Washington State
Institute for
Public Policy

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FIGHT CRIME AND SAVE MONEY:
DEVELOPMENT OF AN INVESTMENT TOOL FOR STATES TO STUDY SENTENCING AND CORRECTIONS PUBLIC POLICY OPTIONS

—*PROGRESS REPORT*—

Summary

Can knowledge about "what works" to reduce crime be used to help a state achieve a win-win outcome of: (1) lower crime, and (2) lower taxpayer spending? This progress report describes the work underway by the Washington State Institute for Public Policy (WSIPP) to develop an analytical tool for Washington, and perhaps other states, to identify evidence-based policy options to reduce crime rates and lower the taxpayer costs of the criminal justice system.

The Pew Charitable Trusts contracted with WSIPP to: (1) develop the tool, (2) apply it to the policy process currently underway in Washington State, and (3) help Pew make the tool available to other states.

We do not present "bottom-line" results in this report. Rather, this progress report simply describes the structure of the tool being constructed. The current plan calls for initial estimates by August 2010. In addition, the tool will be used to support the work of the legislatively directed study being conducted by the Washington State Sentencing Guidelines Commission.

In 2010, The Pew Charitable Trusts and the Washington State Institute for Public Policy (WSIPP) entered into a contract to identify fiscally sound, data-driven policies and practices in sentencing and corrections that protect public safety, hold offenders accountable, and control corrections' costs.

WSIPP is a nonpartisan research arm of the Washington State legislature. One duty is to provide analytical information on Washington's evidence-based and economics-based initiatives. In 1997, WSIPP built its first analytical tool to help the legislature identify cost-beneficial public policies that reduce crime. Since that time, WSIPP has continued to develop the tool, and the legislature has used the findings to alter a number of crime-related public policies in Washington.[1] The legislature has also directed WSIPP to expand the research areas to include K–12 education, early childhood human capital, child welfare, public health, mental health, and substance abuse. The legislature and the MacArthur Foundation have funded WSIPP's work in these varied topics.

The unifying theme in these efforts has been "to calculate the return on investment to taxpayers from evidence-based prevention and intervention programs and policies."[2] While broad in scope, these activities have centered on one straightforward question:

> *Are there more effective ways to use taxpayer dollars to affect particular public policy goals, such as public safety?*

The Pew contract with WSIPP augments this broader effort by focusing on criminal justice sentencing policies. The first task is to build a tool that analyzes adult sentencing policies from a return-on-investment point of view. Second, Pew asked WSIPP to apply the analytical framework to an evidence-based initiative underway in Washington State. Finally, Pew asked WSIPP to develop user-friendly software that would allow other states to use the sentencing tool to identify policy options that can reduce crime and save money.

This progress report describes the project as of April 2010. A full report on the analytical tool is scheduled for August 2010. During the later phase of the project, WSIPP will report on the policy development process in Washington and will also assist Pew in transferring the Washington model to other jurisdictions. The Pew-WSIPP contract terminates in March 2011.

Comments are welcomed and can be directed to Steve Aos at saos@wsipp.wa.gov, or 360-586-2740.

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[1] J. Maki with R. Lieb (2009). *Washington State Institute for Public Policy: Origins and governance,* Olympia: Washington State Institute for Public Policy, Document No. 09-06-4101.
[2] Chapter 564, Laws of 2009, Section 610 (4).

Three Project Elements

As mentioned, WSIPP's contract with Pew includes three main elements. The first element—which is the primary focus of this report—is the development of a general benefit-cost tool to study potential sentencing policy options. The second element is the application of the tool to the sentencing policy effort currently underway in Washington State. The third element is the development of software that will enable the tool to be used by other states, and the provision of assistance to Pew in making the tool available to other jurisdictions.

In this progress report, we briefly describe the status of the three project elements. Two technical appendices then focus more attention on the first project element.

Project Element 1: Development of the Sentencing Tool

WSIPP is developing a sentencing tool to help Washington, and perhaps other states, identify evidence-based policy mixes that can both fight crime and save taxpayers money. The draft model presented in this progress report does not contain final estimates; rather, this progress report describes the structure of the tool being constructed. As we note, the model employs a number of inputs and, at this time, we have not settled on a set of factors that have the most empirical support. Thus, the draft tool presented here reflects the approach we are developing, not specific results. By August 2010, the model will be used to present some initial empirical estimates for Washington State.

The goal of the tool is to help users analyze the net effects of two fundamental types of criminal justice policies available to states: sentencing-related policies and programming policies.

1) As used in this project, sentencing polices are those public policies that affect the average daily population in prison (or jail). They include sentencing policies that determine which convicted offenders go to prison, as well as those that determine the length of stay per sentence. These policies also include any discretion granted to judicial and executive branches that affect the actual length of time served in prison for a given sentence.

2) The second broad type of public policies analyzed reflects programming resources. For convicted offenders, programming resources are those efforts aimed at reducing the rate of criminal recidivism. Some programming resources are directly tied to sentencing resources; drug courts are examples. But most programming resources are used after sentences are handed down. Some programming resources are also "prevention" resources, such as early childhood education, where the goal is to achieve positive outcomes and avoid negative outcomes.

The modeling effort described here conceives of these two generic policies as part of a state's overall portfolio of "evidence-based" crime-fighting resources. That is, we believe there is credible evidence that certain types of incarceration (the product of sentencing policies) can lower crime rates. Similarly, there is evidence that certain types of programming can reduce crime. Both of these generic resources, however, cost taxpayers money.

The purpose of WSIPP's tool is to analyze both resources as a portfolio designed to achieve a more cost-beneficial mix between the two. If a state wants to fight crime and pinch (taxpayer) pennies, what are the tradeoffs between sentencing and programming resources? Some states may have, roughly, an optimal resource mix already, while others may not. The goal of the model is to detect reasonable evidence-based courses of policy action for those states that have opportunities to improve their mix of taxpayer-financed crime-fighting resources.

WSIPP's model is targeted at state-level decisions. This tool does not consider one important type of public resource: policing. Decisions on the level of policing and the deployment of policing resources are primarily matters for local government. A more complete analysis would consider all three resource types: prisons, programming, and policing. Future modeling work could add the significant taxpayer investment made in policing to the range of options analyzed in this modeling framework.

State Budget Shortfalls. As Pew has noted, public policies in the United States have resulted in a long-run increase in the use of incarceration. For the nation as a whole, the incarceration rate (the number of people in prison as a percentage of the total population) has almost tripled over the last two decades.[3]

Because of budget shortfalls in most states and because some states have also decided to re-examine their policy choices, many states have been considering public policies that would reduce levels of incarceration. If adopted widely, these policies would reverse the long-term trend in increased incarceration rates observed by Pew.

The sentencing policy reforms being considered or advocated in some states include: (a) sentencing policies that restrict the types of offenses that result in sentences to prison, (b) sentencing policies that reduce the length of prison sentences, or (c) legislative policies that grant the judicial or executive branches increased discretion of when offenders can be released from prison prior to completing sentence terms.

The Five-Step WSIPP Sentencing Tool.
The basic logic of the tool is straightforward: Can a state trade lower return-on-investment (ROI) crime-fighting resources for higher ROI resources to end up in a crime-neutral position and obtain fiscal savings for taxpayers?

The draft WSIPP model analyzes this question with the following five steps.

1) If a state decides to reduce its incarceration rate, what increase can it expect to see in its crime rate?
2) If a state decides to reduce its incarceration rate, what <u>net</u> decrease can it expect to see in its corrections' budget?
3) If a state uses all or a portion of the net fiscal savings (from step 2) to fund an increase in a portfolio of higher return-on-investment evidence-based programming, then how many avoided crimes can be expected?
4) Are there combinations of steps (1), (2), and (3) that can, on average, result in no net increase in crime and provide a net reduction in criminal justice public spending?
5) Given the uncertainty in these estimates, what are the chances that a course of action could lead to the undesirable results of less public safety and more taxpayer spending?

Uncertainty in the Estimates. As we will indicate, analyzing these policy tradeoffs involves a substantial amount of uncertainty. While there is an increasingly strong evidentiary base of knowledge about what works to reduce crime, there remains a considerable level of variation in particular estimates. To reflect this uncertainty, the fifth step in our modeling approach is designed to estimate the riskiness of any combination of policy options.

As with any investment decision, an investor wants to know the expected gain as well as the risk that the investment strategy could produce an undesired result. WSIPP's model is structured to provide this type of investment information. The bottom-line investment statistics that the draft WSIPP tool produces include the expected return on investment for a set of policy options, along with the risk that the mix of options could lead to less public safety.

The tool in its draft form currently resides on a Microsoft Excel spreadsheet. Uncertainty is addressed using a Monte Carlo simulation approach via the Excel add-on product @*RISK* by Pallisades Corporation. Our spreadsheet accompanies this progress report to Pew. As described below, by August 2010 this draft Excel model will become part of the larger stand-alone benefit-cost model WSIPP is developing.

Project Element 2: Application of the Tool to Washinton's Policy Process

With the financial support from Pew, WSIPP is assisting the Washington State Sentencing Guidelines Commission as it considers policy proposals. The 2009 Legislature directed the Commission to "develop a plan to implement an evidence-based system of community custody for adult felons."[4] Specifically, the Legislature directed the Commission to:

[3] J. Warren, A. Gelb, J. Horowitz, & J. Riordan (2008, February). *One in 100: Behind bars in America, 2008*. Washington, DC: Pew Center on the States, Public Safety Performance Project.

[4] Chapter 564, Section 225, Laws of 2009.

"include provisions for identifying cost-effective rehabilitative programs; identifying offenders for whom such programs would be cost-effective; monitoring the system for cost-effectiveness, and reporting annually to the legislature. In developing the plan, the sentencing guidelines shall consult with: the Washington state institute for public policy; the legislature; the department of corrections; local governments; prosecutors; defense attorneys; victim advocate groups; law enforcement; the Washington federation of state employees; and other interested entities."

The Sentencing Commission formed an Evidence-Based Community Custody (EBCC) committee to address these matters. The EBCC, which is co-chaired by Spokane County Superior Court Judge Kathleen O'Conner and King County Prosecutor Dan Satterberg, includes leaders from the courts, criminal justice attorneys, researchers, local government, and others. WSIPP has been an active participant and the EBCC intends to issue a plan that "will be accompanied by cost models from the Washington State Institute for Public Policy, so the Legislature can determine when and how to phase in the new system."[5] The EBCC intends to develop proposals for the 2011 Legislature, which convenes in January.

During 2010, WSIPP's model described in this report will be used to help measure the benefits and costs of any policy proposals that emerge from the Commission.

Project Element 3: Development of Software

During the next phase of the project, the draft spreadsheet model discussed in this report will be incorporated into an overall benefit-cost model that WSIPP is constructing. This larger modeling effort is being funded by the MacArthur Foundation and the Washington State Legislature. The goal of the larger project is to develop a stand-alone software application to study the benefits and costs of public policies that affect a number of outcomes, including crime, education, child welfare, mental health, substance abuse, employment, public health, and housing. This new model is building on and extending our previous benefit-cost work completed at legislative request.[6]

By August 2010, the draft spreadsheet-based model described in this report will be incorporated into the larger modeling effort.

Two Technical Appendices

This document contains two technical appendices. The first describes the structure of the draft sentencing tool being constructed by WSIPP. The second describes the elements of the larger WSIPP crime model used in the sentencing application.

Comments are welcomed. As always, our goal is to provide the Washington legislature with the best "evidence-based" investment advice we can, and constructive comments will help us achieve this end.

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[5] Washington State Sentencing Guidelines Commission. (2009, December). Evidence based community custody: A progress report from the Sentencing Guidelines Commission and Superior Court Judges' Association. Olympia, WA: Washington State Sentencing Guidelines Commission.

[6] Previous benefit-cost studies prepared by WSIPP for the Washington legislature include:
Evidence-Based Programs to Prevent Children from Entering and Remaining in the Child Welfare System: Benefits and Costs for Washington, Stephanie Lee, Steve Aos, Marna Miller, July 2008, document number 08-07-3901. See: http://www.wsipp.wa.gov/rptfiles/08-07-3901.pdf
Report to the Joint Task Force on Basic Education Finance: School Employee Compensation and Student Outcomes, Steve Aos, Marna Miller, Annie Pennucci, December 2007, document number 07-12-2201. See: http://www.wsipp.wa.gov/rptfiles/07-12-2201.pdf
Benefits and Costs of K–12 Educational Policies: Evidence-Based Effects of Class Size Reductions and Full-Day Kindergarten, Steve Aos, Marna Miller, Jim Mayfield, March 2007, document number 07-03-2201. See: http://www.wsipp.wa.gov/pub.asp?docid=07-03-2201
Evidence-Based Public Policy Options to Reduce Future Prison Construction, Criminal Justice Costs, and Crime Rates, Steve Aos, Marna Miller, Elizabeth Drake, October 2006, document number 06-10-1201. See: http://www.wsipp.wa.gov/rptfiles/06-10-1201.pdf
Evidence-Based Treatment of Alcohol, Drug, and Mental Health Disorders: Potential Benefits, Costs, and Fiscal Impacts for Washington State, Steve Aos, Jim Mayfield, Marna Miller, Wei Yen, June 2006, document number 06-06-3901. See: http://www.wsipp.wa.gov/rptfiles/06-06-3901.pdf
Evidence-Based Adult Corrections Programs: What Works and What Does Not, Steve Aos, Marna Miller, Elizabeth Drake, January 2006, document number 06-01-1201. See: http://www.wsipp.wa.gov/rptfiles/06-01-1201.pdf
Benefits and Costs of Prevention and Early Intervention Programs for Youth, Steve Aos, Roxanne Lieb, Jim Mayfield, Marna Miller, Annie Pennucci, July 2004, document number 04-07-3901.See: http://www.wsipp.wa.gov/rptfiles/04-07-3901.pdf

Technical Appendix A:
The Sentencing Tool

There are five analytical steps to the draft WSIPP sentencing tool, as reflected in the following chain of policy questions.

1) If a state decides to reduce its incarceration rate, what increase can it expect to see in its crime rate?
2) If a state decides to reduce its incarceration rate, what net decrease can it expect to see in its corrections budget?
3) If a state uses a portion of the net fiscal savings (from step 2) to reinvest in a portfolio of higher return-on-investment evidence-based programming, then how many crimes can be expected to be avoided?
4) Are there combinations of steps (1), (2), and (3) that can, together, reliably result in no net increase in crime and provide a net reduction in criminal justice public spending?
5) Given the uncertainty in these estimates, what are the chances that a course of action could lead to the undesirable results of less public safety and more taxpayer spending?

The tool requires a number of inputs in order to produce estimates for these five steps. In this technical appendix, we describe the inputs and computational procedures for each step.

Inputs to Step 1 (of 5): the Crime Effects of Sentencing-Related Policies.

As noted, the sentencing-related policies considered with WSIPP's tool are those that ultimately affect the incarceration rate in a state. These could be sentencing laws that determine which convicted offenders go to prison, how long the sentences are, or whether the executive branch has the discretion to shorten, or lengthen in some cases, sentences. Collectively, these generic sentencing-related policies affect a state's incarceration rate. The analytical task for Step 1 is to estimate the change in the number of crimes that a state could expect to see if incarceration rates are changed on the margin.

There is a fairly large collection of research literature on the effect of incarceration rates on crime.[7] Many of the studies addressing this relationship construct models using state-level data over a number of years to estimate the parameters of an equation of this general form:

$$(1) \quad C_{s,y} = a + b\left(ADP_{s,y}\right) + c\left(X_{s,y}\right) + e$$

In this type of model, crime, ***C***, in state, ***s***, and year, ***y***, is estimated to be a function of average daily prison population, ***ADP***, a vector of control variables, ***X***, and an error term, ***e***. Crime is usually measured with data from the FBI's Uniform Crime Reporting (UCR) system. The variables are divided by population so that they are expressed as rates. The models are almost always estimated with a log-log functional form, at least for the dependent and the main policy variables.

Marginal effects from this generic log-log crime model are then obtained with:

$$(2) \quad C\Delta = E \times \frac{\left(\frac{UCR}{ADP}\right)}{RRate},$$

In equation (2), ***E*** is the crime-prison (constant) elasticity obtained from coefficient ***b*** of the log-log estimation of equation (1), ***UCR*** is the reported crime rate (explained below), ***ADP*** is the incarceration rate (explained below), and ***RRate*** is the reporting rate to police by victims (also explained below). The marginal effects are usually calculated either at the mean values for ***ADP/UCR/RRates*** or the most recent values for ***ADP/UCR/RRates*** when the policy interest changes to current ADP levels. The log-log estimation of the constant elasticity ***E*** implies diminishing returns when incarceration rates are raised and increasing returns when ADP rates are lowered. Several authors have also observed that the state-level time-series data most often used to estimate equation (1) are likely to have unit roots.[8] Thus, to help avoid estimating spurious relationships, some authors estimate equation (1) in first-differences since the time series typically do not exhibit unit roots after differencing once.

[7] A recent survey of this literature and analysis of the empirical estimates from 35 studies is provided in T. B. Marvell (2009). ***Prison population and crime***. This paper will be published in Handbook on the Economics of Crime, Edited by Bruce L. Benson and Paul R. Zimmerman, Edward Elgar Publishing, September 2010.
[8] See, for example, Marvell (2009), W. Spelman (2008). Specifying the relationship between crime and prisons, ***Journal of Quantitative*** Criminology, 24, 149-178.

The dependent variable: crime. In the studies estimating these types of equations, crime is most often measured with data from the FBI's Uniform Crime Reports on the crimes reported to police. Some studies estimate a model of total crime reported to police, while other studies estimate two equations, one for violent crime reported to police, and one for property crime reported to police. Other studies further break the data down and estimate equations for the seven major types of crime aggregated in the UCR data: murder, rape, robbery, aggravated assault, burglary, theft, and motor vehicle theft.

