August 2010

WSIPP's Benefit-Cost Tool for States:
Examining Policy Options in Sentencing and Corrections

In 2010, Pew Center on the States and the Washington State Institute for Public Policy (WSIPP) entered into a contract to develop an analytical tool to assist states in identifying evidence-based policies that can reduce crime and lower corrections' costs.

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

The project's overall goal is to use the best information available to identify sentencing and corrections policies that can help states protect public safety and control taxpayer costs. To accomplish this goal, we have constructed a benefit-cost "investment" model that estimates crime and fiscal outcomes of different combinations of public policies. This report describes the model (as of August 2010) as well as our application of the tool to some hypothetical sentencing policy options in Washington State.

Background

WSIPP is a nonpartisan research unit of the Washington State legislature.[1] One of our duties is to provide information to the legislature on Washington's evidence-based initiatives. This particular role has evolved over the last 15 years.

In the mid-1990s, the legislature directed WSIPP to identify evidence-based juvenile justice programs that could lower juvenile crime. As a result of these assignments, WSIPP built its first benefit-cost analytical tool in 1997 to help the legislature select sound investments in Washington's juvenile justice

Summary

Can knowledge about "what works" to reduce crime be used to help states achieve a win-win outcome of lower crime and lower taxpayer spending?

The Washington State Institute for Public Policy has constructed an analytical tool for the Washington legislature to help identify evidence-based sentencing and programming policy options to reduce crime and taxpayer criminal justice costs.

With additional financial assistance from the MacArthur Foundation, The Pew Charitable Trusts contracted with WSIPP to: (1) develop the tool, (2) apply it to a policy process currently underway in Washington State, and (3) help Pew make the tool available to other interested states.

This report describes the tool (as of August 2010) in detail and illustrates its use by applying it to two hypothetical sentencing policy options in Washington State. The tool assesses benefits, costs, and risks. Results from the two hypothetical examples point to possible win-win policy combinations.

system.[2] That initial effort identified several programs—not then operating in Washington—that could potentially reduce crime and save Washington taxpayers money. In subsequent sessions, the legislature used the results to begin a series of policy reforms.[3] Many "real world" lessons were learned.[4]

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[1] The Washington State Institute for Public Policy was created by the Legislature in 1983. More information on WSIPP can be found on our website at www.wsipp.wa.gov and in: 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] S. Aos, R. Barnoski, R. Lieb (1998). *Watching the Bottom Line: Cost-Effective Interventions for Reducing Crime in Washington,* Olympia: Washington State Institute for Public Policy, Document No. 98-01-1201. Also, S. Aos, P. Phipps, R. Barnoski, R. Lieb (2001). *The Comparative Costs and Benefits of Programs to Reduce Crime, v 4.0,* Olympia: Washington State Institute for Public Policy, Document No. 01-05-1201.

[3] R. Barnoski (2004). *Outcome Evaluation of Washington State's Research-Based Programs for Juvenile Offenders,* Olympia: Washington State Institute for Public Policy, Document No. 04-01-1201.

[4] R. Barnoski (2009). *Providing Evidence-Based Programs With Fidelity in Washington State Juvenile Courts: Cost Analysis,* Olympia: Washington State Institute for Public Policy, Document No. 09-12-1201.

Beginning in the early 2000s, following the initial favorable experience in juvenile justice, the legislature began to direct WSIPP to apply the same benefit-cost approach to other areas of public policy, including K–12 education, early childhood education, child welfare, public health, public assistance and employment, mental health, and substance abuse.[5]

As a result of these legislative assignments, we continue to develop and refine our ability to assess "what works" as well as our approach to evaluating the benefits and costs of public policies that could be selected by the Washington legislature. Our on-going goal is to produce better "bottom-line" estimates for each successive legislative session. Thus, the benefit-cost model is a constant work in progress; constructive comments are always welcomed.

The unifying theme in all of these assignments has been "to calculate the return on investment to taxpayers from evidence-based prevention and intervention programs and policies."[6] 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?

In 2009, WSIPP began a project to develop more fully its overall benefit-cost model, and extend it to several new areas of public policy. This larger modeling effort is being funded by the MacArthur Foundation and the Washington State legislature.

One goal of the larger project is to develop a stand-alone software application to allow other jurisdictions 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 for the Washington legislature.

