive policymaker’ and the associated ‘naive punishments’ do not correctly maximize the social welfare function. The optimal punishments are higher (lower) than the naive punishments for activities which are complements (substitutes) with crimes.

II.4 Relationship to Pigouvian Taxation

These punishments bear some resemblance to a Pigouvian tax. Criminal punishment is a time tax designed to disincentivize socially harmful behaviors. The classic Pigouvian taxation result states that the tax is equal to the
marginal social harm at the optimal activity level. In our model the first-best activity levels are generally not optimal because administering punishment is costly (Kaplow, 1990; Polinsky and Shavell, 1982). Within this second best environment the optimal punishments are partly a function of spillovers from other externality producing activities.

By assumption every crime has a net social cost. Thus it is not optimal to set punishments sufficiently high to achieve first best levels. Instead the optimal activity levels are higher than their first best alternatives. Any optimal ‘tax’ in a setting with second best activity levels will be based on a weighted sum of other activities’ cross price elasticities and the externalities of those activities.

The features of our model are prominent features of the criminal justice system but are also present in any environment in which there is regulation of externality generating activities. For example, administrative cost, measurement error, and political power will likely make it suboptimal to induce the first-best activity levels for polluting activities. If this is the case, regulations and taxes should be set taking into account the spillover effects to other externality causing activities.

III  Applications of the Model

As mentioned in the introduction, legislatures are aware that crimes are interrelated.

“Simply put, prescription drug abuse is one of the fastest growing drug problems in the nation, resulting in ever increasing rates of robberies and other attendant crimes.” - US Senator Sherrod Brown advocating for enforcement against theft of prescription drugs

“Illegal aliens commit horrendous crimes against American citizens, crimes that strain State and Federal judicial systems, police and sheriff departments, and prisons that are already overcrowded and in a financial crisis.” - US Rep-
However, there is no evidence that interrelation is taken into consideration carefully or consistently. Although it is probably true that some immigrants commit other socially costly crimes, it is also likely that some undocumented immigrants avoid crimes with small payoffs because those crimes carry the additional risk of being caught for undocumented immigration. While punishing undocumented immigration may incapacitate some individuals who are committing a variety of crimes, strict enforcement against undocumented immigration will decrease the marginal deterrence of increased participation in other criminal activities. This is an application of marginal deterrence, originally discussed by Stigler (1970), to our model of multiple crimes. Whether enforcement of immigration law would increase undocumented immigrant’s participation in criminal activities is ultimately an empirical question. For a discussion of the existing evidence, see Bell and Machin (2013).

More generally, both unpunished substitutes and harshly punished complements exist in the US criminal justice system. For example, drug possession by itself causes no social harm. Drug possession is punished only because it is a complement with other harmful activities. Similarly, the punishments for carrying a concealed weapon are best explained by the argument that carrying a weapon is related to using it in a harmful way. The controversy around concealed carry laws is at least in part a controversy about whether concealed carry increases or decreases other socially harmful activities. There are numerous studies on both sides of this issue. For example, Lott and Landes (2000) consider whether more relaxed carry laws might increase the chance that others have guns and thereby deter shootings. On the other hand Duggan (2001) links higher rates of gun ownership to additional gun homicides.

In many cases our model suggests a logic underlying existing punishment schemes. For example, if drugs tend to be substitutes, our model explains why it may be optimal to criminalize most drugs, while leaving a few drugs, such as alcohol and tobacco, uncriminalized. This policy is optimal if for relatively low enforcement cost it steers users towards a select few drugs. The more harmful a drug, the better a candidate it makes to be criminalized.

resentative Mo Brooks discussing immigration reform
more inelastic its response to its own punishments, and the larger the cross price elasticities with costly activities, the better a candidate a drug makes to remain legal. Free needle exchanges take this reasoning one step further. If using a clean needle is a near perfect but less socially harmful substitute for sharing needles, then subsidizing a needle exchange is socially optimal.

Looking to medieval English law we find another interesting case. Pollock and Maitland (1899) state that burglary could be excused if committed by a hungry man whose aim was to steal a small amount of food. A sufficiently hungry man’s criminal acts to acquire food might be unresponsive to sanctions. The distinction between ‘theft for food when hungry’ and ‘other theft’ carves out an opportunity for the hungry man to commit a crime for food without society being forced to incur the costs of sanctioning the theft while retaining strong disincentives for other acts which cause more net social harm.