All studies also recognize that not all crime is reported to police and is, thus, not measured in the UCR data. Accordingly, most authors, in drawing conclusions from their analyses, use information from the National Crime Victimization Survey (NCVS) to obtain estimates about how often crime victims say they report crimes to police. The reporting rate information is then used to adjust the coefficients from the parameters estimated with equation (1) to produce estimates of how the total amount of crime changes as prison population is altered (equation (2)).

The UCR data do not match directly with how some states, including Washington, define felony crimes. This applies to two types of crimes in particular: felony sex and theft/larceny. The UCR data only count rapes of females and victims under the age of 12. Additionally, there are other felony sex crime (e.g., child molestation) as defined by the Revised Code of Washington that are not included in the UCR rape category. Similarly, the UCR data count some types of theft crimes that are below the threshold of felony theft in Washington. As explained below, we make adjustments for these two crime types, since the focus of Washington's sentencing laws is felony crime.

The policy variable: average daily prison population. In virtually all studies in the literature, the policy variable of interest is prison average daily population. In most studies, this is measured as the total number of inmates, often expressed as an incarceration rate by dividing by a state population aggregate. Measuring ADP with the total number of offenders—as opposed to more refined categories of offenders such as violent, property, drug, or high-risk/low-risk offenders—is necessary in cross-state analyses, because that is the only information usually available.

Measuring ADP in this way, however, restricts the policy relevance of the findings from the studies. The reason is that the average prisoner is not a very good representation of all prisoners, at least in terms of criminal propensities. There is considerable evidence that offenders sentenced to prison (as well as offenders in general) are quite different in terms of the amount and types of crime they commit. For example, among offenders in Washington's current average daily population, there are some very high risk offenders and others with lower risk.[9]

The typical research study, however, only includes a measure of total ADP and, thereby, only measures the average effect of the average offender sentenced to prison. All of this averaging can mask important differences when it comes time to use the estimates to craft specific sentencing policies.

Given trends in sentencing policies in the United States, this poses at least two empirical problems. First, the average mix of offenders in prison has changed over time, sometimes dramatically. For example, in Washington State, there were virtually no offenders in prison for drug crimes prior to the mid-1980s. Sentencing laws were changed in the late 1980s and the average proportion of drug offenders in ADP increased substantially. The average risk for reoffense has also exhibited long-term trends. Among offenders released from prison in Washington, there has been a 23 percent increase in offenders' risk level between 1991 and 2005.[10] Thus, the average crime/ADP coefficient from most regressions may not be aligned with the current mix of offenders in a state's ADP.

The second reason why parameters in models like equation (1) are limited in their ability to inform actual policy choices facing legislatures is that policy decisions to raise or lower ADP are not usually across-the-board or "average" decisions. A legislature will rarely raise sentences for all types of crimes by a uniform amount, nor will a legislature typically lower sentences uniformly for all types of crimes (although this has been done). Much more often, a legislature will adjust sentencing statutes for particular types of crimes, rather than across-the board changes. If a legislature were to uniformly lower lengths of stay, for example, a high risk sex offender would be treated the same as a low risk drug offender. Since this is likely to be seen as an undesirable policy, if prison ADP is to be adjusted, legislative discussions are more likely to focus on at least some level of selectivity in which types of offenders are released early.

What this means is that the coefficients that are obtained from equations like (1) above can be thought of as only rough guides for the effectiveness of average sentencing changes but, given the wide heterogeneity of criminal propensities in offenders, and given that legislatures usually adjust sentencing policies differentially for different types of crimes, the coefficients that are obtained from these equations probably need to be adjusted to address the specific choices available to legislatures. Our approach attempts to model some of these adjustments.

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[9] E. Drake, S. Aos, & R. Barnoski (2010). *Washington's Offender Accountability Act: Final report on recidivism* outcomes. Olympia: Washington State Institute for Public Policy, Document No.10-01-1201.
[10] Ibid.

Simultaneity Considerations. Another major empirical difficulty, observed by many, in providing credible estimates from models like those in equation (1) is related to the likely nature of the relationship between crime levels and prison levels. Crime may be affected by prison, but there is also evidence that the use of prison is affected by crime. This simultaneous relationship, if not accounted for, will probably bias the coefficient in a model like equation (1) downward. If the provision of prison is not motivated by a change in crime, then a given observed level of prison would have had a larger effect on crime. Instead, the observed effect of prison on crime is muted, because some of the observed relationship reflects the use of more prison as a result of crime changes. In the research literature, there have been only a few attempts to measure the magnitude of this simultaneous relationship.[11] Technically, these models require an exogenous source of variation—an instrumental variable or a discontinuity around some arbitrary sentencing cut-off level—that affects the use of prison but is probably otherwise unrelated to the error term in equation (1). These instrumental variables, however, are hard to find, so there are many more estimates that do not account for simultaneity than those that do. The model we construct here allows different estimates of this apparently important effect to be posited.

WSIPP's Tool to Estimate Changes in Crime Levels From Changes in Incarceration Rates. The first of five major steps in WSIPP's model calculates the expected numbers of crimes that a state will add or subtract if sentencing polices are changed to alter ADP. Equation (3a) describes how WSIPP's tool implements this.

$$(3a)\ \ \Delta C_t = E_t \times S_t \times A_t \times \frac{\frac{\sum_{c=1}^{Ct}(UCR_c \times UCRAdj_c)}{ADP_t}}{RRateAdj_t}$$

Equation (3a) is similar to the general marginal effects calculation shown for equation (2), with additional parameters to explicitly address the issues raised above. For a policy that raises or lowers total prison ADP_t, the change in total crime, ΔC_t, is calculated with an estimate of the total elasticity, E_t, multiplied by a total simultaneity adjustment, S_t, multiplied by an adjustment, A_t, to account for some level of policy selectivity on behalf of a legislative body. S_t is likely to be greater than one while A_t is likely to be less than one if a policy change is selectively applied to lower risk offenders (as opposed to the average risk of the average offender in ADP_t). The marginal effect calculation is then completed by multiplying the sum of UCR crimes after adjustments (described below) divided by total ADP, and then divided by the adjusted reporting rate, $RRateAdj_t$.

For use in some aspects of WSIPP's sentencing model, we are interested in the change in reported crimes, not total crimes. This is given by equation (3b).

$$(3b)\ \ \Delta RC_t = \Delta C_t \times RRateAdj_t$$

Equation (3a), which describes total felony crime in a state, can be broken down into crime subcategories. For example, rather than estimating total crime, two equations (with separate inputs) can produce estimates for violent crime and property crime.

$$(4)\ \ \Delta C_v = E_v \times S_v \times A_v \times \frac{\frac{\sum_{c=1}^{Cv}(UCR_c \times UCRAdj_c)}{ADP_t}}{RRateAdj_v}$$

$$(5)\ \ \Delta C_p = E_p \times S_p \times A_p \times \frac{\frac{\sum_{c=1}^{Cp}(UCR_c \times UCRAdj_c)}{ADP_t}}{RRateAdj_p}$$

For the key inputs in equation (3a), or equations (4) or (5), WSIPP's model allows for user-specified uncertainty in the parameters. For example, for the elasticity parameter, the user can specify low, modal, and high parameters. In Monte Carlo simulation, these three parameters are used to randomly draw from a triangular probability density distribution when the equations are estimated. The user can similarly specify low, modal, and high parameters for the simultaneity adjustment and the policy selectivity adjustment.

Equation (3a), or equations (4) or (5), contains the following user-specified inputs:

Elasticity. We are currently reviewing the literature on the effect of average incarceration on crime. Marvell (2009) has recently reviewed the estimates for a wide range of studies.[12] In addition to the literature review, we are updating our own econometric

[11] S. D. Levitt (1996). The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *The Quarterly Journal of Economics*, May 1996.
[12] Marvell, 2009.

model of the crime-prison relationship for Washington State. Our model estimates an equation similar to equation (1), except we use county-level data from 1982 to 2008 for Washington's 39 counties. We also model different types of average daily prison populations (violent, property, and drug, in addition to total ADP) for total crime, violent crime, and property crime. For the August 2010 report, the literature review and our Washington study will be used to provide low, modal, and high elasticity inputs to WSIPP's sentencing model.

Simultaneity Adjustment. We are currently reviewing the results of studies that have, and have not, estimated prison-crime models that use an instrumental-variables approach to address the simultaneity issue. Marvell (2009) reviewed these studies as well. The low, modal, and high adjustment factors for WSIPP's sentencing model will be derived from these estimates.

Average Policy Adjustment. Policymakers are not likely to apply uniformly the same sentencing practices for offenders with varying risk levels. For example, if a legislature were to lower lengths of stay for offenders in prison, a high risk sex offender would not be treated the same as a low risk drug offender. We are currently in the process of reviewing the literature to determine an appropriate average policy adjustment for different types of offenders.

Uniform Crime Report Adjustments. Not all UCR reported crime categories align with felony conviction data as defined by the Revised Code of Washington. We described the procedures we use to adjust the UCR data.

Reporting Rate Adjustments. The preceding adjustments to the UCR data also require that we make adjustments to the reporting rates in the National Crime Victimization Survey. We describe these adjustments in Appendix B.

Inputs to Step 2 (of 5): the Net Fiscal Effect of Sentencing-Related Policy Changes.

There can be two expected fiscal effects that stem from the results of Step 1. If ADP is lowered by a sentencing policy change, then there should be a fiscal effect on state budgets. We have estimated that a one-unit drop in ADP can be expected to reduce state prison operating costs by about $18,160 (in 2008 dollars) for Washington State. As we explain in Appendix B, this figure is estimated econometrically and measures the marginal budgetary cost of changes to staffing levels and other operating costs of state prisons; it does not include capital costs.

The second fiscal effect stemming from Step 1 has to do with increased, not decreased, fiscal costs. If policies in Step 1 reduce incarceration rates, and if this results in an increase in crime, then some of those new crimes will be processed through the criminal justice system. These increased costs will offset the immediate fiscal savings from the ADP reduction. Thus, the purpose of Step 2 in WSIPP's model is to estimate the <u>net</u> fiscal impact of a Step 1 policy change.

Percentage of Reported Crimes That Result in a Prison or Jail Sentence. To estimate net fiscal effects, we begin by estimating the proportion of crimes reported to police that result in prison or jail sentences, via the combined effects of policing and sentencing laws. For total felony crimes, equations (6) and (7) use information for the most recent year available on the number of prison or jail sentences handed down in a state for the seven felony crime categories. This sum is divided by the previously described UCR data and adjustments.

$$(6)\ \ PrisonProb_t = \frac{\sum_{c=1}^{Ct} PrisonSentences_c}{\sum_{c=1}^{Ct}(UCR_c \times UCRAdj_c)}$$

$$(7)\ \ JailProb_t = \frac{\sum_{c=1}^{Ct} JailSentences_c}{\sum_{c=1}^{Ct}(UCR_c \times UCRAdj_c)}$$

The Washington data sources for equations (6) and (7) are described in Appendix B. Equations (6) and (7) describe the process for an average prison or jail sentence probability. Similar equations, not shown, can be calculated for any of the individual crimes, or for the violent crime or property crime subcategories.

Average Length of Stay in Prison or Jail. The calculations of fiscal effects also use an estimate of the average length of stay for offenders sentenced to prison or jail, by type of felony crime. The data source for Washington State for the variables in (8) and (9) are described in Appendix B.

$$(8)\ \ PrisonLOS_t = \frac{\sum_{c=1}^{Ct}(PrisonLOS_c \times PctTimeServed_c \times PrisonSentences_c)}{\sum_{c=1}^{Ct}(PrisonSentences_c)}$$

$$(9)\ \ JailLOS_t = \frac{\sum_{c=1}^{Ct}(JailLOS_c \times JailSentences_c)}{\sum_{c=1}^{Ct}(JailSentences_c)}$$

Percentage of Prison or Jail Sentences That Receive Community Supervision. In addition to serving institutional time, a person sentenced to prison or jail may also receive a sentence that involves community supervision, which in many states is called parole or probation. The data source for Washington State for the variables in (10) and (11) are described in Appendix B.

$$(10)\ \ PostPrisonCSProb_t = \frac{\sum_{c=1}^{Ct}(PostPrisonSentencesCS_c \times PrisonSentences_c)}{\sum_{c=1}^{Ct}(PrisonSentences_c)}$$

$$(11)\ \ PostJailCSProb_t = \frac{\sum_{c=1}^{Ct}(PostJailSentencesCS_c \times JailSentences_c)}{\sum_{c=1}^{Ct}(JailSentences_c)}$$

Average Length of Stay on Community Supervision. The fiscal-effects model also uses an estimate of the average length of stay for offenders sentenced to prison or jail, by type of felony crime. The data source for Washington State for the variables in (12) and (13) are described in Appendix B.

$$(12)\ \ PostPrisonCSLOS_t = \frac{\sum_{c=1}^{Ct}\begin{pmatrix}PostPrisonCSLOS_c \times \\ PrisonSentences_c\end{pmatrix}}{\sum_{c=1}^{Ct}(PostPrisonCCSentences_c)}$$

$$(13)\ \ PostJailCSLOS_t = \frac{\sum_{c=1}^{Ct}(PostJailCSLOS_c \times PostJailCSSentences_c)}{\sum_{c=1}^{Ct}(PostJailCSSentences_c)}$$

Change in Prison Costs. The change in the present value of prison costs, given the above inputs, is then computed with:

$$(14)\ \ \Delta Prison\$_t = \sum_{y=1}^{PrisonLOS_t} \frac{\Delta RC_t \times PrisonProb_t \times Prison\$}{(1+dis)^{y-1}}, if\ PrisonLOS_t < 1, then\ y = PrisonLOS_t$$

The variable *dis* is the discount rate used in the overall benefit-cost analysis. The data source for Washington State for the variables in (14) are described in Appendix B.

Change in Jail Costs. The change in jail costs, given the above inputs is then computed with:

$$(15)\ \ \Delta Jail\$_t = \sum_{y=1}^{JailLOS_t} \frac{\Delta RC_t \times JailProb_t \times Jail\$}{(1+dis)^{y-1}}, if\ JailLOS_t < 1, then\ y = JailLOS_t$$

The variable *dis* is the discount rate used in the overall benefit-cost analysis. The data source for Washington State for the variables in (15) are described in Appendix B.

Change in Post Prison Community Supervision Costs. The change in post prison supervision costs, given the above inputs is then computed with:

$$(16)\ \ \Delta PostPrisonCS\$_t = \frac{\sum_{y=1}^{PostPrisonCSLOS_t} \frac{\Delta RC_t \times PrisonProb_t \times CS\$}{(1+dis)^{y-1}}, if\ PrisonLOS_t < 1, then\ y = PrisonLOS_t}{(1+dis)^{PrisonLOS_t}}$$

The variable *dis* is the discount rate used in the overall benefit-cost analysis. The data source for Washington State for the variables in (16) are described in Appendix B.

Change in Post-Jail Community Supervision Costs. The change in post-jail supervision costs, given the above inputs is then computed with:

$$(17)\ \ \Delta PostJailCS\$_t = \sum_{y=1}^{PostJailCSLOS_t} \frac{\Delta RC_t \times JailProb_t \times CS\$}{(1+dis)^{y-1}}, if\ PostJailCSLOS_t < 1, then\ y = PostJailCSLOS_t$$

The variable *dis* is the discount rate used in the overall benefit-cost analysis. The data source for Washington State for the variables in (17) are described in Appendix B.

Change in Police Costs. The change in police costs, given the above inputs is then computed with:

$$(18)\ \ Police\$ = \frac{\sum_{c=1}^{Ct} Police\$_c \times (PrisonSentences_c + JailSentences_c)}{\sum_{c=1}^{Ct}(PrisonSentences_c + JailSentences_c)}$$

$$(19)\ \ \Delta Police\$_t = \Delta RC_t \times (PrisonProb_t + JailProb_t) \times Police\$$$

The data source for Washington State for the variables in (18) and (19) are described in Appendix B.

Change in Court Costs. The change in court costs, which includes court personnel, prosecutors, and defenders, given the above inputs is then computed with:

$$(20)\ \ Police\$ = \frac{\sum_{c=1}^{Ct} Court\$_c \times (PrisonSentences_c + JailSentences_c)}{\sum_{c=1}^{Ct}(PrisonSentences_c + JailSentences_c)}$$

$$(21)\ \ \Delta Court\$_t = \Delta RC_t \times (PrisonProb_t + JailProb_t) \times Court\$$$

The data source for Washington State for the variables in (20) and (21) are described in Appendix B.

Change in State Government Fiscal Costs

$$(22)\ \ \Delta StateFiscal\$ = \Delta Prison\$_t + \Delta PostPrisonCS\$_t + \Delta PostJailCS\$_t$$

Change in Local Government Fiscal Costs

$$(23)\ \ \Delta LocalFiscal\$ = \Delta Jail\$_t + \Delta Police\$_t + \Delta Court\$_t$$

Net Change in Fiscal Costs for a One Unit Change in ADP. The result of Step 2 is an estimate of the change in fiscal costs that stem from a one unit change in prison average daily population. The immediate lowering in prison costs from the one unit ADP drop, $Prison\$_t$, is offset by the increase in state and local fiscal costs used to respond to the increase in crime, ($\Delta StateFiscal\$$ + $\Delta StateFiscal\$$). The net fiscal cost savings, $\Delta NetFiscal\$$, is then used in Step 3 to finance an expansion of evidence-based programming.

$$(24)\ \ \Delta NetFiscal\$ = Prison\$_t - (\Delta StateFiscal\$ + \Delta LocalFiscal\$)$$

Inputs to Step 3 (of 5): A Portfolio of Evidence-Based Programs That Reduce Crime.