The 2010 Pew contract with WSIPP augments our broader benefit-cost effort by focusing in-depth attention on one topic in particular: criminal justice sentencing policies. The contract has three tasks.

- The first task is to build a tool that analyzes adult sentencing policies and other crime-related public policies from a return-on-investment point of view.

- The second task is to apply the analytical framework to an evidence-based sentencing initiative underway in Washington State.

- Finally, WSIPP is 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. As we describe, the sentencing-related tool is being built to reside within the larger benefit-cost software WSIPP is constructing.

A subsequent document, in July 2011, will describe the larger benefit-cost tool and final results; the current report focuses only on the sentencing-related application.

This report provides a snapshot of the project as of August 2010. During the subsequent phase, WSIPP will report on the sentencing policy development process in Washington as it unfolds and will also assist Pew in transferring the Washington sentencing tool to other jurisdictions. The Pew-WSIPP contract terminates in March 2011.

[5] Previous benefit-cost studies prepared by WSIPP for the Washington legislature include:
S. Lee, S. Aos, M. Miller (2008). *Evidence-Based Programs to Prevent Children from Entering and Remaining in the Child Welfare System: Benefits and Costs for Washington,* Olympia: Washington State Institute for Public Policy, Document No. 08-07-3901.
S. Aos, A. Pennucci (2007). *Report to the Joint Task Force on Basic Education Finance: School Employee Compensation and Student Outcomes,* Olympia: Washington State Institute for Public Policy, Document No. 07-12-2201.
S. Aos, M. Miller, J. Mayfield (2007). *Benefits and Costs of K–12 Educational Policies: Evidence-Based Effects of Class Size Reductions and Full-Day Kindergarten*, Olympia: Washington State Institute for Public Policy, Document No. 07-03-2201.
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.
S. Aos, J. Mayfield, M. Miller, W. Yen (2006). *Evidence-Based Treatment of Alcohol, Drug, and Mental Health Disorders: Potential Benefits, Costs, and Fiscal Impacts for Washington State,* Olympia: Washington State Institute for Public Policy, Document No. 06-06-3901.
S. Aos, M. Miller, E. Drake (2006). *Evidence-Based Adult Corrections Programs: What Works and What Does Not,* Olympia: Washington State Institute for Public Policy, Document No. 06-01-1201.
S. Aos, R. Lieb, J. Mayfield, M. Miller, A. Pennucci (2004). *Benefits and Costs of Prevention and Early Intervention Programs for Youth,* Olympia: Washington State Institute for Public Policy, Document No. 04-07-3901.
[6] Chapter 564, Washington State Laws of 2009, Section 610 (4).

Project Element 1:
Development of the Sentencing Tool

WSIPP has developed an analytic tool to help Washington, and perhaps other states, identify evidence-based policy mixes that can both fight crime and save taxpayers money. 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.

✓ **Sentencing Policies.** For this project, sentencing policies refer broadly to those public policies that affect the average daily population in prison in a state. They include policies that determine which convicted offenders go to prison, as well as those that determine the length of stay per sentence. They also include any discretion granted to judicial and executive branches that affect the actual length of time served in prison for a given sentence. All these policies affect a state's incarceration rate— which is, simply, the proportion of a state's adult population that is behind bars on any average day. In the United States as a whole, this proportion has increased from about two inmates per thousand adults during an average day in 1970, to about eleven inmates per thousand adults today. In Washington State, in incarceration rates has risen more slowly, from about two inmates per thousand adults in 1970 to about six today.[7]

✓ **Programming Policies.** The second broad type of public policy considered in this analysis reflects programming resources. For convicted offenders, programming resources refer to those governmental efforts aimed at reducing the rate of criminal recidivism. Some programming resources are tied directly to sentencing decisions; drug courts are examples. Most programming resources, however, are used after sentences are handed down. For example, adult offenders sent to prison may participate in certain types of cognitive-behavioral programming designed to reduce the rate of criminal re-offending after release. Programming can be

used for either adult offenders or juvenile offenders; if they work, then subsequent criminal activity is reduced. Some programming resources are also "prevention" resources, such as early childhood education or some home visitation programs for very young children. One goal of prevention programming is to avoid the occurrence of an undesirable outcome, such as crime, before it happens.