The examples in the section suggest that legislatures, judiciaries, and prosecutors already take into consideration crime interrelation. Nonetheless, some might find it odd that a person be punished for a socially harmless activity or that the punishment of one activity be based on the commission of another. This, however, is not as striking as it may initially seem. Note first that the model does not suggest a violation of due process. The criminal must perform an action to be sanctioned and a consistent sanction is applied to each punishable activity. Prior work by legal scholars discusses the significance of prosecutorial discretion when there is information about criminal activities other than the charged offense. Richman and Stuntz (2005) explain that such ‘pretextual prosecution’ is typically allowed under the argument that tax evasion, for example, is a legitimate crime and criminals should not be exempted from prosecution for tax evasion because they engage in more harmful illicit activities. Richman and Stuntz cite Wayte v. United States, 470 U.S. 598 (1985) as the leading case addressing this argument.

Second, the model does not require an expansion of punishment setting powers. Legislatures are free to map an activity to any sanction they like, subject to the constraint that the punishment not be cruel or unusual. If the sanction is a prison sentence and the criminal is a mentally competent adult,
the legislature is given nearly free reign.

Third, the model accepts the utilitarian premise that punishment should be socially optimal. It follows that the effect of punishing activity A on the commission of crime B should be included in the optimal sanction. Outside of a utilitarian structure a punishment may be considered a moral construct that depends only on the act it punishes, but a utilitarian framework cannot accept an a priori punishment—fair, right, or just punishments make sense only insofar as they affect individuals’ utility. It is inconsistent with utilitarianism to accept that a punishment should be designed to deter the crime that it punishes, but no other crime. The optimal utilitarian punishment must take into consideration all of its effects.

IV Empirical Evidence

A large literature attempts to relate policy variables, such as the death penalty, police force size, clearance rate, even gun ownership regulations and the existence of a state lottery, to crime rates. Some of these studies measure responsiveness in a way that can be interpreted as an own price elasticity. Very few studies measure anything like a cross price elasticity. Some studies measure responsiveness in a way that can be interpreted as an own price elasticity. However, very few studies measure anything like a cross price elasticity. Some studies use control variables which could proxy for a price of a related activity, but they do not systematically investigate the relationship. For example Mikesell and Pirog-Good (1990) examine the effect on crime rates of the existence of a state lottery. Corman and Mocan (2000) use Assistance for Families with Dependent Children as a control variable. One reason to include AFDC as a control variable is because it can proxy for the labor market opportunities of the individual. In this sense it is related to the ‘price’ of work in the mainstream labor market.

Kuziemko and Levitt (2004) calculate the the effect on the aggregate crime rate of imprisoning drug, property, or violent offenders. The effect of switching one type of offender for another, at the margin, is not statistically distinct
from zero. This is interpreted as suggestive evidence that some agents in the
criminal justice system are making adjustments in order to minimize the total
crime rate subject to the constraint of a fixed prison system size. Minimiz-
ing the aggregate crime rate is unlikely to coincide with optimal policy. As
described earlier in the paper, the optimal policy does not treat each type of
crime as equivalently costly.

The following two studies calculate cross price elasticities for a group of
crimes. Hakim et al. (1984) calculate cross price elasticities for different prop-
erty crimes using a set of simultaneous equations. Levitt (1998b) calculates
the elasticities of index crimes with respect to arrest rates for the crime itself
as well as the elasticity with respect to an aggregate of other violent crime
arrest rates and an aggregate of other property crime arrest rates.