The logic behind WSIPP's sentencing tool is that if a state decides to reduce its average daily prison incarceration rate, two things will happen: crime will go up and net taxpayer costs will go down. Steps 1 and 2 describe the procedures we use to estimate these values. Next, if a portion of the net taxpayer savings (from Step 2) is used to fund a portfolio of evidence-based programs that have been shown to reduce crime, can the state end up in a "crime-neutral" position and still save taxpayers money? That is, can the increase in crime from the prison reduction be offset by the reduced crime from the portfolio of programs? And, will taxpayers be, on balance, better off?

This section describes the inputs needed to create the portfolio evidence-based crime-reduction programs. It draws on the on-going work of WSIPP, as described in Appendix B. There are three steps to WSIPP's portfolio model.

Review of the Evidence on What Works (and What Does Not). The first step in our process is to produce an estimate of what works and what does not to reduce crime. We begin by analyzing all high-quality research from anywhere in the United States and elsewhere to determine what options have best achieved desired outcomes (and which ones have not).

The goal of this stage of the analysis is to estimate an expected effect of a list of "actionable" public policies. By "actionable" we mean the very specific kinds of decisions that state legislators actually can or do make when they craft legislation. We have found that framing the research question is vital; otherwise, the results of the analysis will be irrelevant to legislators and staff.

For example, it is NOT a useful exercise (from the standpoint of affecting actual public policies) to perform an analysis that answers a question such as: "do evidence-based juvenile justice programs work?" That is an interesting academic question, but a legislature cannot take meaningful steps in crafting legislation with an analysis that answers this too-general question. Rather, to be useful for actual legislation, the analysis must be much more specific; for example, an actionable research question is this: "does the juvenile justice program 'Functional Family Therapy' work?" The later juvenile justice question is one that can find its way into legislative budgets, the former cannot. Thus, we have found that even before the formal assessment of evidence begins, it is critical to formulate the question that can be acted upon by a legislative body or executive agency.

Once relevant and specific research questions are established, then our empirical approach for this first step is to assess systematically, using a meta-analytic framework, the research literature on a given topic. We have found that this approach is particularly helpful in a "real world" policy environment, because it does not have the appearance of "playing favorites." Instead of just reporting the results of one or two favorite studies, a competent meta-analysis reviews all the literature on a topic, after carefully screening and adjusting effect sizes for research design quality. The meta-analysis then produces an expected effect of a public policy option, given the weight of the evidence.

Compute the Economics (Costs and Benefits) of Specific Policy Options. The product of the meta analyses reveals whether a given actionable policy option can affect crime outcomes. Once this mean effect size (and standard error) is estimated, we bring economics into play by answering two basic questions: "How much does it cost to produce the effect, and how much is it worth to people in a state (Washington, in our case) to achieve it?" We have built formal economic models with a consistent set of inputs to measure these costs and benefits. Our crime model is discussed in Appendix B. We present these estimates using standard financial statistics that summarize the cash flows of investments: net present values, benefit-cost ratios, and returns on investment. The analyses provide an internally consistent set of estimates given the estimated effect sizes, the modeling parameters selected, and the modeling structure employed. We present the estimates from three perspectives: direct participants in policy options; taxpayer-only; and the non-taxpayer perspective of people who are not the direct program recipient. The combination of these three perspectives enables a "total state" perspective.

For the sentencing model, we use our benefit-cost model to create an initial portfolio of programs that includes adult corrections programs and juvenile justice programs. From our model for a number of programs, we compute the number of crimes avoided per program participant (and standard error); the program cost per participant, and the benefits of the reduced crimes to taxpayers and to people who were not victimized by the crimes that were avoided.

We then select three of these resources for an example portfolio. We put 40 percent of the portfolio into cognitive behavioral therapy (CBT) for adult offenders; 20 percent into a juvenile justice program called Functional Family Therapy (FFT); and 40 percent into a juvenile justice program called Aggression Replacement Therapy (ART). The weighted average crimes avoided and standard error, the program cost, and the taxpayer and victim savings are shown on the last row of the table on the next page. The portfolio standard error on the crimes avoided assumes no correlation among the programs selected for the portfolio.

Portfolio of Adult Offender and Juvenile Offender Programs to Reduce Crime

Program Name	Percentage of Portfolio	Crimes Avoided per Program Participant	Standard Error	Program Cost Per Participant	Program Fiscal Savings Per Participant	Program Victim Benefits Per Participant
Adult Programs						
Drug court	0%	0.27	0.06	-$4,792	$3,375	$6,494
Cognitive behavior therapy	40%	0.33	0.14	-$517	$3,450	$7,754
Education in prison	0%	0.39	0.18	-$1,055	$4,042	$9,086
Drug treatment in prison	0%	0.30	0.11	-$1,758	$3,139	$7,056
Drug treatment in the community	0%	0.23	0.13	-$629	$3,037	$6,962
Juvenile Programs						
Multi-Dimensional Treatment Foster Care	0%	3.62	1.52	-$7,418	$13,544	$45,731
Functional Family Therapy	20%	1.44	0.45	-$3,134	$8,463	$23,785
Aggression Replacement Training	40%	0.68	0.37	-$1,449	$4,022	$11,303
Multi-Systemic Therapy	0%	1.03	0.33	-$7,076	$6,065	$17,047
Sum or Average	100%	0.6928	0.181	-$1,413	$4,681	$12,380

Number of Initial Purchased Programming Slots from the Sentencing Change. The number of "slots" that can be purchased depends initially on the net fiscal cost savings, *ΔNetFiscal$,* determined in Step 2. This amount is multiplied by the percentage of funds that will be applied to evidence-based programming, *PctProgramming.* The product of the two terms is then divided by the weighted average portfolio cost of the programs purchased, *AvgCostofPortfolioPrograms*, to determine the number of initial slots purchased with the net fiscal savings from the prison ADP reduction.

$$(25)\ InitialSlotsPurchased = \frac{(\Delta NetFiscal\$ \times PctProgramming)}{AvgCostofPortfolioPrograms}$$

Taxpayer Benefits From the Initial Slots Purchased. The evidence-based slots purchased can be expected to generate taxpayer (and victim) benefits. The weighted portfolio per-participant estimate of these benefits, *AvgTaxpayerBenefitofPortfolio*, is multiplied by the number of initial slots purchased to estimate the total taxpayer benefits expected for the initial slots purchased, *InitialTaxpayerBenefits*. The taxpayer benefits of the evidence-based programs are computed exogenously with WSIPP's benefit-cost model described in Appendix B.

$$(26)\ InitialTaxpayerBenefits = IntialSlotsPurchased \times AvgTaxpayerBenefitofPortfolio$$

Cost of Additional Slots Purchased. The expected taxpayer benefits can allow a state to purchase additional evidence-based portfolio slots, *CostofAdditionalSlotsPurchased*, if the state chooses to do so. The total cost of any additional slots is given by:

$$(27)\ CostofAdditionalSlotsPurchased = AdditionalSlotsPurchased \times AvgCostofPortfolioProgram$$

Total Slots Purchased. Equation (28) then sums the initial and additional evidence-based portfolio slots purchased to arrive at the total number of slots purchased, *TotalSlotsPurchased*.

$$(28)\ TotalSlotsPurchased = InitialSlotsPurchased + AdditionalSlotsPurchased$$

Number of Crimes Avoided With Purchased Programs. The expected number of crimes avoided, *AvoidedCrimes*, is the product of the number of slots and the average crimes avoided per slot, *AvgCrimesAvoidedPerSlot*. The crimes avoided per slot from the evidence-based programs are computed exogenously with WSIPP's benefit-cost model described in Appendix B.

$$(29)\ AvoidedCrimes = TotalSlotsPurchased \times AvgCrimesAvoidedPerSlot$$

Net Change in Crime. The net change in crime, *CrimeChange*, is determined by subtracting the avoided crimes as a result of the combination of evidence-based policies from the increase in crimes from the prison ADP reduction, ΔC_t, (from equation 3a).

$$(30)\ CrimeChange = \Delta C_t - AvoidedCrimes$$

At described thus far, total crimes avoided are estimated as felony crimes for an average offender. The total crime estimates, however, can be analyzed as violent, property, and drug crimes. The August 2010 version of the model will contain this capability. This is important because the offenders associated with a prison ADP reduction will, in all likelihood, not be the same offenders who receive the evidence-based programming. Thus, it will be important to select policy combinations that balance the crime ledger for both violent and property crimes, not simply the total number of crimes.

Step 4 (of 5): Combinations of Policies

The model described here requires several key inputs. At this time, we have not settled on a set of factors that have the most empirical support. Thus, the draft tool presented here reflects the approach we are developing, not specific results. By August 2010, the model will be used to present some initial empirical estimates for Washington State. Once a set of inputs are identified, the model can be run to solve for equation (30).

Step 5 (of 5): Risk Analysis

Analyzing these policy tradeoffs involves a substantial amount of uncertainty. While there is an increasingly strong evidentiary base of knowledge about what works to reduce crime, there remains a considerable level of variation in particular estimates. To reflect this uncertainty, the fifth step in our modeling approach is designed to estimate the riskiness of any combination of policy options.

As with any investment decision, an investor wants to know the expected gain, as well as the risk, that the investment strategy could produce an undesired result. WSIPP's model is structured to provide this type of investment information. The bottom-line investment statistics that the draft WSIPP tool produces include the expected return on investment for a set of policy options, along with the risk that the mix of options could lead to less public safety.

We estimate the known uncertainty surrounding many of the inputs to the model. When the software is completed, we will use a Monte Carlo approach to vary the following key inputs in the model. (The tool in its draft form also uses a Monte Carlo simulation approach via the Excel add-on product @RISK by Pallisades Corporation.)

Factors that affect crimes generated from prison ADP reductions:

- Elasticity
- Simultaneity adjustment to the elasticity
- Multiplicative factors adjusting for ADP-reduction policies that target lower risk offenders in prison

Marginal cost factors that affect the net prison fiscal savings from the ADP reductions:

- Prison
- Jail
- Community supervision
- Police
- Courts

Savings from the evidence-based programs:

- Effect size

Technical Appendix B:
Computational Procedures and Monetary Valuation of Crime Outcomes

This appendix describes WSIPP's benefit-cost model that monetizes taxpayer and victim benefits associated with evidence-based programs. The appendix is organized as follows:

WSIPP's benefit-cost model monetizes taxpayer and victim benefits associated with programs that reduce crime. In this appendix, we describe the methods, data sources, and estimation procedures for four broad categories of inputs to the model used to calculate the value of reducing crime to taxpayers and crime victims. The computational steps used to estimate the monetary value of avoided crime, given the inputs, are not included in this document. Those equations will be included in the larger benefit-cost model due August 2010.

The current version of WSIPP's model approaches the crime valuation question from two perspectives. We estimate the value to taxpayers if a crime can be avoided. We also compute a victimization cost that can be averted when crime is avoided.[13] To model avoided crime costs from these two perspectives, we estimate life-cycle costs of avoiding seven major types of crime and 11 types of costs incurred as a result of crime. In addition to computing monetary values of avoided crime, the model is also used to estimate and count the number of prison beds and victimizations avoided when crime is reduced.

In addition to information about the effect size of a particular program and the age of the program participant, the crime model is driven by four broad types of inputs: per-unit crime costs; sentencing probabilities and resource-use estimates; longitudinal criminological information about different populations; and estimates of multiple crimes per officially recorded crimes, such as arrests or convictions. The data sources and estimation procedures we use for each of these four categories of inputs are described.

B.1 Per-Unit Crime Costs

In WSIPP's benefit-cost model, the costs of the criminal justice system paid by taxpayers are estimated for each significant part of the publicly financed system in Washington. The sectors modeled include the costs of police and sheriffs, superior courts and county prosecutors, local juvenile corrections, local adult corrections, state juvenile corrections, and state adult corrections. The estimated costs include operating costs and annualized capital costs for the capital-intensive sectors. As noted, we also include estimates of the costs of crime to victims.

For criminal justice system costs, the estimates are *marginal* operating and capital costs.[14] Marginal criminal justice costs are defined as those costs that change over a period of several years as a result of changes in a crime workload measure. Some short-run costs change instantly when a workload changes. For example, when one prisoner is added to the state adult corrections' system, certain variable food and service costs increase immediately, but new staff are not typically hired right away. Over the course of a governmental budget cycle, however, new corrections' staff are likely to be hired to reflect the change in average daily population of the prison. In WSIPP's analysis, these "longer-run" marginal costs have been estimated. The longer-run marginal costs reflect both the immediate short-run changes in expenditures, as well as those operating expenditures that change after governments make adjustments to staffing levels, often in the next few budget-writing cycles.

Exhibit B.1 shows a screen shot, taken from WSIPP's benefit-cost model, that displays an array of per-unit costs for the 11 sectors and seven types of crime modeled. The estimates for each row in Exhibit B.1 are described below.

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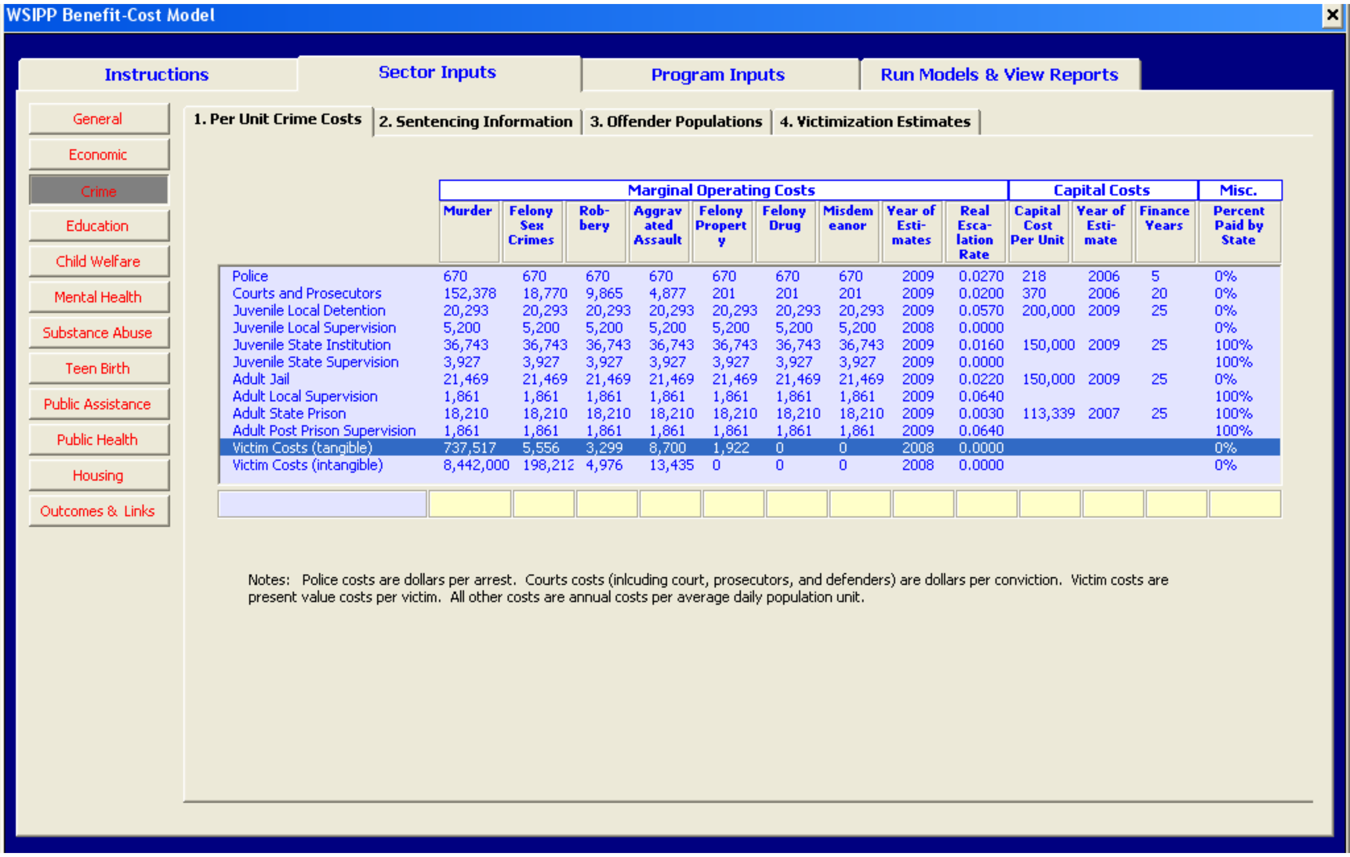
[13] There are other costs of crime that have been posited by some commentators, including private costs and other public sector costs. WSIPP's current model does not address these additional cost categories, or only indirectly. Future versions of this model may incorporate some of these additional cost categories.

[14] As noted, a few average cost figures are currently used in the model when marginal cost estimates cannot be reasonably estimated.