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. As we will discuss, we believe there is credible evidence that certain types of incarceration (the product of sentencing policies) can lower crime rates. Similarly, there is credible evidence that certain types of programming can reduce crime. Both of these generic resources, however, cost taxpayers money, and there is uncertainty in all of the estimates. The differential crime fighting effectiveness and costs of the resources imply that return-on-investment tradeoffs are important when considering policy choices.

The purpose of WSIPP's tool, therefore, is to analyze both resources as a part of an overall portfolio of public policies designed to lower crime and lower overall taxpayer spending.

If a state wants to fight crime and pinch (taxpayer) pennies, then what are the tradeoffs between sentencing and programming resources, and what mix of resources can help a state lower crime and lower the taxpayer costs of crime? The goal of the model is to help states detect reasonable evidence-based courses of policy action, given the current state of knowledge about "what works" to reduce crime and save taxpayers money.

Policing Resources Not Considered. WSIPP's model is targeted at state-level decisions. The tool does not currently consider one important type of public resource: policing. Decisions on the level and deployment of policing resources are primarily matters for local government. A more complete analysis, however, would consider all three resource types: prisons, programming, and policing. This is a limitation of the current WSIPP model, and future work could add policing to the range of options analyzed. For the present, however, the WSIPP model focuses on prison incarceration and evidence-based programming as the two basic components of an overall state-level crime fighting public policy portfolio.

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[7] 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. Similar results are reported in: J. Warren, A. Gelb, J. Horowitz, & J. Riordan (2008). *One in 100: Behind Bars in America, 2008.* Washington, DC: Pew Center on the States, Public Safety Performance Project.

The Structure of the WSIPP Sentencing Tool.
We provide a brief overview of the approach adopted in the WSIPP model; those interested in a technical description, as well as the "user manual" for the software application, are encouraged to refer to the Appendix.

The overall goal of the model is to estimate the net change in crime in a state, along with the net change in taxpayer spending, with different mixes of incarceration and programming policies.

For example, if particular sentencing policies are changed and prison average daily population (ADP) is reduced, then a legislature could decide to use some or all of the fiscal savings to increase funding of evidence-based programming. If so, then the empirical question is this: Would the combination of reduced prison ADP and increased evidence-based programming result in the "win-win" outcomes of net crime reduction for the state along with net savings to taxpayers? Additionally, what are the risks that this strategy could produce the undesirable result of more crime?

The same question can be asked in reverse. If particular sentencing policies are changed and prison ADP is increased, then what is the optimal mix of evidence-based programs and incarceration under this scenario?

The purpose of the WSIPP sentencing tool is to allow users to enter state-specific input factors endorsed by each state, and then test bottom-line results on crime levels and taxpayer savings for different combinations of public policy choices. The riskiness of different strategies is also assessed.

The model structure is sketched in Exhibit 1. The process begins by computing an estimate of the initial change in taxpayer spending if prison ADP is increased or decreased. The second effect modeled is the change in the number of crimes that is likely to be the consequence of the ADP change. This second step is the most difficult empirically, given the current state of knowledge about how incarceration policies affect crime rates. As we discuss, current research indicates that not all sentencing policies are equal; some are more likely to be effective than others in reducing crime.