<table>
<thead>
<tr>
<th>Study</th>
<th>Crimes studied</th>
<th>‘Prices’</th>
<th>Result</th>
</tr>
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<tbody>
<tr>
<td>Levitt</td>
<td>Index crimes</td>
<td>Arrest rates, arrest rates for groups of other index crimes</td>
<td>Cross price elasticities negative and about half the magnitude of own price elasticities; negative elasticities ∈ [−0.012, −0.298], robbery +0.062 with respect to pecuniary crime arrest rate; larceny +0.048 with respect to violent crime arrest rate</td>
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<td>(1998b)</td>
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<tr>
<td>Hakim et al.</td>
<td>Auto theft; burglary; larceny; robbery</td>
<td>Clearance rates</td>
<td>Negative own price elasticities ∈ [−0.171, −0.891]; most cross price elasticities are positive ∈ [−0.329, 1.444]</td>
</tr>
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The cross price elasticities calculated by Levitt (1998b) are about half as
large as own price elasticities. An important question to ask is how signifi-
cant these cross price elasticities are. A simple interpretation would be that
cross price effects should account for about half of punishments. Below we
detail more precise approaches to determining the importance of cross price
elasticities.
First, we estimate the potential gains from reallocating existing police resources across crimes. Additional details of these calculations can be found in the appendix. The computational method uses existing data to find the arrest rates which minimize the aggregate harm to victims of index crimes while keeping enforcement costs constant. Our approach is motivated in part by the availability of information about the cross price effects of crime.

IV.1 Sources of Data

We consider only index crimes and use data about the number of each type of offense and the number of arrests for each type of offense as reported in the FBI Uniform Crime Reports (UCR). The elasticities of crime rates with respect to arrest rates come from Levitt (1998b), and the reported costs for each additional crime come from McCollister et al. (2010). These costs include per crime cost to the criminal justice system, lost productivity of offenders, tangible costs to the victim and intangible costs to the victim. The estimates reported in McCollister are $8.98 million per murder, $241 thousand per rape, $42 thousand per robbery, and $107 thousand per assault. The harm for each burglary is $6462. The harm per incident of larceny is $3532 and the harm of auto theft is $10772 per offense.

IV.2 Computational Method

Levitt (1998b) reports elasticities of index crimes with respect to index crime arrest rates. We convert the elasticities reported by Levitt to an elasticity with respect to arrests. Arrests for crime \( i \), \( a_i \), can be interpreted as the ‘price’ of crime to the individual\(^\text{10}\), and the reported number of each crime, \( x_i \) can be interpreted as a ‘demand’ for crime. The demand for each crime has an elasticity with respect to each category of arrest. Assuming that these elasticities are constant over the relevant range of arrests, these are the demand functions describing the amount of each crime that occurs for any

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\(^{10}\text{For these computations we ignore the length of sanctions.}\)
given combination of arrests:

\[ x_j(a) = K_j \prod_i a_i^{\varepsilon_{ji}} \]

where \( K_j \) is a constant determined by the observed values of \( x_i \) and \( a_i \). \( \varepsilon_{ij} \) is the price elasticity of demand for crime \( j \) with respect to price \( i \).

We assume that the costs per offense, \( B_j \), reported in McCollister et al. (2010) are constant in the relevant region, so the total harm to victims is \( \sum_j B_j x_j(a) \). We compute the cost for an arrest of each type of crime (see appendix VI.2), and assuming that this cost \( A_i \) is constant in the relevant region, the problem of finding the arrest rates that minimize the harm to victims while holding enforcement costs constant is:

\[ \min \sum_j B_j x_j(a) \text{ subject to } \sum_i A_i a_i = \bar{A} \]

To compute the optimal arrest rates, we test combinations of arrests which satisfy the constraint \( \sum_i A_i a_i = \bar{A} \) and are within a certain range of the 2010 arrest rates. We then use the demand functions and per crime costs to compute the harm to victims associated with each of those combinations of arrests. These arrest rates map to crime levels which then map to total victim harm. We record the combination of arrests that yield the lowest total victim harm and then repeat the computation for arrests that are similar to that combination of arrests. This algorithm terminates when no tested vector of arrests lowers total victim harm.

**IV.3 Estimates of the Harm Reduction**

The 2010 crime levels correspond to a total victim harm of approximately $296 billion. Assuming that the current arrest rates are optimized using only own price elasticities (i.e. assuming the naive optimum) and keeping enforcement cost constant, using cross price elasticities reduces the harm to $288 billion. This represents a 3% reduction in harm to victims by reallocating
existing enforcement resources.

A similar exercise minimizes total victim harm allowing enforcement expenditures to vary. Because the cross price elasticities reported in Levitt are mostly negative, this approach causes enforcement expenditure to rise. The reduction of harm to victims is about $34 billion but is offset by a $19 billion increase in enforcement costs resulting in a net reduction in total cost of crime of $14 billion. These values are associated with large changes in levels of enforcement. Assumptions about the constant marginal harm of crime, the constant marginal cost of enforcement, and the constant Slutsky matrix are less tenable for large changes. Nonetheless, this suggests that changing enforcement levels based on cross-crime elasticities can have significant benefits in addition to the benefits of reallocating existing enforcement resources.