Exhibit B.1



	Marginal Operating Costs									Capital Costs			Misc.
	Murder	Felony Sex Crimes	Rob-bery	Aggravated Assault	Felony Property	Felony Drug	Misdemeanor	Year of Esti-mates	Real Esca-lation Rate	Capital Cost Per Unit	Year of Esti-mate	Finance Years	Percent Paid by State
Police	670	670	670	670	670	670	670	2009	0.0270	218	2006	5	0%
Courts and Prosecutors	152,378	18,770	9,865	4,877	201	201	201	2009	0.0200	370	2006	20	0%
Juvenile Local Detention	20,293	20,293	20,293	20,293	20,293	20,293	20,293	2009	0.0570	200,000	2009	25	0%
Juvenile Local Supervision	5,200	5,200	5,200	5,200	5,200	5,200	5,200	2008	0.0000				0%
Juvenile State Institution	36,743	36,743	36,743	36,743	36,743	36,743	36,743	2009	0.0160	150,000	2009	25	100%
Juvenile State Supervision	3,927	3,927	3,927	3,927	3,927	3,927	3,927	2009	0.0000				100%
Adult Jail	21,469	21,469	21,469	21,469	21,469	21,469	21,469	2009	0.0220	150,000	2009	25	0%
Adult Local Supervision	1,861	1,861	1,861	1,861	1,861	1,861	1,861	2009	0.0640				100%
Adult State Prison	18,210	18,210	18,210	18,210	18,210	18,210	18,210	2009	0.0030	113,339	2007	25	100%
Adult Post Prison Supervision	1,861	1,861	1,861	1,861	1,861	1,861	1,861	2009	0.0640				100%
Victim Costs (tangible)	737,517	5,556	3,299	8,700	1,922	0	0	2008	0.0000				0%
Victim Costs (intangible)	8,442,000	198,212	4,976	13,435	0	0	0	2008	0.0000				0%

Notes: Police costs are dollars per arrest. Courts costs (inlcuding court, prosecutors, and defenders) are dollars per conviction. Victim costs are present value costs per victim. All other costs are annual costs per average daily population unit.

Police and Sheriff's Office Per-Unit Costs

This section describes the steps we use to estimate the annual marginal operating costs of local police agencies in Washington State, along with the expected long-run real rate of change in these costs. We also describe our estimate of the capital cost of police operations. All of these cost parameters are entered into the crime model, as shown in Exhibit B.1.

Police Operating Costs. For an estimate of marginal operating costs of local police agencies, we conducted a time-series analysis of annual county-level data for police expenditures and arrests for all local police agencies in Washington's 39 counties. From the Washington State Auditor, local city and county police expenditure data were collected for 1994 to 2008, the earliest and latest years electronically available. The Auditor's data for the expenses include all local police expenditures (Budget and Reporting System (BARS) code 521). We excluded the Crime Prevention (BARS 521.30) subcategory since it was an irregular expenditure. These nominal annual dollar amounts were adjusted to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council.

We also collected arrest information for Washington police agencies from the National Archive of Criminal Justice Data maintained by the University of Michigan.[15] Data were collected for calendar years 1994 to 2007, the earliest and latest years available as of December 2009. Arrest data for 1993 were unavailable on the Michigan website, thus limiting the number of years we could include in our analysis.

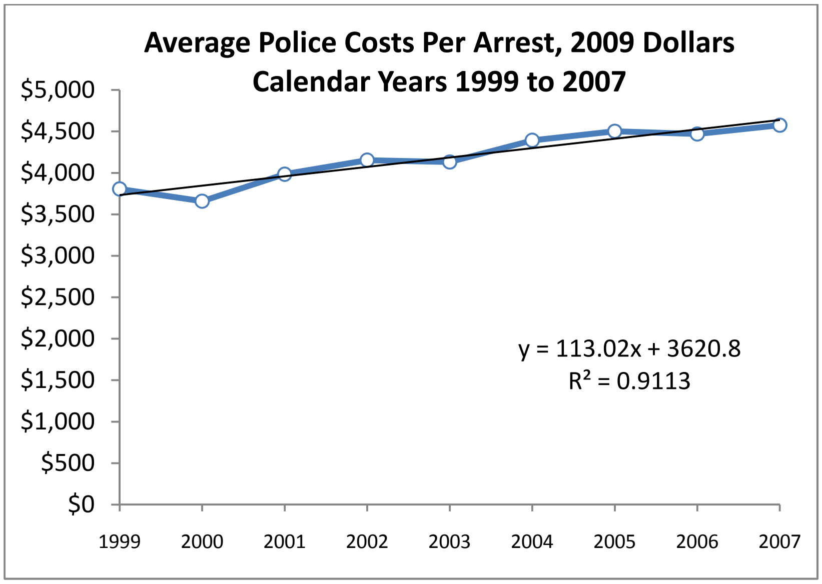
We aggregated the city and county expenditure and arrest data for individual police agencies to the county level. This was done to account for any jurisdictional overlap in county sheriffs' offices and city police units. We also aggregated to the county level because, over the years included in our analysis, some newly incorporated cities took on responsibilities formerly assigned to county sheriffs. Aggregating thus allowed for a more consistent cost-arrest data series for the years in our study.

[15] The data are from the FBI's "Uniform Crime Reporting Program Data [United States]: County-Level Detailed Arrest and Offense Data" by year.

Since the latest arrest data were for 2007, the resulting balanced multiple time-series panel dataset initially consisted of 546 county-by-year observations.

We had to limit our analysis to 1999 to 2007 because visual inspection of the arrest data for years 1996 to 1998 revealed what appeared to be significant anomalies in the data, possibly due to reporting or other unknown factors during those years. Therefore, in our regression analyses, our dataset begins in 1999.

We computed the statewide average cost per arrest (in 2009 dollars) for 1999 to 2007and plotted the results.



Over the entire 1999 to 2007 timeframe, the average statewide cost is $4,185 per arrest, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 1999 ($3,734) and 2007 ($4,638) and calculated the average escalation rate for the eight years, using the following formula, where FV is the 2007 estimated cost, PV is the 1999 estimate, and N is eight years.

$$(1)\ Rate = (FV/PV)^{1/N}$$

The annual rate of real escalation is .027. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1.

Next, to estimate the marginal annual operating costs of police agencies, we conducted a time-series analysis of the panel data for Washington's 39 counties for 2001 to 2007. The restriction to 2001 (for the dependent variable) was because, after testing different lag structures of right-hand side variables, and to preclude using arrest data before 1999, our sample dependent variable began in 2001. Thus the balanced panel includes a total of 273 observations (39 counties for 7 years). We tested models where we disaggregated the arrest data into five types: arrests for murder, rape, robbery, aggravated assault, and all nonviolent arrests. After testing a variety of specifications, we did not find a specification with stable or intuitively reasonable results. At this time, we do not know if there are measurement errors in the arrest data, or if there are other tests to be explored. Therefore, we estimated a simple model with total arrests. This model, however, is unsatisfactory because it implies, for example, that the cost for an arrest for murder is the same as the cost for an arrest for burglary. We intend to examine the historical arrest data in greater detail so that a more intuitive equation can be estimated with disaggregated arrest types. The arrest data do not include the traffic operations of local police agencies. To capture this effect, data from the Washington State Administrative Office of the Courts were obtained on the number of traffic infraction filings in county courts.

In our time series analysis, we first tested each data series for unit roots. The data series are: real police expenditures (M_POLICER), total arrests (A_TOT), and traffic infractions (TRAFFIC). If unit roots are present, then a simple regression in levels can produce spurious results.[16] We tested for unit roots with the Im, Pesaran, and Shin (IPS) panel unit root test for individual unit root processes.

- For the M_POLICER expenditure series, the IPS test without time trends failed to reject the null hypotheses that the series has a unit root (IPS p-value of 1.00). With time trends included, the IPS test continued to indicate a unit root (IPS p-value .34). In first-differences, on the other hand, the IPS test indicated a lack of a unit root (IPS p-value .000).
- For the two right-hand side variables, the IPS tests indicated a lack of a unit root for A_TOT (IPS p-value of .000), but a unit root for TRAFFIC (IPS p-value of .88).
- With the IPS test indicating a unit root in the dependent variable (M_POLICER), we proceeded to construct a model in first-differences.

We tested alternative lag specifications of the arrest and traffic variables. Our preferred model also included period and county fixed effects and a lagged dependent variable. The following results were obtained and the coefficients entered in the crime model, as shown in Exhibit B.1. The sum of the arrest lags is $670. An identical model but without including a right-hand side dependent variable produced quite similar results.

Dependent Variable: M_POLICER-M_POLICER(-1)
Method: Panel Least Squares
Date: 04/17/10 Time: 10:29
Sample (adjusted): 2001 2007
Periods included: 7
Cross-sections included: 39
Total panel (balanced) observations: 273
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	956767.2	171084.1	5.592380	0.0000
M_POLICER(-1)-M_POLICER(-2)	-0.468607	0.097310	-4.815585	0.0000
A_TOT-A_TOT(-1)	240.6135	331.7045	0.725385	0.4690
A_TOT(-1)-A_TOT(-2)	428.8218	319.8050	1.340886	0.1813
TRAFFIC-TRAFFIC(-1)	109.2628	87.19574	1.253075	0.2115
TRAFFIC(-1)-TRAFFIC(-2)	123.4954	97.02971	1.272759	0.2044
TRAFFIC(-2)-TRAFFIC(-3)	350.3366	115.0134	3.046049	0.0026

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.679778	Mean dependent var	1013022.
Adjusted R-squared	0.607657	S.D. dependent var	3244727.
S.E. of regression	2032410.	Akaike info criterion	32.05417
Sum squared resid	9.17E+14	Schwarz criterion	32.72847
Log likelihood	-4324.395	Hannan-Quinn criter.	32.32485
F-statistic	9.425402	Durbin-Watson stat	1.964607
Prob(F-statistic)	0.000000		

[16] J. M. Wooldridge (2009). *Introductory econometrics: A modern approach*. Mason, OH: South-Western Cengage Learning, p. 636.

Police Capital Costs. An estimate of the capital costs used by local police to make arrests in Washington was calculated from capital expenditure data for local police agencies in Washington for 2006. These data were obtained from the most recently available United States Bureau of Justice Statistics annual survey: Justice Expenditure and Employment Extracts, 2006, published December 1, 2008 (NCJ 224394). Local government police capital expenditures in Washington were reported as $53,703,000 for 2006 (Table 4, Justice system expenditure by character, State and type of government, fiscal 2006). The total number of arrests in Washington during 2006 was 246,388, obtained from FBI's Uniform Crime Reports for 2006. Thus, the average police capital cost per arrest was $218 in 2006 dollars. This parameter was entered into the crime model, as shown in Exhibit B.1, along with an assumed five financing for these police resources. In our crime model, the total capital cost per arrest is converted to an annualized capital payment, with equation (2), assuming a five-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per arrest converted to the base year dollars chosen for the model.

$$(2)\ PMT = \frac{iPV}{1-(1+i)^{-n}}$$

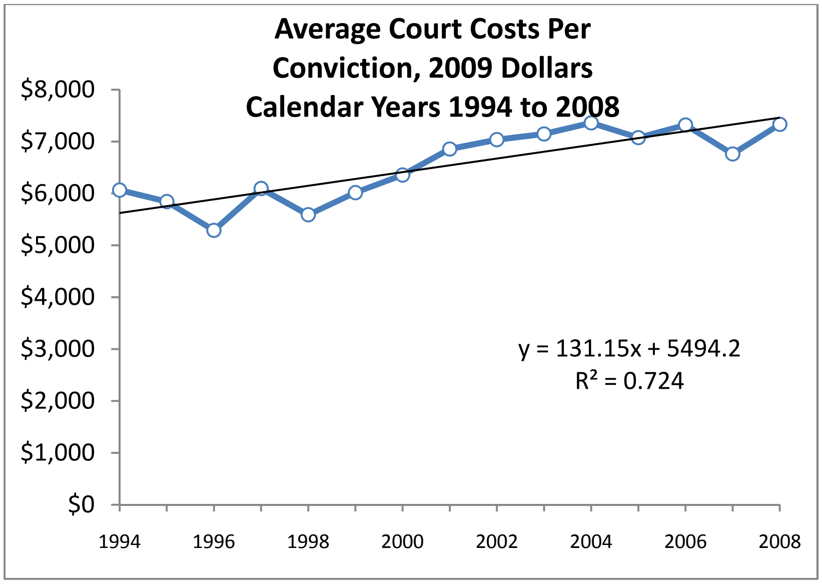
Superior Courts and County Prosecutors Per-Unit Costs

This section describes the steps we use to estimate marginal annual operating costs, and the long-run rate of change in these costs, of county superior courts and prosecutors in Washington State. Our focus is the cost of obtaining convictions in courts, so we combined court costs and prosecutor costs into one category to reflect the public costs to process cases through the courts that respond especially to felony crime. The cost parameters are entered into the crime model, as shown in Exhibit B.1.

Court and Prosecutor Operating Costs. For an estimate of marginal operating costs of superior courts in Washington, we conducted a time series analysis of annual county-level data for court and prosecutor expenditures and court convictions for all local agencies in Washington's 39 counties. From the Washington State Auditor, local county court and prosecutor expenditure data were collected for calendar years 1994 to 2008, the earliest and latest years electronically available. The Auditor's data for the expenses includes all local court and prosecutor expenditures (BARS code 512 for courts and BARS code 515 for prosecutors). The court data include the costs of administration (BARS 512.10), superior courts (BARS 512.20), and county clerks (BARS 512.30). For court expenditure data, we excluded district courts (BARS 512.40) since they do not process felony cases (the main subject of interest in our benefit-cost analysis) and expenditures for law library (BARS 512.70) and indigent defense (BARS 512.80; this latter category was excluded because the data were not available for the entire time frame under review. The prosecutor data include costs for administration-legal (515.10) and legal services (515.2). For prosecutor offices, we excluded facilities-legal services (515.50), consumer affairs-legal services (515.60), crime victim and witness program-legal (515.70), and child support enforcement-legal services (515.80). All nominal annual dollar amounts were adjusted to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council.

We also collected court conviction and other case-processing information from the Washington State Administrative Office of the Courts. We collected statewide data for calendar years 1994 to 2008 and county-level data for calendar years 1997 to 2008, the earliest and latest years available as of December 2009.

We computed the statewide average cost per conviction (in 2009 dollars) for 1994 to 2008 and plotted the results.



Over the entire 1994 to 2008 timeframe, the average statewide cost is $6,563 per conviction, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 1994 ($5,625) and 2008 ($7,461) and calculated the average escalation rate for the 14 years, using equation (1), where FV is the 2008 estimated cost, PV is the 1994 estimate, and N is 14 years.

The annual rate of real escalation is .020. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1.

Next, to estimate the marginal annual operating costs of courts, we conducted a time-series analysis of the panel data for Washington's 39 counties for 1999 to 2008. The restriction to 1999 (for the dependent variable) was because, after testing different lag structures of right-hand side variables, and since our county-level court data began in 1997, our sample dependent variable had to begin in 1999. Thus, the balanced panel includes a total of 390 observations (39 counties for 10 years). Conviction data were categorized into four types of violent convictions and one for all other convictions.

In our time-series analysis, we first tested each data series for unit roots. The six data series are: real total court expenditures (M_COURTALLR), convictions for homicide offenses (C_HOM), convictions for sex offenses (C_SEX), convictions for robbery offenses (C_ROB), convictions for aggravated assault offenses (C_ASSLT), convictions for all non-violent offenses (C_NONVIOL). If unit roots are present, then a simple regression in levels can produce spurious results.[17] We tested for unit roots with the Im, Pesaran, and Shin (IPS) panel unit root test for individual unit root processes.

- For all of the variables, the IPS tests generally indicated a lack of unit roots. For example, IPS test without time trends rejected the null hypotheses that the series have unit roots (IPS p-values of .0028 for M_COURTALLR, .0000 for C_HOM, .0000 for C_SEX, .0000 for C_ROB, .0000 for C_ASSLT, .0006 for C_NONVIOL).
- With the IPS test indicating a lack of unit roots in the variables, we had the option to construct models in levels or first-differences.

We tested models both in levels and first-differences, along with alternative lag specifications for the conviction variables. Our preferred model was a first-difference model where we included lags of each of the violent felony conviction variables along with a variable for all other convictions, as well as county and time fixed effects. We also included a lagged dependent variable. This model produced coefficients for the violent conviction variables that made the most intuitive sense.

[17] Ibid., p. 636.

Dependent Variable: M_COURTALLR-M_COURTALLR(-1)
Method: Panel Least Squares
Date: 02/04/10 Time: 10:01
Sample (adjusted): 1999 2008
Periods included: 10
Cross-sections included: 39
Total panel (balanced) observations: 390
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	158006.5	86235.19	1.832274	0.0678
M_COURTALLR(-1)-M_COURTALLR(-2)	-0.113178	0.168569	-0.671403	0.5024
C_HOM(-1)-C_HOM(-2)	152377.9	125366.9	1.215456	0.2250
C_SEX(-1)-C_SEX(-2)	18770.28	11395.58	1.647154	0.1005
C_ROB(-1)-C_ROB(-2)	9865.480	29782.45	0.331252	0.7407
C_ASSLT(-1)-C_ASSLT(-2)	4876.710	9512.385	0.512670	0.6085
C_NONVIOL-C_NONVIOL(-1)	200.5611	1503.985	0.133353	0.8940

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.209477	Mean dependent var	167352.1
Adjusted R-squared	0.084781	S.D. dependent var	2196761.
S.E. of regression	2101577.	Akaike info criterion	32.08216
Sum squared resid	1.48E+15	Schwarz criterion	32.63132
Log likelihood	-6202.021	Hannan-Quinn criter.	32.29985
F-statistic	1.679903	Durbin-Watson stat	1.973011
Prob(F-statistic)	0.003621		

Court Capital Costs. An estimate of the capital costs used by the court system in Washington was calculated from capital expenditure data for courts in Washington for 2006. These data were obtained from the most recently available United States Bureau of Justice Statistics annual survey: Justice Expenditure and Employment Extracts, 2006, published December 1, 2008 (NCJ 224394). Local government court expenditures in Washington were reported as $19,144,000 for 2006 (Table 4, Justice system expenditure by character, State and type of government, fiscal 2006). The total number of criminal (adult and juvenile) convictions in Washington during 2006 was 51,709, obtained from the Washington State Administrative Office of the Courts. Thus, the average court capital cost per conviction was $370 in 2006 dollars. This parameter was entered into the crime model, as shown in Exhibit B.1, along with an assumed 20-year financing period. In our crime model, the total capital cost per conviction is converted to an annualized capital payment, with equation (2), assuming a 20-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per conviction converted to the base year dollars chosen for the model.