Exhibit 1

Structure of the WSIPP Sentencing Tool
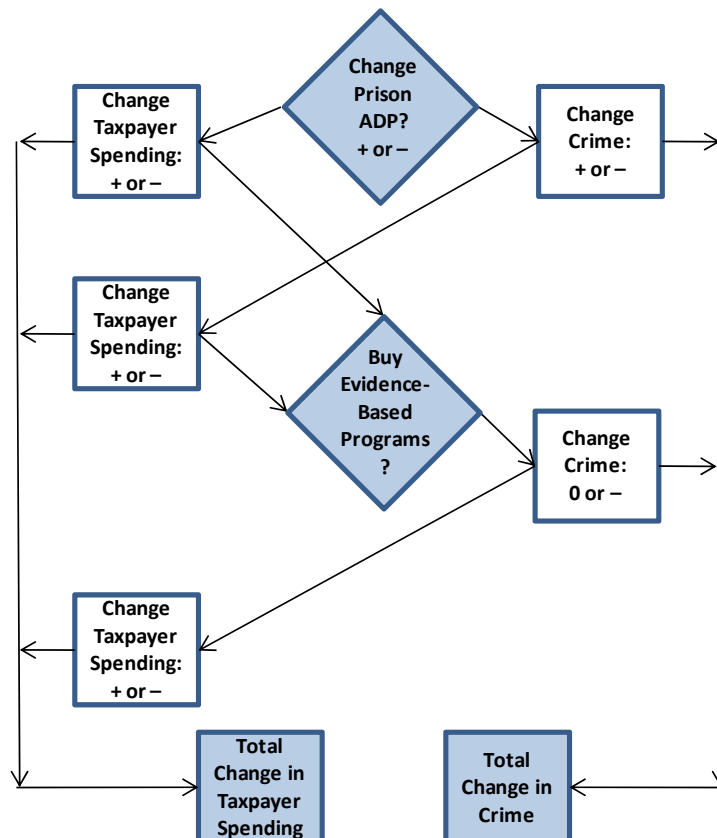
Next, if prison ADP is lowered and crime increases, then other state and local taxpayer resources will be needed to respond to the increased crime. If, on the other hand, ADP is raised and crime goes down, then other taxpayer spending can be lowered in the criminal justice system.

To the degree taxpayer spending goes down initially, a legislative decision could be made to apply a portion of these funds to purchase a portfolio of evidence-based and economically sound programs for adult and juvenile offenders. If these programs are purchased, then crime can be expected to go down and other taxpayer spending will also decline. The model also allows for a second round of decisions about purchasing additional evidence-based programming from the net taxpayer proceeds from the first round of purchased evidence-based programs.

Finally, the model adds up the results of the steps. The total change in crime is tallied along with the total change in taxpayer spending. Combinations of options can then be compared on these two key outcomes.

The policy decision points in the model are the initial change in sentencing policies and the two opportunities to finance evidence-based programming. Each of these parameters is modeled as user-selected inputs.

It is important to note that the sentencing policies states adopt are designed not only to affect current and future crime levels, they are also designed to promote justice for the criminal actions of offenders. The WSIPP benefit-cost tool focuses on combinations of sentencing and programming policies that affect current and future crime levels and system costs; the model does not purport to address the other justice-related public policy reasons used to establish particular policies.

State-Level Inputs to the Model. As noted in detail in the Appendix, a characteristic of this model is its use of a number of state-specific inputs. Each user needs to enter and take "ownership" of the inputs; a model's outputs are, of course, only as good as the inputs. The inputs we have entered are those we selected for Washington State based on our analyses (described in the Appendix). As with any investment model, it is important to continually update and refine the inputs as new and better information becomes available.

Central inputs to the model are those pertaining to a state's level of crime reported to police and average daily prison population. Incarceration rates and crime levels vary significantly from state to state, and this variation is important to assess when estimating the marginal changes in crime that can be expected from marginal changes in ADP.

States also differ on the main sentencing-related determinants of average daily population, including prison probabilities and lengths of stay for different types of offenses. Marginal cost parameters for criminal justice system elements are also likely to vary considerably by state and will reflect local labor market conditions. In addition, the parameters take account of the degree to which state and local budgetary processes actually alter expenditures in response to changes in crime-related workloads.

Other inputs are not as state-specific but are, nonetheless, key parameters for which anyone who uses this application needs to be responsible. These include the estimates and assumptions about the effectiveness of prison and evidence-based programming in reducing crime. Based on our current reading of the empirical research literature, we describe our choices for these input parameters in the Appendix.

Uncertainty in the Estimates. Another characteristic of the modeling approach is its attention to the considerable level of uncertainty that exists in the input parameters. While there is an increasingly strong evidentiary base of knowledge about what works to reduce crime, significant variation in particular estimates remains. To reflect this uncertainty, our modeling approach is designed to estimate the riskiness of different combinations of policy options. We do this by varying key model inputs and then implementing a Monte Carlo portfolio simulation.

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 WSIPP tool produces include the expected change in crime and taxpayer spending, along with the risk that the mix of options could lead to the undesirable result of less overall public safety.

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

With financial support from Pew Center on the States, 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."[8] Specifically, the Legislature directed the Commission to:

> *"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'Connor 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."[9] As the EBCC process unfolds, 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 or the EBCC.