These estimates are conservative. These estimates only account for the seven index crimes and one aspect of expenditure on criminal justice. The harm from non-index crimes, wrongful convictions and other social burdens are not factored into these estimates. Additionally, Levitt groups crimes when making his estimates and his econometric specification suffers from division bias. We expect both of these factors to artificially reduce the variance in responsiveness across activities. The welfare impact of reallocating existing resources is driven by the variation in cross price elasticities, relative to own price elasticities. There may be a larger effect if the elasticities were computed for each crime arrest pair.

IV.4 Estimates of Marginal Effects

An alternative calculation of the significance of the cross price elasticities considers the effects of a small change from current enforcement levels. For example, a small increase in the enforcement against assault will decrease assaults. It will also affect other crime rates. The elasticities of each crime with respect to the arrest rate for each other crime allows us to calculate the change in the number of crimes that would occur in response to a change in each crime’s arrest rate.
Using the UCR data and Levitt’s elasticities we can calculate the change in the number of each index crime that would result from a 1% increase in the arrest rate for assault. Such an increase would lead to approximately 1306 fewer assaults according to Levitt (1998b). Using Levitt’s estimates the increase in assault arrest rates would decrease the number of murders by 14.3 and decrease the number of rapes by 6.6 but the change would increase the number of robberies by 213. The changes in property crimes would include 193 fewer burglaries, 1331 fewer larcenies and 301 fewer auto thefts.

Using per crime cost estimates from McCollister et al. (2010), we find that the assault arrest rate change described above would reduce the harm to victims by about $270 million. The decrease in assaults alone would be valued at $140 million, while the decreases in the number of murders and rapes would correspond to a decreased burden of $129 million and $1.5 million. The increase in robberies would increase the harm to victims by $9.0 million. The decrease in burglaries larcenies and auto thefts would correspond to reduced harms valued at $1.2 million $4.7 million and $3.2 million.

The significant insight from this calculation is that approximately half of the harm reduction is due to a reduction in crimes other than assault. In this example, the decline in murder represents a large fraction of the harm reduction from a marginal increase in arrests for assault. The actual benefits of raising the arrest rate for assault is almost 2 times as large as would be calculated by a policymaker who did not include the effect on other crimes. When we use a small negative value for the own price elasticity of murder, we find that cross crime effects only account for 10% of the marginal harm reduction. However, if we use Levitt’s measured, positive own price elasticity for murder, then increasing the arrest rate for murder actually increases the

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11The cross price elasticities reported by Levitt are for groups of crimes. To use the example of murder and nonnegligent manslaughter, Levitt reports the percentage change in the number of murders associated with a 1% change in the ‘arrest rate for violent index crimes excluding murder’. To calculate the change in the number of murders we first calculate the change in the ‘arrest rate for violent index crimes excluding murder’ which occurs when the arrest rate for assault rises 1%. In this example, the change in assault arrest rates causes the ‘arrest rate for violent index crimes excluding murder’ to rise by roughly 0.623%. Given the reported cross price elasticity of -0.129 and 14,722 murders in 2010, we calculate the decrease in murders reported above.
net harm to victims. If increasing arrests for murder increases the number
of murders, then the cross crime effects are the only gain from increased ar-
rests for murder. Repeating the calculations for the other arrest rates we
find that cross crime effects account for between 29% and 67% of the harm
reduction at the margin. Refer to the table in appendix VI.3 for more details.

V Conclusion

This paper generalizes prior work on criminal punishments by allowing
multiple interrelated crimes. The insights extend beyond crime to any en-
vironment with spillovers between socially harmful or beneficial activities.
When a friction makes first best activity levels suboptimal, the optimal pol-
icy intervention accounts for spillover effects of other externality generating
activities. Crime is an excellent application since the most common sanction,
incarceration, is sufficiently costly to ensure that the activities are not set to
their first best levels.