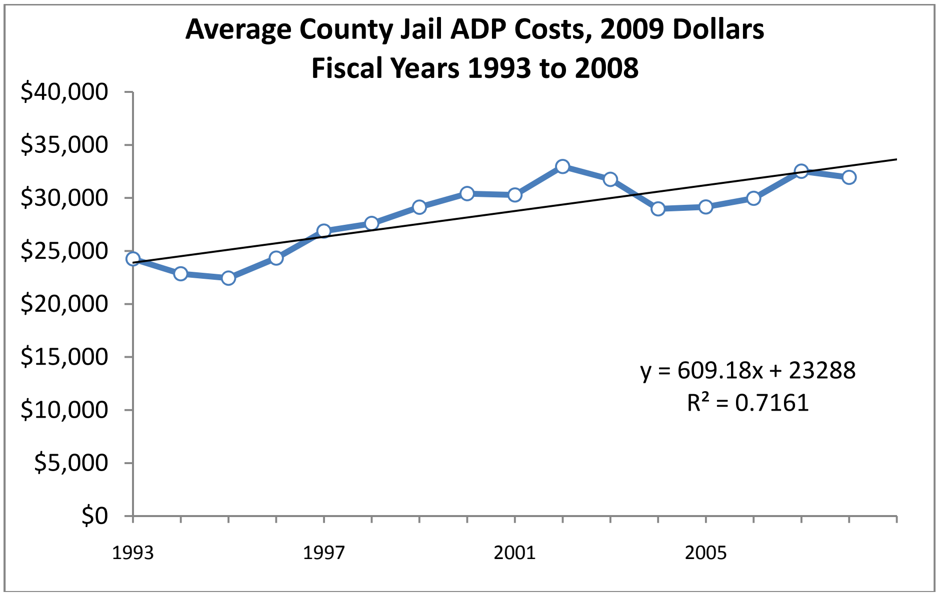
Local Adult Jail Per-Unit Costs

This section describes the steps we use to estimate marginal annual jail operating costs, and the long-run rate of change in these costs, of the county-run adult jail system in Washington State. We also describe our estimate of the capital cost per jail bed. All of these cost parameters are entered into the crime model, as shown on Exhibit B.1. In WSIPP's model, two types of users of local county-run adult jails are analyzed: convicted felons who serve both pre-sentence and post-sentence time at a local jail, and felons who serve pre-sentence time at local jails and post-sentence time at a state institution. WSIPP assumes the same annualized per-day jail cost for both these events.

Jail Operating Costs. For an estimate of marginal operating costs of county jails, we conducted a time-series analysis of annual county-level data for jail expenditures and average jail population for each of Washington's 39 counties for calendar years 1995 to 2008. Thus, the balanced multiple time series panel dataset consists of 546 observations. From the

Washington State Auditor, local jail expenditure data for counties were collected for 1993 to 2008, the earliest and latest years available. The Auditor's data for the expenses includes all local jail expenditures (BARS code 527) except local probation costs (BARS code 527.40). These nominal annual dollar amounts were adjusted to 2009 dollars (JAILREAL) using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council. The average daily jail population data (JAILADP) was obtained from the Washington Association of Sheriffs and Police Chiefs.

We computed the statewide average cost per jail ADP (in 2009 dollars) and plotted the results.



Over the entire 1993 to 2008 timeframe, the average statewide cost is $28,927 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown of the chart) for this series. From this line, we computed the predicted values for 1993 ($23,897) and 2008 ($33,035) and calculated the average escalation rate for the 15 years, using equation (1), where FV is the 2008 estimated cost, PV is the 1993 estimate, and N is 15 years.

The annual rate of escalation is .022. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1.

To estimate the marginal annual operating costs of county jails, we conducted a time-series analysis of the panel data for Washington's 39 counties for 1993 to 2008. Thus the balanced panel includes a total of 546 observations. First, we tested each data series (JAILADP and JAILREAL) for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[18] We tested for unit roots with a panel unit root test, the Im, Pesaran, and Shin (IPS) test for individual unit root processes.

- For the JAILREAL expenditure series, the test without time trends failed to reject the null hypotheses that the series has a unit root (IPS p-value of 1.00). With time trends included, the IPS test continued to indicate a unit root (p-value .713). In first-differences, the test indicated a lack of a unit root (IPS p-value .000).
- For the JAILADP series, the IPS test without time trends failed to reject the null hypotheses that the series has a unit root (IPS p-value of .975). With time trends included, the IPS test continued to indicate a unit root (p-value .582) In first-differences, the test indicated a lack of a unit root (IPS p-value .000).
- With the IPS test indicating unit roots in both JAILREAL and JAILADP series, and no unit roots in first-differences, we proceeded to construct a model in first-differences.

Since the two series have unit roots, we tested to determine if the two series together are cointegrated.[19] We used two versions of a panel cointegration test in EVIEWS. Both the Pedroni Engle-Granger test (p-value .000) and the Kao Engle-

[18] Ibid., p. 636.
[19] Ibid., p. 639.

Granger test (p-value .000) rejected the null hypothesis of no cointegration. We concluded that the two series together are I(0) cointegrated.

Since the two unit root series are cointegrated, we estimated an error correction model in first-differences. We tested alternative lag specifications of the JAILADP variable and concluded that three lags were appropriate. For the error correction term, we computed a cointegrating parameter from a simple model of: JAILREAL = a + b(JAILADP).

The sum of the three ADP variables was $21,469. The F-test of joint significance for the three ADP variables is marginally significant with a p-value of .113. The short-run marginal cost from the regression is the first lag term ($3,457). We included cross-section (county) and period (year) fixed effects in the specification. We also included a lagged dependent variable on the right-hand side. Without this variable, the sum of the three ADP coefficients totaled $37,637, an amount that seemed much higher than we expected. Thus, we included the lagged dependent variable in the model.[20]

Dependent Variable: JAILREAL-JAILREAL(-1)
Method: Panel Least Squares
Date: 01/21/10 Time: 14:36
Sample (adjusted): 1995 2008
Periods included: 14
Cross-sections included: 39
Total panel (balanced) observations: 546
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-682109.7	264036.1	-2.583395	0.0101
JAILREAL-1)-JAILREAL(-2)	0.359767	0.089133	4.036304	0.0001
JAILADP-JAILADP(-1)	3456.648	3050.223	1.133244	0.2577
JAILADP(-1)-JAILADP(-2)	8348.148	6128.536	1.362177	0.1738
JAILADP(-2)-JAILADP(-3)	9663.879	4591.016	2.104954	0.0358
JAILRREAL(-1)-39640.36*JAILADP(-1)	-0.266495	0.089148	-2.989351	0.0029

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.683040	Mean dependent var	439983.7
Adjusted R-squared	0.646742	S.D. dependent var	2286829.
S.E. of regression	1359189.	Akaike info criterion	31.18121
Sum squared resid	9.03E+14	Schwarz criterion	31.63038
Log likelihood	-8455.470	Hannan-Quinn criter.	31.35680
F-statistic	18.81750	Durbin-Watson stat	2.024971
Prob(F-statistic)	0.000000		

Jail Capital Costs. Local Adult Jail capital costs for new beds were estimated from an informal internet review of current estimates for a variety of new jails around the country. We placed the estimate at $150,000 capital cost per county jail bed. In our crime model, the total capital cost per bed is converted to an annualized capital payment, with equation (2), assuming a 25-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per bed converted to the base-year dollars chosen for the model.

[20] We also ran the preferred model shown above, but without the error correction. The coefficients from the three ADP variable totaled $44,980—again, this sum seems too large based on prior expectations.

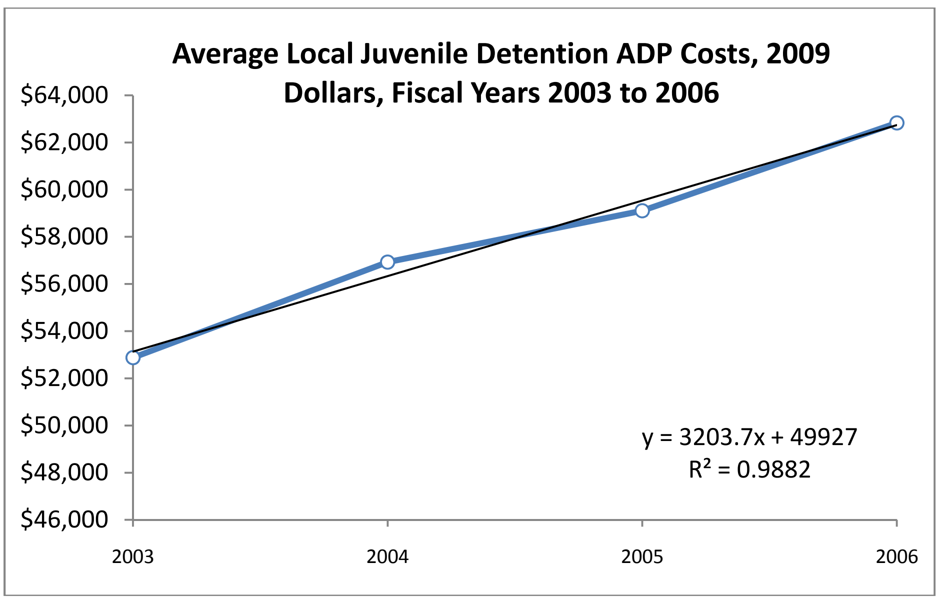
Local Juvenile Detention and Probation Per-Unit Costs

This section describes the steps we use to estimate marginal annual detention operating costs, and the long-run rate of real (inflation-adjusted) change in these costs of county-run juvenile detention facilities in Washington. We also describe our estimate of the capital cost per detention bed, as well as our estimate for the marginal annual costs of local juvenile probation and the real rate of annual escalation in these costs. All of these estimated cost parameters are entered into the crime model, as shown in Exhibit B.1.

Detention Operating Costs. For an estimate of the marginal operating cost of state juvenile offender institutions, we conducted a time-series analysis of annual data for detention expenditures and average daily admissions to juvenile detention facilities in Washington. From the Washington State Auditor, local juvenile detention operating expenditure data for counties were collected for 1993 to 2008, the earliest and latest years available. The Auditor's data for the expenses includes the categories for residential care&custdy-juvenilesvc (BARS 527.60) and juvenile facilities (BARS 527.80). Unfortunately, visual inspection of these historical data revealed significant problems and gaps, apparently caused by inconsistent reporting. We concluded that a consistent series could only be used for four years, 2003 to 2006. These nominal annual dollar amounts were adjusted to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council.

To our knowledge, there is not a consistent statewide data series available for the average daily population of the county juvenile detention facilities. Instead, we collected annual admission data for the juvenile facilities; this information is collected and published by the Washington State Governor's Juvenile Justice Advisory Committee. From other data we have analyzed previously, it appears the average length of stay of a juvenile detention admission is about 12 days. Using this figure, along with the actual admission data, we estimated the average daily population (ADP) of the facilities statewide.

We computed the average costs per institutional ADP (in 2009 dollars) and plotted these data on this chart.



Over the 2003 to 2006 timeframe, the average annual cost is $57,780 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 2003 ($53,131) and 2006 ($62,742) and calculated the average escalation rate for the three years, using formula (1), where FV is the 2006 estimated cost, PV is the 2003 estimate, and N is three years.

The annual rate of real escalation is .057. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1. Because this is a high escalation rate, it will be important to seek additional information for this parameter.

Next, to estimate the marginal annual operating costs of police agencies, we conducted a time-series analysis of the panel data for Washington's 39 counties for 2003 to 2006. Because of the reasons mentioned above regarding the lack of a longer time series, we could not conduct unit root tests for these data. Since a regression in levels indicated a very high R-squared, and this often can indicate unit roots, and since so many of our other analyses of criminal justice data have revealed unit roots, we proceeded to construct a first-difference regression model.

We tested alternative lag specifications of the admission data. Our preferred model contained two lags and also a lagged dependent variable. Because of the lagging and, unfortunately, the already short time series, the model only had two periods for the 20 counties in Washington with juvenile detention facilities. The sum of the two admission coefficients is $667. We converted this to an estimate of the annual marginal cost per ADP by, again, assuming a 12-day average length of stay. The result was an estimate of $20,293 per annual ADP for juvenile detention marginal operating expenditures, in 2009 dollars. The following are the regression results obtained to support these calculations.

Dependent Variable: JUVDETREAL-JUVDETREAL(-1)
Method: Panel Least Squares
Date: 02/05/10 Time: 17:16
Sample (adjusted): 2005 2006
Periods included: 2
Cross-sections included: 20
Total panel (balanced) observations: 40
White cross-section standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	80820.93	8253.006	9.792908	0.0000
JUVDETREAL(-1)-JUVDETREAL(-2)	-0.139491	0.082108	-1.698865	0.0980
JUVDETADM-JUVDETADM(-1)	445.0912	246.1837	1.807964	0.0790
JUVDETADM(-1)-JUVDETADM(-2)	222.0772	57.98376	3.829989	0.0005

R-squared	0.087247	Mean dependent var	44115.96
Adjusted R-squared	0.011185	S.D. dependent var	333851.7
S.E. of regression	331979.4	Akaike info criterion	28.35817
Sum squared resid	3.97E+12	Schwarz criterion	28.52706
Log likelihood	-563.1635	Hannan-Quinn criter.	28.41924
F-statistic	1.147044	Durbin-Watson stat	2.026817
Prob(F-statistic)	0.343320		

Local Detention Capital Costs. Per-bed capital costs for a new detention facility would run $200,000 per bed.[21] In our crime model, the total capital cost per arrest is converted to an annualized capital payment, with equation (2), assuming a 25-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per bed converted to the base-year dollars chosen for the model.

Local Juvenile Probation Per-Unit Costs

We searched for longitudinal time-series data to estimate the average annual cost of county-run juvenile probation services in Washington. Unfortunately, we did not locate a consistent set of expenditure information or average daily caseload information that would have allowed us to perform a valid time-series analysis. The expenditure data from the Washington State Auditor contain a considerable number of county jurisdictions that do not report, every year, their juvenile court expenditures. And, as far as we know, there is not a data source for the average daily juvenile court probation caseloads in Washington.

Therefore, we estimated marginal juvenile court probation costs with the following procedures.

1) From the State Auditor, we collected statewide juvenile court probation expenditure data for calendar year 2008, the latest year reported as of March 2010. These data appear to be reasonably complete with the exception of Snohomish County that did not report juvenile county probation expenditures that year. The total reported expenditures for juvenile probation for the state was $29,203,723 for 2008. Again, this figure does not include Snohomish County.

[21] Capital costs for a typical new local juvenile detention facility were estimated from personal communication with Washington's Juvenile Rehabilitation Administration staff.

2) From the Administrative Office of the Courts, we collected the reported number of juvenile court community supervision sentences and sentences with detention and community supervision for 2008. The total was 5,660.

3) From a WSIPP survey of juvenile court activities in 1995, we calculated that the average length of stay on juvenile court probation in Washington is 6.8 months.[22]

4) We then estimated the 2008 average daily probation caseload of juvenile courts as 3,207 (5,660 times 6.8 divided by 12 months).

5) We adjusted the statewide average daily caseload to remove Snohomish County by subtracting an estimate of Snohomish's average daily caseload. Snohomish had 705 juvenile court community supervision sentences and sentences with detention and community supervision in 2008. An estimate of the average daily caseload in Snohomish for 2008 was 400 (705 times 6.8 divided by 12 months), assuming the same 6.8-month average length of stay on juvenile court probation. Thus, after removing Snohomish, an estimate of the adjusted statewide average daily probation caseload was 2,808 in 2008.

6) We then computed the average expenditure per average annual daily caseload to be $10,401 (29,203,723 divided by 2,808).

7) From this estimate of the *average* expenditure per average annual caseload, we estimated the *marginal* expenditure per average annual caseload. We found from our time-series analysis of the community supervision costs of the Department of Corrections that the ratio of marginal costs to average costs was .50 (see local community supervision section where marginal DOC community supervision costs are estimates as $1,861 and average costs are $3,707). Multiplying $10,401 by .50 provides an estimate, $5,200 in 2008 dollars, of the marginal cost per average annual juvenile court caseload. This estimate is included as a parameter in the crime model, as shown in Exhibit B.1.

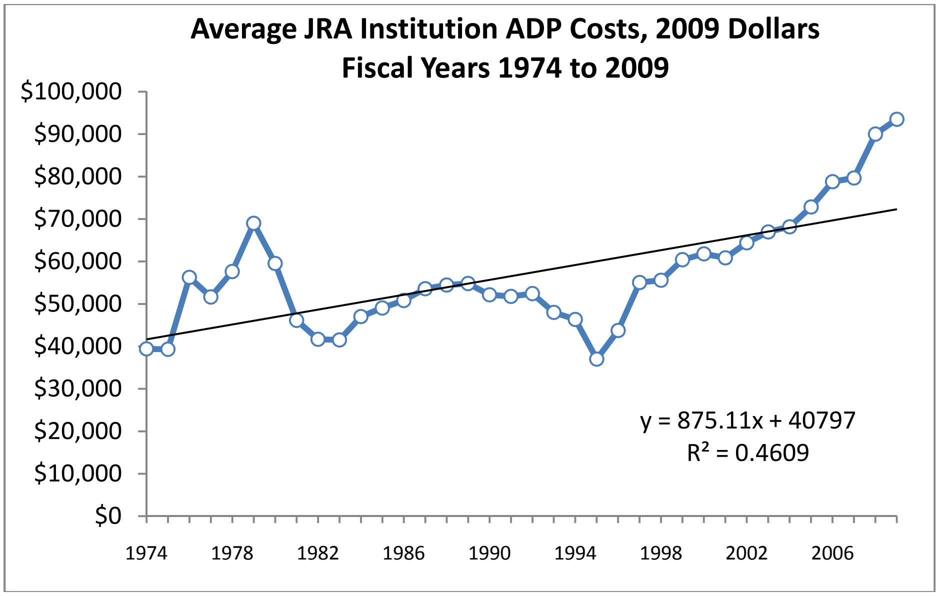
State Juvenile Rehabilitation Administration (JRA) Per-Unit Costs

This section describes the steps we use to estimate marginal annual institution operating costs, and the long-run rate of real (inflation-adjusted) change in these costs, of the Washington State Juvenile Rehabilitation Administration (JRA). JRA is Washington's state juvenile justice agency; juvenile offenders are sentenced to JRA based on Washington's sentencing laws and practices. We also describe our estimate of the JRA capital cost per institutional bed as well as our estimate for the marginal annual costs of community supervision for juvenile parole supervision in Washington, and the real rate of annual escalation in these costs. All of these estimated cost parameters are entered into the crime model, as shown in Exhibit B.1.