Independent from these efforts, the WSIPP model can also be used to assist the Washington legislature and legislative staffs and executive agencies as sentencing and programming policies are considered.

Two Example Sentencing Policy Changes

Thus, while at this time (August 2010) there are no official EBCC proposals on the table in Washington, for purposes of illustration, we used the new WSIPP model to estimate the crime and taxpayer effects of two example sentencing policies.

Example Sentencing Option 1: reduce prison length of stay by 60 days for lower-risk offenders whose current conviction is not a murder or sex offense.

The first hypothetical sentencing option involves a reduction in the length of prison sentences for certain types of offenders. This type of option could be implemented either through legislative authorization of executive early release policies, or through legislative changes to Washington's sentencing system.

The state of Washington has implemented an actuarial risk assessment process to categorize adult felony offenders by their probability of felony re-conviction.[10] Using the assessment system, the prison population in Washington is classified into four groups based on the type of reconviction risk: "high violent," "high non-violent," "moderate," and "lower." For example, among offenders sentenced to prison, the high-violent group has an overall three-year felony recidivism rate of 60 percent, with a 24 percent violent felony reconviction rate.[11] This group represents about 31 percent of all offenders in prison. Exhibit 2 summarizes the key statistics for the four classified groups.

To develop this particular hypothetical sentencing option, we used the lower-risk group and further excluded all lower-risk offenders whose current conviction is murder or any sex offense. This restricted lower-risk group represents 7 percent of Washington's total prison population and has a three-year felony reconviction rate of 16 percent and a violent felony reconviction rate of 3 percent.

[8] Chapter 564, Section 225, Laws of 2009.
[9] Washington State Sentencing Guidelines Commission. (2009). *Evidence Based Community Custody: A Progress Report from the Sentencing Guidelines Commission and Superior Court Judges' Association.* Olympia, WA: Washington State Sentencing Guidelines Commission.

[10] 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.
[11] E. Drake & R. Barnoski (2009). *New Risk Instrument for Offenders Improves Classification Decisions,* Olympia: Washington State Institute for Public Policy, Document No. 09-03-1201.

Exhibit 2			
36-Month Felony Reconviction Rates Among Offenders in Washington's Prison System			
Risk Classification	**Percent of Prison ADP**	**Total Re-conviction Rate**	**Violent Re-conviction Rate**
High Violent	31%	60%	24%
High Non-Violent	36%	51%	9%
Moderate	19%	28%	8%
Lower	14%	13%	4%
Total	100%	44%	13%

Source: E.K. Drake & R. Barnoski (2009). *New Risk Instrument for Offenders Improves Classification Decisions*, Olympia: Washington State Institute for Public Policy, Document No. 09-03-1201, Exhibits 1 and 2.

There are about 18,400 offenders currently in prison in Washington. Therefore, using the 7 percent prevalence, about 1,288 of all offenders currently in prison would be classified as lower-risk offenders not convicted of a murder or sex offense. This lower-risk group currently serves an average prison length of stay of 1.59 years. If the legislature authorized a 60-day prison length of stay reduction for this group of offenders, then the average daily prison population would decrease by about 133.[12]

This selected group of offenders has, as noted, a reduced level of risk for re-conviction. The group's three-year felony recidivism rate is about 64 percent lower than the average reconviction rate for all offenders who leave prison.[13] We can use this average risk information in the WSIPP modeling tool to compute refined estimates of how this sentencing policy option would likely affect crime levels and taxpayer costs in Washington.[14]

For this example, we assumed that 80 percent of the direct prison cost savings (stemming from the 133 ADP reduction) would be invested in a representative portfolio of evidence-based adult and juvenile corrections programming.[15]

The model produces three "bottom-line" outcomes:

a) the net change in criminal victimizations in Washington—a measure of an average result;

b) the percentage of the time that we would expect this sentencing option to result in lower crime—a measure of risk; and

c) the net change in taxpayer spending on the criminal justice system in Washington.