The main intuitive contribution is that complementary (substitutable)
crimes should be punished more (less) harshly than they would be if pun-
ishments were set for each crime in isolation. Moreover, making few as-
sumptions, we provide a precise formulation for how to find the optimal
punishments. The optimal punishment is proportional to the sum of the re-
 sponsiveness of each crime with respect to that punishment, weighted by the
measure of the costliness of that crime. A corollary of this insight is that
social harm is neither sufficient nor necessary for an activity to be punished
under the optimal criminal justice policy. The optimal punishments are based
on the relationships with all activities, whether they are criminalized or not
and whether they are harmful, beneficial, or benign. Some harmful activities
should not be punished at all because of their substitutability, while other
benign or beneficial activities should be punished because they are comple-
ments with harmful activities.

Applying this insight to criminal punishments promises significant bene-
fits to society. For index crimes alone and using conservative assumptions,
current enforcement spending could be reallocated to reduce the harm to victims by approximately $8 billion, or about 3% of the total harms to victims.

In future work we intend to allow nonlinear punishments in the model. We also plan to apply this paper’s insights to similar problems in Pigouvian taxation. Possible policy questions include the taxation of pollution, hiring based on big data (e.g. using zip code as a signal for future employee retention), taxation of unhealthy foods, subsidies for public health projects, and other principal agent problems with multiple activities.

References


VI Appendix

VI.1 Estimate of the Cost

Let $a_i$ be the arrests for crime $i$, $x_j$ be the quantity of crime $j$, and $C(x(a), q(a))$ be the total cost of crime. We define $q_i(a_i) = a_i \forall i$ for notational convenience. Each index crime $j$ is assumed to be a function of arrests for each index crime. We assume that $\frac{\partial C}{\partial q_i}$ and $\frac{\partial C}{\partial x_i}$ are constant. Thus the total cost of crime is:

$$
\sum_i \frac{\partial C}{\partial q_i} a_i + \sum_j \frac{\partial C}{\partial x_j} x_j(a_1, ..., a_n) = \sum_i A_i a_i + \sum_j B_j x_j(a_1, ..., a_n)
$$

where $A_i = \frac{\partial C}{\partial q_i}$ and $B_j = \frac{\partial C}{\partial x_j}$. The total differential of $x_j(a)$ is:

$$
dx_j = \sum_i \frac{\partial x_j}{\partial a_i} da_i = \sum_i \varepsilon(x_j, a_i) \frac{x_j}{a_i} da_i \implies \frac{dx_j}{x_j} = \sum_i \varepsilon(x_j, a_i) \frac{da_i}{a_i}
$$

where $\varepsilon(y, z)$ is the elasticity of $y$ with respect to $z$. Assuming that the elasticities are constant:

$$
\int \frac{1}{x_j} dx_j = \sum_i \left[ \varepsilon(x_j, a_i) \int \frac{1}{a_i} da_i \right] \implies \ln(x_j) = \sum_i \varepsilon(x_j, a_i) \ln(a_i) + k_j
$$

where $k_j$ is a constant of integration. We have:

$$
x_j = \exp \left[ \sum_i \varepsilon(x_j, a_i) \ln(a_i) + k_j \right] = e^{k_j} \prod_i \exp [\varepsilon(x_j, a_i) \ln(a_i)] = e^{k_j} \prod_i a_i^{\varepsilon(x_j, a_i)}
$$

We then return to the cost function as a function of $a$ only:

$$
C(a) = \sum_i A_i a_i + \sum_j \left[ B_j e^{k_j} \prod_i a_i^{\varepsilon(x_j, a_i)} \right]
$$

Our aim is:
\[
\min_{a_i \geq 0} C(a) \text{ such that } \sum_i A_i a_i = \bar{A}
\]

where \( \bar{A} \) is the total cost of arrest at the current level of arrests.

Solving this problem for index crimes requires estimates of \( A_i, B_j, \) and \( \varepsilon(x_j, a_i) \). McCollister et. al. provides \( B_j \). We use the reported information in McCollister et. al., Levitt, and the UCR to find \( A_i \) and \( \varepsilon(x_j, a_i) \).