Institutional Operating Costs. For an estimate of the marginal operating cost of state juvenile offender institutions, we conducted a time-series analysis of annual data for institutional expenditures and average daily institutional population for JRA for fiscal years 1974 to 2009. The expenditure data were obtained from the Washington State's Legislative Evaluation and Accountability Program (LEAP) for Agency 300 (Juvenile Rehabilitation Administration) for code 2000 (institutional services). The LEAP data series for JRA begins in fiscal year 1974. We converted the expenditure data to 2009 dollars (JRAREAL) using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council. The average daily population for JRA institutions (JRAADP) series is from the Washington State Caseload Forecast Council for Fiscal Years 1997 to 2009, with data from 1974 to 1996 taken from annual reports of the Governor's Juvenile Justice Advisory Committee and data from various issues of the Databook series published by the Washington State Office of Financial Management.

We computed the average costs per institutional ADP (in 2009 dollars) and plotted these data on this chart.

[22] M. Burley & R. Barnoski (1997). *Washington state juvenile courts: Workloads and costs.* Olympia: Washington State Institute for Public Policy, Document No. 97-04-1201, Table 2.



Over the entire 1974 to 2009 timeframe, the average cost is $56,373 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 1974 ($41,642) and 2009 ($72,271) and calculated the average escalation rate for the 35 years, using formula (1), where FV is the 2009 estimated cost, PV is the 1974 estimate, and N is 35 years.

The annual rate of escalation is .016. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1. The data plotted on the chart reveals that in the last five years, the growth in real average costs has been on a steeper incline compared with the annual growth rate over the entire period of record. Thus, our estimate of .016 may be on the low side if recent trends persist.

To estimate the marginal annual operating cost of a state institutional bed, we conducted a time-series analysis of these data. First, we tested each data series (JRAADP and JRAREAL) for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[23] We tested for unit roots with an Augmented Dickey-Fuller (ADF) test.

- For the JRAREAL expenditure series, the ADF test failed to reject the null hypotheses that the series has a unit root, with p-values of .511 without a time trend and .620 with a time trend, indicating a unit root with both tests. In first-differences, on the other hand, the ADF p-value for the JRAREAL series is 0.000.
- For the JRAADP series, the p-values were .299 without a time trend and .760 with a time trend, indicating a unit root in both tests. In first-differences, the ADF p-value for the JRAADP series is 0.049.
- With both JRAREAL and JRAADP series indicating unit roots in levels and no unit roots in first-differences, we proceeded to construct a model in first-differences.

Since the two series have unit roots, we tested to determine if the two series together are cointegrated.[24] We used an Engle-Granger test to determine whether the residuals from a cointegrating regression of the two series are integrated of order 1 (i.e., I(1), unit root). The resulting tau-statistic from the regression was -1.03, which is well below the Engle-Granger critical value of -3.9 (p-value .01) for the null hypothesis that the residual series has a unit root. Therefore, this test did not reject the null hypothesis that the two series, jointly, have a unit root. We concluded that the two series together are I(1) and, therefore, not I(0) cointegrated.

[23] Wooldridge, p. 636.
[24] Ibid., p. 639.

We then computed a first-difference model with three lags on the first-differenced JRAADP variables and obtained the following result:

Dependent Variable: JRAREAL-JRAREAL(-1)
Method: Least Squares
Date: 01/20/10 Time: 15:53
Sample (adjusted): 1975 2009
Included observations: 35 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-321480.3	928044.0	-0.346406	0.7315
JRAADP-JRAADP(-1)	5845.823	16565.04	0.352901	0.7266
JRAADP(-1)-JRAADP(-2)	28438.73	18767.99	1.515279	0.1402
JRAADP(-2)-JRAADP(-3)	2458.799	13179.94	0.186556	0.8533
RPCI(-1)-RPCI(-2)	2276.323	888.6560	2.561534	0.0157

R-squared	0.257160	Mean dependent var	1038534.
Adjusted R-squared	0.158115	S.D. dependent var	5199909.
S.E. of regression	4771140.	Akaike info criterion	33.72563
Sum squared resid	6.83E+14	Schwarz criterion	33.94783
Log likelihood	-585.1986	Hannan-Quinn criter.	33.80233
F-statistic	2.596387	Durbin-Watson stat	2.090018
Prob(F-statistic)	0.056213		

After testing different model specifications, our preferred model includes three lagged first-difference JRAADP variables and a first-differenced covariate (RPCI, real per capita income). We examined multiple lags in the JRAADP variables and three lags seemed appropriate. The sum of the three lagged coefficients is $36,743, in 2009 dollars. This is our estimate of the marginal operating cost of an annual JRA bed.[25] The three ADP variables were jointly significant with a p-value on the F test of .0473. The short-run marginal cost from the regression is the first lag term ($5,846).

JRA Capital Costs. JRA capital costs for typical new institutional beds were estimated from personal communication with JRA staff. Per-bed capital costs for a new medium secure facility would run $125,000 to $175,000 per bed. In our crime model, the total capital cost per arrest is converted to an annualized capital payment, with equation (2), assuming a 25-year financing term (n), the bond financing rate entered in the model (i), and setting PV equal to the capital cost per bed converted to the base year dollars chosen for the model.

JRA Parole Costs. We were unable to obtain a long-term data set to analyze the marginal cost of JRA parole services. The electronic data for parole expenditures were only available starting in fiscal year 2000 and, beginning in fiscal year 2006, there was a significant accounting change that rendered the post-2005 data unusable for measuring parole expenditures. We do have consistent parole average daily population data from 1981 through 2009. We intend to obtain earlier expenditure data which may allow a regression analysis. In the meantime, we calculated an average parole cost by summing inflation-adjusted JRA parole costs from 2000 to 2005: $43,044,069 (in 2009 dollars). The sum of the average daily parole caseloads during these same years was 5,481. Thus, the average annual expenditure per parole average daily population is $7,853, in 2009 dollars. From this estimate of the average expenditure per average annual caseload, we estimated the marginal expenditure per average annual caseload. We found from our time-series analysis of the community supervision costs of the Department of Corrections that the ratio of marginal costs to average costs was .50. Multiplying $7,853 by .50 provides an estimate, $3,927 in 2009 dollars, of the marginal cost per average annual JRA parole caseload. This estimate is included as a parameter in the crime model, as shown in Exhibit B.1.

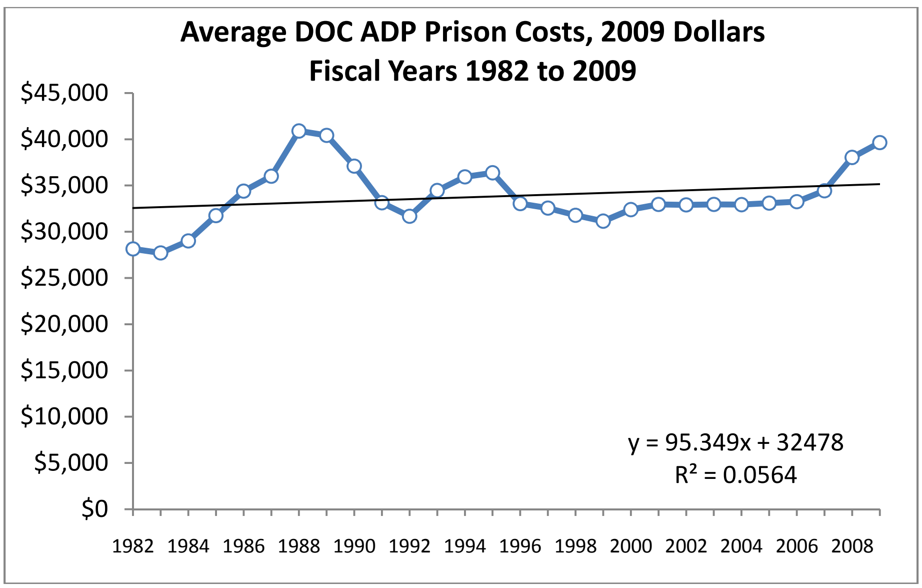
[25] We also estimated a model identical to our preferred model but with a lagged first-differenced dependent variable on the right-hand side. The sum of the three ADP coefficients was $39,138, only slightly larger than our preferred model. For purposes of our benefit-cost model, which is to compute benefit-cost estimates of evidence-based programs that reduce crime, our preference is to use the slightly more cautious estimate.

State Department of Corrections (DOC) Per-Unit Costs

This section describes the steps we used to compute estimates of Washington Department of Corrections' marginal annual prison operating costs and the long-run rate of change in these costs. We also provide our estimate of the capital cost of a prison bed. Additionally, we describe our estimate for the annual cost of community supervision for adult felony offenders in Washington, and the real rate of annual escalation in this cost.

Prison Operating Costs. For prison operating costs, we analyzed annual data for DOC institutional expenditures and average daily prison population for fiscal years 1982 to 2009. The expenditure data were obtained from Washington State's Legislative Evaluation and Accountability Program (LEAP) for Agency 310 (Department of Corrections) for code 200 (correctional expenditures); the LEAP data series for DOC begins in fiscal year 1982. The "correctional expenditures" category pertains to operating expenses for running the state's prison system, not the community corrections system. We converted the expenditure data to 2009 dollars using the United States Implicit Price Deflator for Personal Consumption Expenditures from the US Department of Commerce, as published and forecasted by the Washington Economic and Revenue Forecast Council. The average daily prison population (ADP) series is from the Washington State Caseload Forecast Council for fiscal years 1993 to 2009, with data for earlier years taken from various issues of the Databook series published by the Washington State Office of Financial Management.

We computed the average cost per prison ADP (in 2009 dollars) for 1982 to 2009 and plotted the results.



Over the entire 1982 to 2009 timeframe, the average cost is $33,951 per ADP, in 2009 dollars. Over these years, there has been a slight upward trend in the inflation-adjusted per-unit costs, as revealed by the linear regression line shown in the Exhibit. To compute an estimate of the long-run growth rate in real cost per average daily population, we calculated the predicted values from the regression line for 1982 ($32,573) and 2009 ($35,148) and calculated the annual rate of escalation for the 27 years using equation (1), where FV is the 2009 cost estimate, PV is the 1982 estimate, and N is 27 years.

The annual rate of real escalation in average costs is .003. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1.

To estimate marginal prison operating costs, we conducted a time-series analysis of total annual real operating costs (DOCREAL) and the total annual prison average daily population (DOCADP). First, we tested each data series for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[26] We tested for unit roots with an Augmented Dickey-Fuller (ADF) test.

- For the DOCREAL expenditure series, the ADF test failed to reject the null hypotheses that the series has a unit root with p-values of .9999 without a time trend and .9978 with a time trend. In first-differences, on the other hand, the ADF p-value for the DOCREAL series was 0.0146, indicating a lack of a unit root in a first-differenced data series.

[26] Wooldridge, p. 636.

- For the DOCADP series, the p-values for the ADF test were .8668 without a time trend and .2744 with a time trend; both tests indicate that the DOCADP series in levels has a unit root. In first-differences, the ADF p-value for the DOCADP series was 0.0458 indicating a lack of a unit root in first-differences.
- With both DOCREAL and DOCADP series indicating unit roots in levels and no unit roots in first-differences, we proceeded to construct models in first-differences.[27]

Assuming the two series have unit roots, we tested to determine if the two series together are cointegrated.[28] We used an Engle-Granger test to determine whether the residuals from the cointegrating regression were integrated of an order of 1 (i.e., I(1), a unit root). The resulting tau-statistic from the regression was -2.667, which is below the Engle-Granger critical value of -3.9 (p-value .01). Therefore, this test did not reject the null hypothesis that the two series, jointly, have a unit root. We concluded that the two series together are I(1) and, therefore, not cointegrated.

Dependent Variable: DOCREAL-DOCREAL(-1)
Method: Least Squares
Date: 01/18/10 Time: 16:09
Sample (adjusted): 1983 2009
Included observations: 27 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12790705	6212729.	2.058790	0.0521
DOCADP-DOCADP(-1)	4495.187	6295.155	0.714071	0.4830
DOCADP(-1)-DOCADP(-2)	-4288.905	5011.822	-0.855758	0.4018
DOCADP(-2)-DOCADP(-3)	6745.884	3736.465	1.805419	0.0854
DOCADP(-3)-DOCADP(-4)	6968.766	2879.800	2.419879	0.0247
RPCI(-1)-RPCI(-2)	2355.135	3505.699	0.671802	0.5090

R-squared	0.128695	Mean dependent var	21124103
Adjusted R-squared	-0.078759	S.D. dependent var	14953657
S.E. of regression	15531362	Akaike info criterion	36.14775
Sum squared resid	5.07E+15	Schwarz criterion	36.43571
Log likelihood	-481.9946	Hannan-Quinn criter.	36.23338
F-statistic	0.620356	Durbin-Watson stat	1.290263
Prob(F-statistic)	0.685814		

Since the two unit root series are not jointly cointegrated, we did not estimate an error correction model and, instead, estimated a first-difference model.[29] The following results were obtained.

After testing different model specifications, our preferred model includes regressors with four lagged first-difference DOCADP variables and a first-differenced covariate (RPCI, real per capita income). We examined different numbers of lags in the DOCADP variables, and four lags seemed appropriate empirically and logically given our knowledge of state budgeting processes. The four DOCADP lags are jointly statistically significant (F test p-value .0085). The three positive DOCADP lags are jointly significant (p-value 0.0042). The short-run marginal cost from the regression is the first lag term ($4,495).

The unadjusted sum of the coefficients (the long-run multiplier) on the four DOCADP distributed lags is ($13,921). In our judgment, the negative term on the second distributed lag (-$4,289) does not make intuitive sense. Other things being equal, agency budgets are unlikely to be cut when ADP increases, or raised when ADP decreases. To test the reasonableness of this point, we conducted four separate univariate first-difference models: (1) $\Delta DOCREAL_t = a + b(\Delta DOCADP_t)$; (2) $\Delta DOCREAL_t = a + b(\Delta DOCADP_{t-1})$; (3) $\Delta DOCREAL_t = a + b(\Delta DOCADP_{t-2})$; and finally, (4) $\Delta DOCREAL_t = a + b(\Delta DOCADP_{t-3})$. The b coefficients in these four models were $8,671, $9,248, $1,655, and $717, respectively. The sum of these coefficients is $20,291. Significantly, the coefficient in the second univariate model was a positive number. Based on the intuitive reasoning against a negative coefficient, as well as the univariate evidence, we did not include the negative value from the second coefficient (in our preferred model) in our sum of estimated impacts. The resulting sum of the three positive coefficients is $18,210.

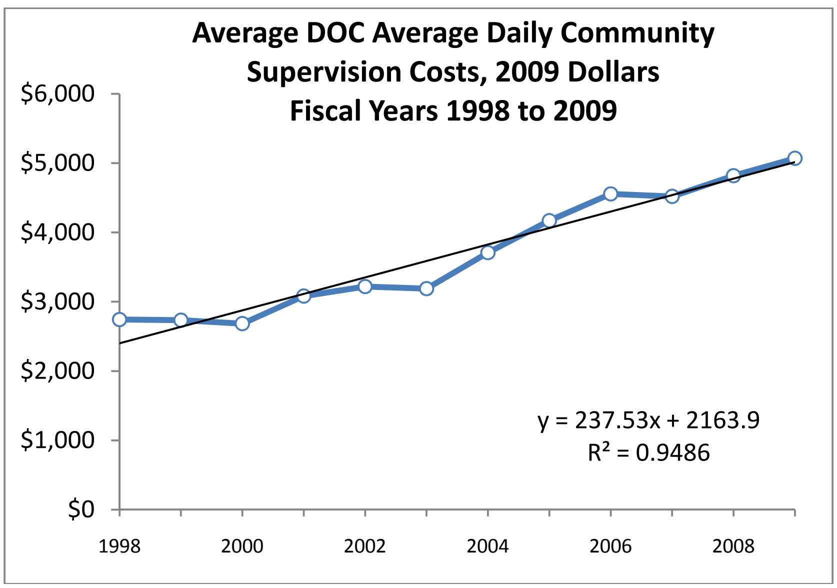
[27] Wooldridge, p. 643.
[28] Wooldridge, p. 639.
[29] Wooldridge, p. 643.

This figure, \$18,210 per ADP (in 2009 dollars), represents our preferred estimate of the long-run incremental expenditures to DOC for a year in prison. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1.[30]

The readily available annual time series for this analysis, unfortunately, was limited from 1982 to 2009, because expenditure data (DOCREAL) were only available from 1982 onward. We intend to obtain earlier expenditure data, which may allow more precise regression estimates.