We would expect opposing effects from this two-part option. First, since this example sentencing option reduces prison ADP, we would expect the ADP action alone to reduce prison spending initially, but we would expect it also to increase crime in Washington and, therefore, require additional criminal justice system spending to process those crimes. Second, since this sentencing option would also direct 80 percent of the initial prison savings to be spent on high return-on-investment adult and juvenile corrections programming, we would expect lower crime and lower taxpayer spending from this second part of the two-part option.[16]

Thus, since this option is likely to have results that move in opposite directions, the focus of the analysis is on the net outcomes for Washington.

With these inputs, we ran the WSIPP model 10,000 times accounting for the known uncertainty in the key parameters. Exhibit 3 shows that the option results in an expected net reduction in the number of victimizations in Washington. The initial effect of reducing prison ADP by 133 is expected to increase the number of victimizations, on average, by 201. This is offset by the reduced 581 victimizations from the purchased slots in high return-on-investment juvenile and adult programs. The net result is an expected reduction of 380 victimizations.

As noted, one key aspect of the WSIPP model is its explicit modeling of the uncertainty that underlies the estimates. We ran the model 10,000 times, each time varying randomly all of the uncertainty that we believe resides in the model. The end result is an estimate of risk. Exhibit 3 shows that in 96 percent of the cases, net victimizations declined. Therefore, in 4 percent of the 10,000 runs, net victimizations increased from this example sentencing option.

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[12] This number, of course, is just an example calculation for illustrative purposes; if the legislature actually passed a bill to carry out any particular sentencing option, specific information for current offenders would need to be calculated. In this illustrative case, we simply apply Little's Law with a steady state admission level by multiplying the change in ADP for a 60-day reduction: 133 ADP reduction = (18,400 X .07) / 1.59 X (60/365).

[13] 16 percent divided by 44 percent, minus 1.

[14] See Appendix D1 for details.

[15] The 80 percent value was chosen for illustrative purposes only; the legislature would, of course, adopt a specific number if it decided to implement an option such as the one discussed here.

[16] We describe in the Appendix the empirical basis for these expected effects.

Net Change in Victimizations	**-380**
Change from the lower prison ADP	+201
Change from the high ROI program portfolio	-581
Probability That Net Victimizations are Reduced	**96%**
Net Change in Taxpayer Costs (Millions)	**-$5.5**
Net change to prison budget from ADP change	-$0.6
Change in other CJS costs from ADP change	+$0.7
Change in CJS costs from high ROI portfolio	-$5.6

Notes:
ROI = Return on Investment
CJS = Criminal Justice System
ADP = Prison Average Daily Population

The net change to the prison budget from the ADP change is "net" because it is the change in taxpayer spending after 80 percent of the funds are used to pay for the high ROI programs.

The $5.5 million net reduction in taxpayer costs include estimated effects on both state and local taxpayer spending on the criminal justice system. If the model is restricted to only include the estimated effect on state criminal justice budgets, then the net reduction in taxpayer spending is about $2.4 million.

Finally, Exhibit 3 shows the net taxpayer impact from the analysis. The net change overall is reduced taxpayer spending of $5.5 million. This overall figure includes three separate elements. First, the net change in the prison budget declined $0.6 million from the ADP change. This figure is labeled "net" because it reflects the change in taxpayer spending after 80 percent of the funds were used to pay for the high ROI programs. The second fiscal effect is additional taxpayer spending, $0.7 million, to pay for the costs to process through the criminal justice system the additional crimes from the ADP reduction effect. Finally, the purchase of the high return on investment adult and juvenile programs resulted in decreased taxpayer spending of $5.6 million. The net result of these three effects is -$5.5 million.

The $5.5 million net reduction in taxpayer costs reported includes estimated effects for both state and local taxpayer spending on the criminal justice system. If the model is restricted to only include the estimated effect on state criminal justice budgets, then the net reduction in taxpayer spending is about $2.4 million. The WSIPP model contains a "switch" to allow users interested in just state (not local)

criminal justice system costs.[17] Again, all of these estimates are for Washington State, using Washington-specific inputs selected by WSIPP.

Example Sentencing Option 2: reduce prison length of stay by 60 days for all offenders in prison.

As a second hypothetical option illustrating use of the WSIPP tool, we made a simple modification to the first sentencing option. The first sentencing option restricted the population affected by the 60-day sentence-length reduction to lower-risk offenders (we also further restricted the lower-risk group to exclude offenders whose conviction was murder or sex offenses). For the second example, all other parameters are held the same, but we apply the 60-day reduction option to all offenders in prison, not just lower-risk offenders.