Levitt reports elasticities of crimes with respect to arrest rates for own price elasticities and average arrest rates for cross price elasticities. For the own price elasticities, the elasticity with respect to arrests, \( \varepsilon(x_i, a_i) \), is the same as Levitt’s reported elasticity with respect to arrest rates, \( \varepsilon(x_i, \frac{a_i}{x_i}) \):

\[
\varepsilon(x_i, \frac{a_i}{x_i}) = \frac{\partial x_i}{\partial (a_i/x_i)} \frac{a_i/x_i}{x_i} \implies \\
\varepsilon(x_i, a_i) = \frac{\partial x_i}{\partial a_i} \frac{a_i}{x_i} = \frac{\partial x_i}{\partial a_i} \frac{a_i/x_i}{x_i} = \varepsilon(x_i, \frac{a_i}{x_i}) \cdot x_i \frac{1}{a_i/x_i x_i} = \varepsilon(x_i, \frac{a_i}{x_i})
\]

For cross price elasticities we must modify Levitt’s estimates. To convert Levitt’s elasticities to \( \varepsilon(x_j, a_i) \), we use the 2010 nationwide counts of crime and arrests from the UCR. Levitt reports the elasticity with respect to the arrest rate for substitute and non-substitute crimes, where violent crimes are assumed to be substitutes with each other and non-substitutes with pecuniary crimes and vice-versa. The equation for computing the cross price elasticity is the same for substitutes and non-substitutes. For example, if Levitt’s categories imply that crime \( j \) is not a substitute for crime \( i \), then using \( k \) as an index for all of the crimes that Levitt categorizes as non-substitute crimes including \( i \):

\[
\varepsilon(x_j, \frac{\sum a_k}{\sum x_k}) = \frac{\partial x_j}{\partial (\frac{\sum a_k}{\sum x_k})} \left( \frac{\sum a_k}{\sum x_k} \right) \implies \\
\varepsilon(x_j, \frac{\sum a_k}{\sum x_k}) = \frac{\partial x_j}{\partial \left( \frac{\sum a_k}{\sum x_k} \right)} \frac{\sum a_k}{\sum x_k} x_i
\]
\[ \varepsilon(x_j, a_i) = \frac{\partial x_i}{\partial \left( \frac{\sum a_k}{\sum x_k} \right)} a_i = \varepsilon(x_j, \sum a_k \frac{x_i}{\sum x_k}) \frac{1}{\sum x_k} \frac{a_i}{\sum a_k} = \varepsilon(x_j, \sum a_k \frac{x_i}{\sum x_k} \sum a_k) \]

If Levitt considers crime \( j \) a substitute for crime \( i \), then using \( h \) as an index for all of the crimes Levitt considers substitutes (\( j \) is not included in this set of crimes):

\[ \varepsilon(x_j, \sum a_h \frac{x_i}{\sum x_h}) = \frac{\partial x_j}{\partial \left( \frac{\sum a_h}{\sum x_h} \right)} \frac{\left( \sum a_h \right)}{\sum x_h} \]

\[ \varepsilon(x_j, a_i) = \frac{\partial x_i}{\partial \left( \frac{\sum a_h}{\sum x_h} \right)} a_i = \frac{\partial x_i}{\partial \left( \frac{\sum a_h}{\sum x_h} \right)} a_i = \varepsilon(x_j, \sum a_h \frac{a_i}{\sum x_h} \sum a_h) \]

Since Levitt reports a small positive own price elasticity for murder, this approach would imply that additional arrests for murder reduce costs, even in the absence of an effect on crime levels. To resolve this we replace the entry for murder’s own-price elasticity with a small negative value.

The Slutsky matrix is made up of these elasticities of demand for each crime with respect to the number of each type of arrest. The Slutsky matrix is not symmetric which may be because there are income effects and heterogeneous agents.

We can make the Slutsky matrix symmetric by averaging each pair of off diagonal terms, computing \( \frac{\varepsilon(x_j, a_i) + \varepsilon(x_i, a_j)}{2} \) and using that value for both \( \varepsilon(x_j, a_i) \) and \( \varepsilon(x_j, a_i) \). Leaving the Slutsky matrix asymmetric leads to similar results.