Prison Capital Costs. DOC capital costs for new institutional beds were estimated. Capital cost estimates for the relatively new Coyote Ridge medium security facility in Washington were obtained from legislative fiscal staff. The 2,048 bed facility cost \$232,118,000 (thus, a per-bed cost of \$113,339) and was completed in 2008. We recorded this per-bed cost figure as 2007 dollars since it is likely that was when most of the construction dollars were spent. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1. In our crime model, the total construction costs per-bed are converted to an annualized capital payment, with equation (2), assuming a 25-year financing term, the bond financing rate entered in the model, and setting PV equal to the per-bed construction cost converted to the base year dollars chosen for the model.

Community Supervision Operating Costs. We analyzed Department of Corrections' community supervision cost for all felony offenders on active supervision regardless of sentence type (prison or jail). For community supervision costs, we analyzed annual data for DOC community supervision expenditures and average daily community population for Fiscal Years 1998 to 2009. The expenditure data were obtained from Washington State's Legislative Evaluation and Accountability Program (LEAP) for Agency 310 (Department of Corrections) for code 300 (community supervision); the LEAP data series for DOC begins in fiscal year 1982. Community supervision population data were obtained from the Washington Caseload Forecast Council, which maintains data back to fiscal year 1998. We calculated annual cost per average daily community population and converted to 2009 dollars using the aforementioned price index. The 2009 cost per average daily community population is \$5,069.



Over the 1998 to 2009 period, there was a significant upward trend in the inflation-adjusted per-unit costs, as revealed by the linear regression line shown in the Exhibit. To compute an estimate of the long-run growth rate in real cost per average daily population, we calculated the predicted values from the regression line for 1998 (\$2,401) and 2009 (\$4,777) and calculated the annual rate of escalation for the 11 years using equation (1) where FV is the cost estimate for 2009, PV is the estimate for 1998, and N is 11 years.

The annual rate of real escalation in average costs is 0.064. This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1. This estimate seems high, and it will be useful to monitor actual expenditure trends in the years ahead.

[30] As an additional test, we ran our preferred model with a lagged first difference dependent variable on the right-hand side of the equation. The results were somewhat similar to our preferred model (e.g., the sum of the three positive lagged DOCADP coefficient was \$15,413, but the three coefficient together were only marginally significant with a F-test p-value of .1111).

To estimate marginal community supervision operating costs, we conducted a time-series analysis of total annual real operating costs (DOCCSREAL) and the total annual community supervision average daily population (DOCCSADP). First, we tested each data series for unit roots. If unit roots are present, then a simple regression in levels of two unit root series can produce spurious results.[31] We tested for unit roots with an Augmented Dickey-Fuller (ADF) test.

- For the DOCCSREAL expenditure series, the ADF test failed to reject the null hypotheses that the series has a unit root with p-values of .8446 without a time trend, but was significant at .0276 with a time trend. In first-differences, on the other hand, the ADF p-value for the DOCCSREAL series was 0.0263, indicating a lack of a unit root in a first-differenced data series.
- For the DOCCSADP series, the p-values for the ADF test were .2243 without a time trend and .2682 with a time trend; both tests indicate that the DOCCSADP series in levels has a unit root. In first-differences, the ADF p-value for the DOCCSADP series was 0.1318 indicating, marginally, a lack of a unit root in first-differences.
- With both DOCCSREAL and DOCCSADP series indicating, generally, unit roots in levels (with the exception of an ADF test with a time trend for DOCCSREAL) and, marginally, no unit roots in first-differences, we proceeded to construct models in first-differences. We also tested models in levels.

Assuming the two series have unit roots, we tested to determine if the two series together are cointegrated.[32] We used an Engle-Granger test to determine whether the residuals from a cointegrating regression of the two series are integrated of order 1 (i.e., I(1), a unit root). The resulting tau-statistic from the regression was -1.45, which is well below the Engle-Granger critical value of -3.9 (p-value .01) for the null hypothesis that the residual series has a unit root. Therefore, this test did not reject the null hypothesis that the two series, jointly, have a unit root. We concluded that the two series together are I(1) and, therefore, not cointegrated.

Since the two unit root series are not jointly cointegrated, we did not estimate an error correction model. Since there was some ambiguity over the existence of unit roots, we ran a basic regression in both levels and first-differences. The following first-difference results, our preferred approach, were obtained. The sum of the three coefficients total $1,861 per ADP, in 2009 dollars.[33] This point estimate is included as a parameter in the crime model, as shown in Exhibit B.1. The three ADP variables are jointly significant with a p-value on the f-test of .0042.

Dependent Variable: DOCCSREAL-DOCCSREAL(-1)
Method: Least Squares
Date: 01/19/10 Time: 16:50
Sample (adjusted): 2001 2009
Included observations: 9 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9209858.	1150172.	8.007374	0.0005
DOCCSADP-DOCCSADP(-1)	1193.120	220.3772	5.413988	0.0029
DOCCSADP(-1)-DOCCSADP(-2)	449.9942	659.9840	0.681826	0.5256
DOCCSADP(-2)-DOCCSADP(-3)	217.7877	483.4093	0.450525	0.6712

R-squared	0.542175	Mean dependent var	8708889.
Adjusted R-squared	0.267480	S.D. dependent var	5067302.
S.E. of regression	4336970.	Akaike info criterion	33.70435
Sum squared resid	9.40E+13	Schwarz criterion	33.79201
Log likelihood	-147.6696	Hannan-Quinn criter.	33.51519
F-statistic	1.973736	Durbin-Watson stat	2.347624
Prob(F-statistic)	0.236419		

This first-difference model is our preferred model. Our model in levels revealed a negative relationship between community supervision average daily population and real expenditures, which does not make intuitive budgeting sense. The first-difference model, shown above, produced the most plausible estimates, given our knowledge of state budget processes.

[31] Wooldridge, p 636.
[32] Wooldridge, p 639.
[33] We ran this same model with a lagged first difference dependent variable on the right-hand side and the sum of the three coefficients was $2,407. For purposes of our benefit-cost model, which is to compute benefit-cost estimates of evidence-based programs that reduce crime, our preference is to use the non-lagged dependent variable model since it produces a slightly more cautious estimate.

Victimizations Per-Unit Cost

In addition to costs paid by taxpayers, many of the costs of crime are borne by victims. Some victims lose their lives. Others suffer direct, out-of-pocket, personal or property losses. Psychological consequences also occur to crime victims, including feeling less secure in society. The magnitude of victim costs is very difficult—and in some cases impossible—to quantify.

In recent years, however, analysts have taken significant steps in estimating crime victim costs. We use a consistent set of estimates (McCollister, 2010), with some modifications, in the WSIPP benefit-cost model.[34] These crime victim costs build on and modify the previous work prepared for the U.S. Department of Justice by Miller, Cohen, and Wiersema (1996).[35]

These studies divide crime victim costs into two types:

a) *Tangible* victim costs, which include medical and mental health care expenses, property damage and losses, and the reduction in future earnings incurred by crime victims; and

b) *Intangible* victim costs, which place a dollar value on the pain and suffering of crime victims. In these two studies, the intangible victim costs are computed, in part, from jury awards for pain, suffering, and lost quality of life.

The McCollister study divides total tangible costs of crime into tangible victim costs, criminal justice system costs, and crime career costs of offenders (estimates of the economic productivity losses for offenders). In WSIPP's model, we only include McCollister's tangible victim costs since we estimate criminal justice costs separately. We currently do not make estimates of the crime career costs of offenders.

We also use McCollister's intangible victim costs with one exception. McCollister computes a "corrected risk-of-homicide cost" as part of crime specific intangible victim costs. This is done because, according to McCollister, the FBI's Uniform Crime Reports (UCR) classifies some homicides as other non-homicide crimes when certain offense information is lacking. This FBI reporting practice requires the adjustment made by McCollister. For application to WSIPP's benefit-cost model, however, this adjustment is not necessary. WSIPP's crime cost estimates are applied to accurately classified conviction data from Washington State; convictions for homicide are not misclassified as other crimes in the Washington system. See section B.4 of this Technical Appendix for a description of WSIPP data sources for counting convictions.

WSIPP's model also has one crime category for felony property crimes. The McCollister study breaks WSIPP's property crime classification into motor vehicle theft, household burglary, and larceny/theft. We use these three categories and compute a weighted average property category using the estimated number of crimes calculated for Washington as weights.

WSIPP's modified McCollister crime victim cost estimates are included in the crime model, as shown in Exhibit B.1.

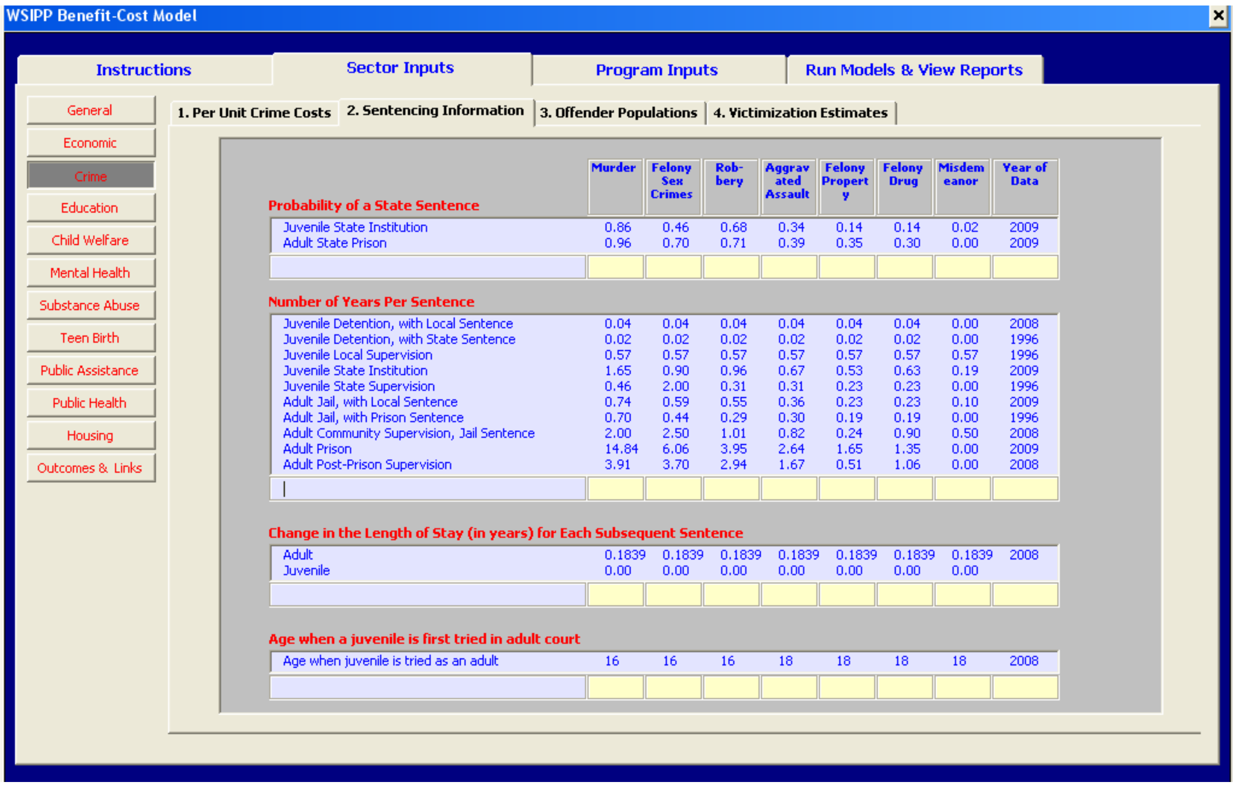
[34] K. E. McCollister, M. T. French, & H. Fang (2010). The cost of crime to society: New crime-specific estimates for policy and program evaluation. *Drug and Alcohol Dependence, 108*(1), 98-109.
[35] T. R. Miller, M. A. Cohen, and B. Wiersema. (1996) *Victim Costs and Consequences: A New Look*. Research Report. Washington DC: National Institute of Justice.

B.2 The Criminal Justice System's Response to Crime

Not all crime is reported to, or acted upon by, the criminal justice system. When crimes are reported by citizens or detected by police or other officials, however, the use of taxpayer-financed resources begins. The degree to which these resources are used depends on the crime as well as the policies and practices governing the criminal justice system's response. In the preceding section, we describe the *per-unit* marginal cost estimates used in our model. In this section, we discuss *how many units* of the criminal justice system are used when a crime occurs.

Once a person is convicted for a criminal offense, sentencing policies and practices in Washington affect the use of different local and state criminal justice resources. Exhibit B.2 is a screen shot from WSIPP's benefit-cost model that displays how criminal justice resources in Washington State are used in response to crime. The estimates for each row in Exhibit B.2 are described below.

Exhibit B.2



	Murder	Felony Sex Crimes	Rob-bery	Aggravated Assault	Felony Property	Felony Drug	Misdemeanor	Year of Data
Probability of a State Sentence								
Juvenile State Institution	0.86	0.46	0.68	0.34	0.14	0.14	0.02	2009
Adult State Prison	0.96	0.70	0.71	0.39	0.35	0.30	0.00	2009
Number of Years Per Sentence								
Juvenile Detention, with Local Sentence	0.04	0.04	0.04	0.04	0.04	0.04	0.00	2008
Juvenile Detention, with State Sentence	0.02	0.02	0.02	0.02	0.02	0.02	0.00	1996
Juvenile Local Supervision	0.57	0.57	0.57	0.57	0.57	0.57	0.57	1996
Juvenile State Institution	1.65	0.90	0.96	0.67	0.53	0.63	0.19	2009
Juvenile State Supervision	0.46	2.00	0.31	0.31	0.23	0.23	0.00	1996
Adult Jail, with Local Sentence	0.74	0.59	0.55	0.36	0.23	0.23	0.10	2009
Adult Jail, with Prison Sentence	0.70	0.44	0.29	0.30	0.19	0.19	0.00	1996
Adult Community Supervision, Jail Sentence	2.00	2.50	1.01	0.82	0.24	0.90	0.50	2008
Adult Prison	14.84	6.06	3.95	2.64	1.65	1.35	0.00	2009
Adult Post-Prison Supervision	3.91	3.70	2.94	1.67	0.51	1.06	0.00	2008
Change in the Length of Stay (in years) for Each Subsequent Sentence								
Adult	0.1839	0.1839	0.1839	0.1839	0.1839	0.1839	0.1839	2008
Juvenile	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Age when a juvenile is first tried in adult court								
Age when juvenile is tried as an adult	16	16	16	18	18	18	18	2008

Probability of a State Sentence. The first block of information in Exhibit B.2 displays parameters indicating the probability that a person convicted for one of the seven crime categories modeled will receive a sentence to a juvenile state institution (instead of local juvenile detention) or adult state prison (instead of local adult jail). For example, if an adult offender is convicted of robbery, there is a 71 percent chance the offender will receive a prison sentence and a 29 percent chance of receiving a jail sentence. These sentencing probabilities were obtained from the Washington State Sentencing Guidelines Commission.[36]

Number of Years Per Sentence. We estimate the average number of years various criminal justice resources are used for each of the crime categories.

[36] Juvenile sentencing information obtained from SGC staff via email on March 10, 2010. Adult sentencing information obtained from Table 1 of Sentencing Guidelines Commission (2009). *Statistical summary of adult felony sentencing*. Olympia, WA: Sentencing Guidelines Commission.

Juvenile Detention (with local or state sentence). Unfortunately, Washington does not have an annual reporting system on local juvenile detention length of stay. Therefore, the average length of stay at local juvenile detention facilities and the average length of local probation were estimated from an earlier survey of juvenile courts conducted by WSIPP.[37]

Juvenile Local Supervision. The average length of stay on probation was also estimated from the same survey of juvenile courts conducted by WSIPP.[38]

Juvenile State Institution. The average length of stay in a juvenile state institution was estimated using data obtained from the Sentencing Guidelines Commission.[39]

Juvenile State Supervision. The average length of stay on juvenile parole was estimated using information obtained from the Juvenile Rehabilitation Administration.[40]

Adult Jail, with Local Sentence. The average length of stay in jail for local sentences was estimated using data from the Sentencing Guidelines Commission.[41]

Adult Jail, with Prison Sentence. Analysis from the Department of Corrections on the credit for time served in jail was used to estimate the total length of stay in jail prior to prison.[42]

Adult Community Supervision and Adult Post Prison Supervision. These numbers were obtained from the Sentencing Guidelines Commission.[43]

Adult Prison. The information for the average sentence received for adults sentenced to a state prison comes from Sentencing Guidelines Commission data. As a result of good-time reductions to some prison sentences, the average time actually served is often shorter than the original sentence. Exhibit B.2 shows the average prison length of stay, which is computed in the model by multiplying the sentence length of stay by an average percentage good-time reduction. The data on the average sentence reductions, by crime, were obtained from an analysis supplied by the Washington State Department of Corrections.

Change in the Length of Stay for Each Subsequent Sentence. In Washington, the sentence for a crime is based on the seriousness of the offense and the offender's criminal history. The Sentencing Guidelines Commission (SGC) publishes a grid showing the sentence by seriousness and the number of previous convictions. The sentence length for a given crime increases as criminal history increases.

To account for these lengthening sentences, we use the sentencing grid and WSIPP's average length of stay data to create a new sentencing grid weighted for the frequency of conviction and the likelihood of prison. This enables us to estimate the effect of increasing trips through the criminal justice system on sentence length.

We estimate this first, by determining the average length of stay for recidivists convicted of the following offense categories: murder, sex, robbery, assault, property, drug, and misdemeanor. We assume offenders who released from prison have at least three prior offenses and then determine the following:

- Likelihood of conviction.
- Likelihood of going to prison if convicted.
- Average length of stay (LOS).