To enable a side-by-side comparison of Option 1 and Option 2, we analyze Option 2 for the same 133 ADP reduction just discussed.[18] In Exhibit 4 we repeat the results for Option 1, alongside the new results for Option 2. The results are quite different in terms of net bottom lines. Option 1 results in a net victimization reduction of 380 while Option 2, though still a net reduction, is only 23. The difference is attributable to the change in victimizations stemming from the reduced prison ADP—because Option 1 focuses on lower-risk offenders, the net increase in crime is smaller than Option 2, which included all offenders regardless of risk level.[19]

The difference between the two options also shows up in the measure of risk—the percentage of time we would expect victimizations to go down. For Option 1, this was 96 percent. It was reduced to just 54 percent for Option 2. Thus, Option 1 is considerably less risky in terms of the probability that crime would be increased than Option 2, and it saves more money.

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[17] The model also contains a "switch" to allow user to exclude capital amortization and debt service costs from the calculation of total taxpayer costs.
[18] If all offenders in prison in Washington (18,400) were given 60-day reductions in sentence-length, prison ADP would be reduced by about $1,621 = (18,400) / 1.865 \times (60/365)$, where the average length of stay in prison for all offenders is 1.865 years.
[19] Technically, the crime-prison elasticities we adopted for these two options are quite different. For Option 1, which focuses on lower-risk offenders, the elasticity is -.11. For Option 2, which is applied to all offenders, the elasticity is -.31.

<table>
<tr><td colspan="3">**Exhibit 4**
Results of Two Examples of Washington State
Sentencing/Programming Policy Options

Reduced 133 Prison ADP (via 60-day prison length-of-stay reductions) for:
Option 1: lower-risk non-murder and non-sex offenders
Option 2: all offenders (not differentiated by risk)
Both Options include the same increased funding for high
return on investment programming</td></tr>
<tr><td></td><td>**Option 1**</td><td>**Option 2**</td></tr>
<tr><td>**Net Change in Victimizations**</td><td>**-380**</td><td>**-23**</td></tr>
<tr><td>   Change from the lower prison ADP</td><td>+201</td><td>+558</td></tr>
<tr><td>   Change from the high ROI program portfolio</td><td>-581</td><td>-581</td></tr>
<tr><td>**Percentage of Time Net Victimizations are Reduced**</td><td>**96%**</td><td>**54%**</td></tr>
<tr><td>**Net Change in Taxpayer Costs (Millions)**</td><td>**-$5.5**</td><td>**-$4.1**</td></tr>
<tr><td>   Net change to prison budget from ADP change</td><td>-$0.6</td><td>-$0.6</td></tr>
<tr><td>   Change in other CJS costs from ADP change</td><td>+$0.7</td><td>+$2.0</td></tr>
<tr><td>   Change in CJS costs from high ROI portfolio</td><td>-$5.6</td><td>-$5.5</td></tr>
<tr><td colspan="3">Notes:
The net change to the prison budget from the ADP change is "net" because it is the change in taxpayer spending after 80 percent of the funds are used to pay for the high ROI programs.</td></tr>
</table>

Summary of Results From the Options

The two hypothetical options demonstrate the types of policy choices for which the WSIPP tool was designed to analyze. While these two examples are for illustrative purposes only, the tool reveals what criminologists call the "risk principle." From the standpoint of policies designed to reduce crime, it is better to focus resources (prison and programming) on offenders who pose higher risk to society for criminal re-offending.[20]

In particular, Option 1—which focuses on reducing lengths of prison sentences for lower-risk offenders coupled with increased correctional programming for higher-risk offenders—points to a policy mix than can reduce crime overall and reduce taxpayer spending with a high degree of probability—a win-win goal, which many legislatures may want to pursue.

There is additional evidence, discussed in the Appendix, that sentencing policies such as Option 1, which reduce lengths of prison stay, are likely to be more beneficial than options that reduce the certainty of sentences.[21]

Project Element 3: Software Development and Next Steps

The third element of the work plan is for WSIPP to develop a software application that could enable other states to adopt WSIPP's approach to analyzing sentencing options. The software application is described in the Appendix. This is the initial version of the tool; there are, no doubt, software improvements that will need to be implemented in the next phase of the contract. During this third phase of the contract, WSIPP will also assist Pew in transferring the tool to other interested locales.