\( A_i \) is a measure of the costliness of arrests of type \( i \) computed as follows. If the arrest rates are set independently in order to control each crime separately, the own-price-elasticities and the victim harms imply a marginal cost \( A_i \) of additional arrests of type \( i \). This is equivalent to assuming that current punishments correspond to the naive punishments and computing the cost per arrest which satisfies the naive first order conditions. Equating the
marginal cost of additional arrests for crime \( i \) with the marginal decrease in harm to victims associated with crime \( i \) and rewriting the expression in terms of the information from McCollister et. al., Levitt, and the UCR:

\[
A_i = \frac{\partial C}{\partial x_i} \frac{\partial x_i}{\partial a_i} \implies A_i = B_i \varepsilon(x_i, \frac{a_i}{x_i}) \frac{x_i}{a_i}
\]

The vectors of arrests which satisfy the constraint \( \sum_i A_i a_i = \bar{A} \) can be constructed by creating random vectors in the null space of \( A \) and adding them to any vector which satisfies the constraint. By constructing many random combinations of arrests which satisfy the constraint, we can simply check which of those combinations of arrests has the lowest cost. We restrict the search to a region around a starting value, initially set at 2010 arrest rates, and repeat the process starting with the combination of arrests associated with the lowest cost from the previous iteration.

VI.2 Tables of Previous Empirical Work
<table>
<thead>
<tr>
<th>Study</th>
<th>Crimes studied</th>
<th>‘prices’</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marvell and Moody (1994)</td>
<td>Index crimes</td>
<td>Total prison population</td>
<td>Murder -0.065; Agg Assault 0.056; Robbery -0.260; Rape -0.113; Burglary -0.253; Larceny -0.138; Auto theft -0.200</td>
</tr>
<tr>
<td>Marvell and Moody (1996)</td>
<td>Index crimes</td>
<td>Number of police officers</td>
<td>Murder -0.36; Agg Assault -0.35; Robbery -0.63; Rape -0.20; Burglary -0.33; Larceny -0.22; Auto theft -0.85</td>
</tr>
<tr>
<td>Evans and Owens (2007)</td>
<td>Index crimes</td>
<td>Number of police officers</td>
<td>Elasticities: Murder -0.84; Rape -0.42; Agg Assault -0.96; Robbery -1.34; Burglary -0.59; Larceny -0.08; Auto theft -0.85</td>
</tr>
<tr>
<td>Levitt (1997)</td>
<td>Index crimes</td>
<td>Number of police officers</td>
<td>2SLS results</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Murder ∈ [-1.18, -3.05]; Rape ∈ [0.67, -0.27]; Agg Assault ∈ [-0.36, -1.09]; Robbery ∈ [-0.38, -1.20]; Burglary ∈ [-0.05, -0.58]; Larceny ∈ [0.26, -0.43]; Auto theft ∈ [0.14, -0.61]</td>
</tr>
<tr>
<td>Corman and Mocan (2000)</td>
<td>Murder, robbery, burglary, auto theft</td>
<td>Arrests; police</td>
<td>Elasticity with respect to arrests: Murder -0.34; Robbery -0.94; Burglary -0.36; Auto Theft -0.40</td>
</tr>
<tr>
<td>Shepherd (2002)</td>
<td>Index crimes</td>
<td>Truth In Sentencing legislation (increases punishment for violent felonies)</td>
<td>Murder: -1.178; Agg Assault -44.809; Robbery -39.615; Rape -4.226; Burglary 174.721; Larceny -89.486; Auto theft 70.252</td>
</tr>
<tr>
<td>Benson et al. (1992)</td>
<td>Aggregate Property</td>
<td>Probability of arrest</td>
<td>-0.826</td>
</tr>
<tr>
<td>Levitt (1998a)</td>
<td>Aggregate violent; aggregate property</td>
<td>Differences in juvenile and adult punitiveness</td>
<td>Violent -0.121 Property -0.050</td>
</tr>
<tr>
<td>Kessler and Levitt (1999)</td>
<td>Aggregate crime</td>
<td>Sentence enhancement legislation in California</td>
<td>After legislation, crime rates for crimes eligible for sentence enhancement diverge from ineligible crimes in California, relative to the national rates</td>
</tr>
<tr>
<td>Study</td>
<td>Crimes studied</td>
<td>‘prices’</td>
<td>Result</td>
</tr>
<tr>
<td>-----------------------</td>
<td>---------------------------------------------</td>
<td>--------------------------------------------------------------------------</td>
<td>------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Shepherd (2004)</td>
<td>Types of murder</td>
<td>Probability of sentence; probability of execution</td>
<td>Elasticities for seven subcategories of murder</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>By intimates: -0.04; Acquaintance -0.012; Stranger -0.002; Crime of Passion -0.04; Felonies -0.001; White -0.017; African American -0.02</td>
</tr>
<tr>
<td>Ehrlich (1975)</td>
<td>Murder</td>
<td>Probability of arrest, conditional probability of conviction, conditional probability of execution</td>
<td>Variety of specifications, reporting point estimates: Pₐ ∈ [-1.82, -2.25]; Pₑ</td>
</tr>
<tr>
<td>Dezhbakhsh et al. (2003)</td>
<td>Murder</td>
<td>Probability of arrest, conditional probability of conviction, conditional probability of execution</td>
<td>Pₐ ∈ [-2.184, -10.096]; Pₑ</td>
</tr>
<tr>
<td>Durlauf et al. (2010)</td>
<td>Murder</td>
<td>Probability of Arrest, Death Sentence and/or Execution</td>
<td>Net lives saved can vary greatly based on specification</td>
</tr>
<tr>
<td>Duggan (2001)</td>
<td>Gun and nongun homicide; all index crimes</td>
<td>One year lagged gun ownership (may be a proxy for victim precaution or a proxy for ease of committing violent crime)</td>
<td>Gun Homicide: 0.306; 0.223; nongun homicide: 0.020; 0.040; homicide: 0.180; 0.210; Agg Assault -0.007; -0.013; Robbery -0.016; 0.069; Rape -0.052; -0.092; Burglary -0.002; 0.094; Larceny 0.081; 0.032; Auto theft 0.043; 0.019</td>
</tr>
<tr>
<td>Lott and Mustard (1997)</td>
<td>Index crimes</td>
<td>‘shall issue’ laws (gun ownership - may be a proxy for victim precaution or a proxy for ease of committing violent crime)</td>
<td>Murder: -0.049; Agg Assault -0.0701; Robbery -0.0221; Rape -0.0527; Burglary 0.00048; Larceny 0.03342; Auto theft 0.0714</td>
</tr>
<tr>
<td>Kuziemko and Levitt (2004)</td>
<td>Aggregate crime</td>
<td>Share of prisoners incarcerated for violent, pecuniary, and drug crime</td>
<td>Cannot reject equal impact at the margin of incarcerating different types of prisoners</td>
</tr>
</tbody>
</table>
### VI.3 Table of the impact of a small change in each arrest rate