Next, we determine what the offense seriousness level is upon the fourth conviction. We do this by matching the length of stay for the offense category with the seriousness level in the sentencing grid and with a sentence most similar to the length of stay. For example, the average length of stay in prison for murder (all offenses from manslaughter through first degree murder) is 13.4 years. This length of stay, with three prior offenses, is closest to the sentence at Seriousness Level XIII.

We then weight the sentences in the grid for the likelihood of recidivism in the offense categories and the likelihood of going to prison.

[37] R. Barnoski & M. Burley (1997). *Washington State juvenile courts: Workloads and costs.* Olympia: Washington State Institute for Public Policy, Document No. 97-04-1201.
[38] Ibid.
[39] Received via email on March 10, 2010.
[40] Received via phone conversation on April 18, 1997.
[41] SGC 2009, Table 1.
[42] Received via phone conversation on November 7, 1996.
[43] Received via email on April 6, 2010.

Finally, we create a single grid with increased average sentences by increased number of prior convictions. We plot this weighted average sentence by number of offenses. The result is a linear relationship; the slope indicates that each subsequent conviction increases the average prison sentence by an additional 0.1839 year. As of April 2010, we have not computed a similar procedure for juvenile repeat offenders sentenced to state institutions.

Age When a Juvenile Is First Tried in Adult Court. Under Washington's current laws, the age at which a youth is considered an adult varies for specific types of crimes. Exhibit B.2 contains information on the maximum age for juvenile court jurisdiction by type of crime. The actual determination of juvenile or adult court jurisdiction depends on several factors, in addition to a person's age and his or her crime. The model uses the information in Exhibit B.2 as representative of the typical decisions made pursuant to current Washington State law.

B.3 Criminological Information for Different Populations[44]

Offender Populations. In order to estimate the long-run effectiveness of programs, we combine program effect sizes with crime information for various offender populations in Washington State. Recidivism parameters are calculated using WSIPP's criminal records database. This database is a synthesis of criminal charge information for all individuals in Washington State.[45] Recidivism is defined as any offense committed after release to the community, or after initial placement in the community, that results in a conviction in Washington State. This includes convictions in juvenile and adult court.

We selected the 1993 cohort of offenders, which provides a long-term recidivism follow-up period of 15 years to observe subsequent convictions. A one-year adjudication period is included in the follow-up to allow for court processing of any offenses that occur at the end of the 15-year follow-up. These recidivism data include the probability of any reoffense, the type of reoffenses, the timing of reoffenses over the 15-year period, and the volume of reoffenses.

We collect recidivism data on five general populations of offenders who became "at-risk" for recidivism in the community during calendar year 1993. For adult offenders, we observe recidivism patterns for (1) offenders released from Department of Corrections' (DOC) facilities, and (2) offenders sentenced directly to DOC community supervision. For juvenile offenders, we observe recidivism patterns for (3) youth released from Juvenile Rehabilitation Administration (JRA) facilities, (4) youth sentenced to diversion through local-sanctioning courts, and (5) youth sentenced to detention/probation through local-sanctioning courts.

In order to apply the most appropriate crime distribution for a given population receiving a program, we further break down the general offender populations into various offense and risk for reoffense categories. Offense categories are based upon most serious current offense for which the offender was convicted prior to the 15-year follow-up period. For both adults and juveniles, risk for reoffense was calculated using criminal history data to determine offenders' probability of future reoffense and broken into low, moderate, and high risk categories.[46]

Thus, we calculated separate crime distributions for 45 populations (nine offender categories for each of the five general populations). The nine offender categories include:

1) The general population of offenders (e.g., DOC offenders releasing from prison, or juvenile offenders sentenced to diversion)

Risk for future reoffense categories (mutually exclusive):

2) High risk offenders
3) Moderate risk offenders
4) Low risk offenders

Most serious current offense categories (mutually exclusive):

5) Violent offenders
6) Sex offenders
7) Property offenders
8) Drug offenders
9) Misdemeanor offenders

For each population, we calculate the percentage of the cohort that was reconvicted for a felony or misdemeanor in Washington during the 15-year follow-up period. Next, for those who were reconvicted, we compute a probability density distribution for each of the 45 populations using lognormal, gamma, or weibull distributions, which indicate when convictions are likely to happen over the 15-year follow-up period.

From the recidivism data, we also calculate the total number of adjudications defined as the number of "trips" through the criminal justice system during the 15-year follow-up period. It is possible for offenders to have multiple offense convictions for each trip through the system. Thus, we also calculate the total number of offenses during the follow-up period. Recidivism

[44] We are in the process of updating our crime population data. From April 2010 onward, however, we will use the crime populations as described above. For this report, scenarios are based upon the crime populations as described in: S. Aos, M. Miller, & E. Drake (2006). *Evidence-based public policy options to reduce future prison construction, criminal justice costs, and crime rates.* Olympia: Washington State Institute for Public Policy, Document No.06-10-1201.
[45] Criminal history data are from the Administrative Office of the Courts and the Department of Corrections.
[46] See R. Barnoski & E. Drake (2007). *Washington's Offender Accountability Act: Department of Corrections' static risk instrument*. Olympia: Washington State Institute for Public Policy, Document No. 07-03-1201. See also R. Barnoski (2004). *Assessing risk for re-offense: Validating the Washington State juvenile court assessment*. Olympia: Washington State Institute for Public Policy, Document No. 04-03-1201.

adjudications and offenses are broken into the following offense categories: murder, sex, robbery, assault, property, drug, and misdemeanor. Using this information, we then determine the average number of adjudications a person has through the criminal justice system. In addition, we calculate the average number of offenses per adjudication. Finally, we compute the average time between sentences over the follow-up period.

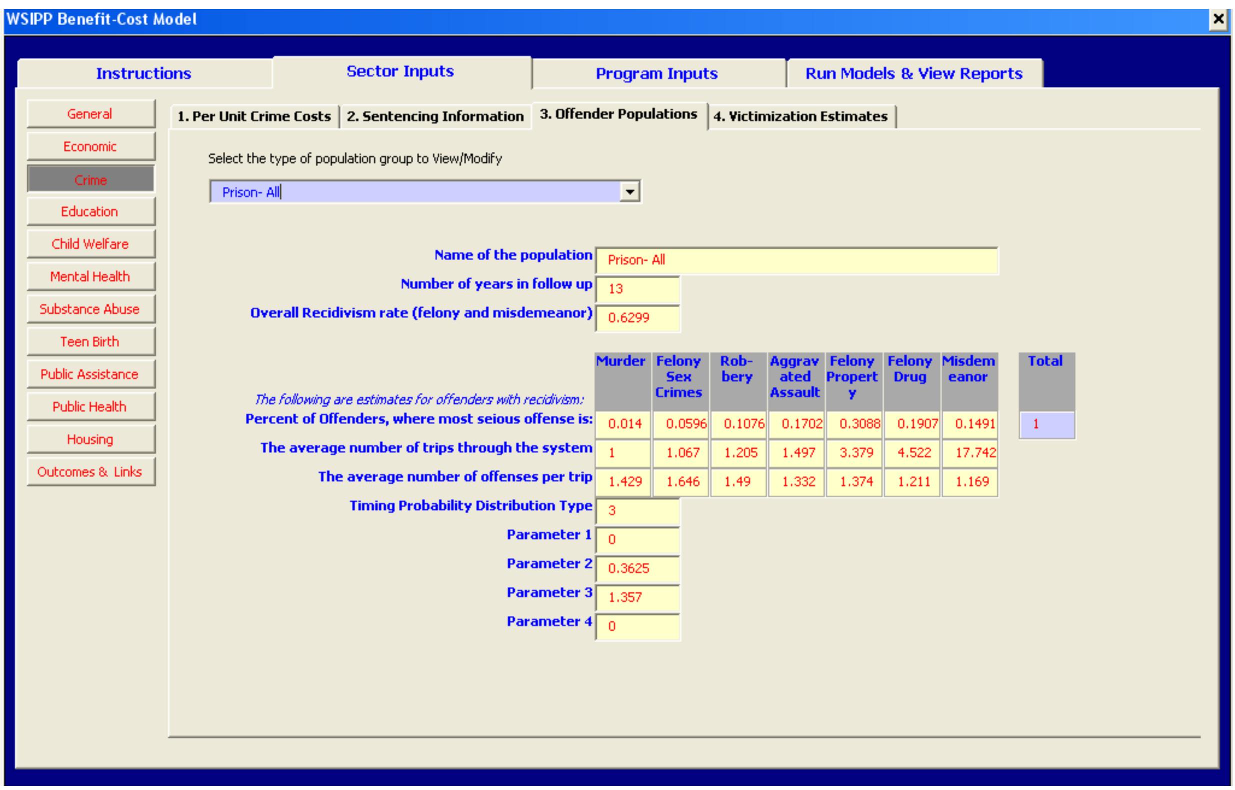
Non-Offender Populations. For prevention programs, we similarly estimate long-run crime distributions for non-offender populations by calculating the probability of obtaining a conviction over the life-course. These crime data also include the types of offenses, the timing of offenses over the life-course, and the volume of offenses. We select the 1974 birth cohort because this gives us the longest follow-up period (36 years) possible with Washington State criminal records data.

To determine the impact of prevention programs on future crime, we calculate the probability of obtaining a conviction over the life-course. This is done in three steps:

First, using OFM state population data, we abstracted the number of people living in Washington State born in 1974 for each of the follow-up years. For example, in 1994, there were 66,709 20-year-olds (1974 birth cohort) living in Washington. Second, we selected felony and misdemeanor offenders who were born in 1974 (n=78,517) to determine how many were convicted at age 8, age 9, age 10, and so on. Finally, we calculated the average size of the 1974 cohort weighted by crime propensity at each follow-up year.

Exhibit B.3 is a screen shot from WSIPP's cost-benefit model which displays recidivism information for one of the 45 crime populations.

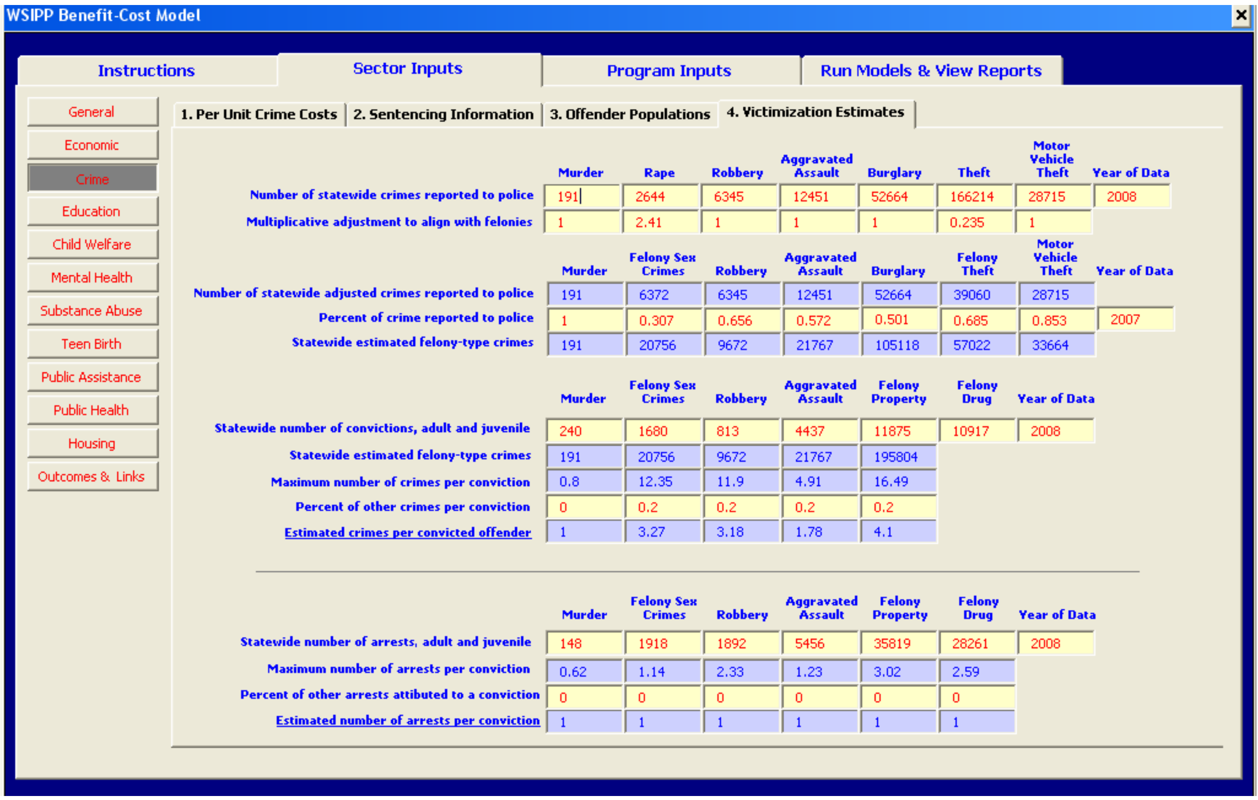
Exhibit B.3



B.4 Estimates of Victimizations Per Conviction

Once a person is convicted for a criminal offense, sentencing policies and practices in Washington affect the use of different local and state criminal justice resources. Exhibit B.4 is a screen shot from WSIPP's benefit-cost model which displays how criminal justice resources in Washington State are used in response to crime. Yellow boxes contain inputs entered by WSIPP while blue boxes contain calculations. Inputs in Exhibit B.4 are described below.

Exhibit B.4



	Murder	Rape	Robbery	Aggravated Assault	Burglary	Theft	Motor Vehicle Theft	Year of Data
Number of statewide crimes reported to police	191	2644	6345	12451	52664	166214	28715	2008
Multiplicative adjustment to align with felonies	1	2.41	1	1	1	0.235	1	

	Murder	Felony Sex Crimes	Robbery	Aggravated Assault	Burglary	Felony Theft	Motor Vehicle Theft	Year of Data
Number of statewide adjusted crimes reported to police	191	6372	6345	12451	52664	39060	28715	
Percent of crime reported to police	1	0.307	0.656	0.572	0.501	0.685	0.853	2007
Statewide estimated felony-type crimes	191	20756	9672	21767	105118	57022	33664	

	Murder	Felony Sex Crimes	Robbery	Aggravated Assault	Felony Property	Felony Drug	Year of Data
Statewide number of convictions, adult and juvenile	240	1680	813	4437	11875	10917	2008
Statewide estimated felony-type crimes	191	20756	9672	21767	195804		
Maximum number of crimes per conviction	0.8	12.35	11.9	4.91	16.49		
Percent of other crimes per conviction	0	0.2	0.2	0.2	0.2		
Estimated crimes per convicted offender	1	3.27	3.18	1.78	4.1		

	Murder	Felony Sex Crimes	Robbery	Aggravated Assault	Felony Property	Felony Drug	Year of Data
Statewide number of arrests, adult and juvenile	148	1918	1892	5456	35819	28261	2008
Maximum number of arrests per conviction	0.62	1.14	2.33	1.23	3.02	2.59	
Percent of other arrests atributed to a conviction	0	0	0	0	0	0	
Estimated number of arrests per conviction	1	1	1	1	1	1	

Number of statewide crimes reported to the police. Uniform Crime Report (UCR) data for all policing agencies are obtained from the Washington Association of Sheriffs and Police Chiefs. We adjust the data to account for non-reporting agencies. The data are then aggregated to statewide annual data.

Multiplicative adjustment to align UCR data with Washington felonies. Two of the UCR-reported crime categories, rape and felony theft, do not align with felony conviction data as defined by the Revised Code of Washington. Thus, we apply a multiplicative adjustment factor to align reported crimes with felony convictions.

Rape, as defined by the UCR, does not include other sexual assaults, sexual offenses with male victims, or victims under the age of 12. We adjust UCR reported rapes using National Crime Victimization Survey data to estimate male victims[47] and other sexual assaults.[48] Data from the National Incident Based Reporting System are used to adjust for the percentage of all sex offenses where victims are under age 12.[49]

[47] US Department of Justice, (2008). *Criminal Victimization in the United States, 2006 Statistical Tables* (NCJ 223436), Table 2. Washington, DC.
[48] Ibid., Table 1.
[49] US Department of Justice, (2000). *Sexual assault of young children as reported to law enforcement* (NCJ 182990). Washington, DC.

Theft is adjusted to include only thefts valued at $750 or more, the cutoff for a felony theft, as defined by the Revised Code of Washington. We use National Crime Victimization Survey data of thefts reported to the police to estimate this figure.[50]

Percentage of crimes reported to the police. We adjust our victimization estimates to include crimes not reported to the police using reporting rate data obtained from the National Crime Victimization Survey.[51]

Statewide number of convictions, adult and juvenile. Adult and juvenile felony conviction data are obtained from the Administrative Office of the Courts.[52]

Percentage of other crimes per conviction. In order to estimate the total number of crimes per convicted offender, we apply a multiplicative factor to adjust for the likely possibility that there are multiple victimizations per conviction. To our knowledge, no research exists to date that indicates the appropriate value. Thus, we simply apply an estimate of 20 percent. A value of zero would imply one victimization per conviction, while a value of one would imply all crimes are attributed to those offenders convicted.

Statewide number of arrests, adult and juvenile. Arrest data were obtained from the Washington Association of Sheriffs and Police Chiefs. We adjust the data to account for non-reporting agencies. The data are then aggregated to statewide annual data.

Percentage of other arrests attributed to a conviction. There is a provision in the model to account for all other arrests attributed to a conviction; however, we do not currently use this information.

[50] Criminal Victimization in the United States, NCJ 223436, Table 100.
[51] Criminal Victimization in the United States, NCJ 223436.
[52] Washington State Administrative Office of the Courts, Superior Court Annual Tables, http://www.courts.wa.gov/caseload/?fa=caseload.display_subfolders&folderID=Superior&subFolderID=ann&fileID=dsp_caseload_Superior_ann.

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