<table>
<thead>
<tr>
<th>1% increase in</th>
<th>Changes in each type of offense due to a 1% change in each arrest rate</th>
<th>Total harm reduction</th>
<th>Harm reduction from cross crime effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Murder arrests</td>
<td>Murder: -1.47, Rape: -0.18, Robbery: 5.83, Assault: -14.64, Burglary: -5.28, Larceny: -36.51, Auto Theft: -8.25</td>
<td>$14m</td>
<td>$1.6m</td>
</tr>
<tr>
<td>Robbery arrests</td>
<td>Murder: -3.94, Rape: -1.81, Robbery: -1225.38, Assault: -146.75, Burglary: -52.93, Larceny: -366.01, Auto Theft: -82.74</td>
<td>$106m</td>
<td>$54m</td>
</tr>
<tr>
<td>Assault arrests</td>
<td>Murder: -14.34, Rape: -6.57, Robbery: 212.55, Assault: -1305.68, Burglary: -192.54, Larceny: -1331.35, Auto Theft: -300.97</td>
<td>$270m</td>
<td>$131m</td>
</tr>
<tr>
<td>Burglary arrests</td>
<td>Murder: -1.05, Rape: -25.22, Robbery: -102.19, Assault: -27.75, Burglary: -6765.59, Larceny: 2388.87, Auto Theft: -409.06</td>
<td>$62m</td>
<td>$19m</td>
</tr>
<tr>
<td>Larceny arrests</td>
<td>Murder: -4.59, Rape: -110.65, Robbery: -448.38, Assault: -121.77, Burglary: -1272.88, Larceny: -17869.25, Auto Theft: -1794.84</td>
<td>$191m</td>
<td>$127m</td>
</tr>
<tr>
<td>Auto theft arrests</td>
<td>Murder: -0.26, Rape: -6.22, Robbery: -25.21, Assault: -6.85, Burglary: -71.57, Larceny: 589.34, Auto Theft: -547.28</td>
<td>$9.9m</td>
<td>$4.0m</td>
</tr>
</tbody>
</table>