There are several known technical enhancements that will add useful features to the tool. For example, the model now computes crime effects from prison ADP changes on "total" crime but not the two subcategories "violent" crime and "property" crime.[22] This important modeling issue can be addressed during the next phase.

Additionally, the current version of the tool provides a limited portfolio of evidence-base programming resources. We are updating these reviews and will provide a more comprehensive list in the next version.

[20] D. A. Andrews & J. Bonta. (2006). *The Psychology of Criminal Conduct* (4th ed.). Newark, NJ: Lexis/Nexis. See also, M. W. Lipsey (2009). The Primary Factors That Characterize Effective Interventions With Juvenile Offenders: A Meta-Analytic Overview. *Victims and Offenders*, *4,* 124-147.
[21] See the excellent new review: S. N. Durlauf & D. S. Nagin (2010). *The Deterrent Effect of Imprisonment.* National Bureau of Economic

Research working paper. http://www.nber.org/confer/2010/CRIs10/Durlauf_Nagin.pdf
[22] These categories refer, generally, to the definitions employed by the FBI in the Uniform Crime Reporting system of accounts, see the Appendix.

Appendices

There are four appendices to this report.

    Appendix A displays information about WSIPP and its Board of Directors.
    Appendix B describes the market potential of evidence-based programs in Washington State.
    Appendix C provides a screen shot of WSIPP's sentencing software application.
    Appendix D has two parts.
        1) Technical description of the WSIPP sentencing and programming portfolio model.
        2) Technical description of the WSIPP model to compute the benefit and costs of crime prevention.

Appendix A

Washington State Institute for Public Policy

The Washington legislature created the Washington State Institute for Public Policy in 1983. A Board of Directors—representing the legislature, the governor, and public universities—governs the Institute and guides the development of all activities.

The Institute's mission is to carry out non-partisan research—at legislative direction—on issues of importance to Washington State. The Institute conducts research activities using its own policy analysts and economists, specialists from universities, and consultants. Institute staff work closely with legislators, legislative and state agency staff, and experts in the field to ensure that studies answer relevant policy questions. Fiscal and administrative services for the Institute are provided by The Evergreen State College.

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Appendix B

Market Potential of Evidence-Based Programs in Washington State

The goal of the WSIPP sentencing 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.

In order to develop a practical programming portfolio to offset sentencing policy impacts, users must have knowledge of the market penetration rate of each evidence-based program included in the portfolio. It would be unrealistic to select a portfolio of programs that exceed state or local agencies' capacity to deliver such a portfolio. For use in Washington State, Exhibit B.1 displays the pertinent information for the evidence-based programs in the adult and juvenile correctional systems. For example, Aggression Replacement Training (ART) is used by the courts for youth on probation. Approximately, 4,715 youth were eligible for ART, and 1,832 youth (39 percent of the market) were served during Fiscal Year 2010. That means 61 percent of the market was unserved. Thus, when we select portfolios, expansion is restricted to a realistic market potential. The number served is based on "intent to treat." That is, we calculate the number of people who, at the very least, began the program.

The agencies use eligibility criteria for each individual program to determine how many people from their jurisdiction are eligible for the program. For example, the juvenile courts use the Washington State Juvenile Court assessment to determine how many youth are eligible and the Department of Corrections uses its Offender Needs Assessment.[23]

Exhibit B.1
Evidence-Based Programs in Washington State

Evidence-Based Program	Annual Number Eligible for Program[#]	Number Served in Fiscal Year 2010[#]	Percentage of Market Unserved
Department of Corrections			
Cognitive Behavioral Treatment in Prison	11,819	4,288	64%
Cognitive Behavioral Treatment in the Community	13,410	2,342	83%
Correctional Industries (prison)	10,246	1,102	89%
Drug Treatment (prison)	10,684	2,594	76%
Drug Treatment (community)	12,855	4,459	65%
Education in Prison (basic education or post-secondary)	4,727	4,382	7%
Employment Training and Job Assistance (community)	12,054	1,627	87%
Vocational Education (prison)	9,654	2,842	71%
Juvenile Court			
Aggression Replacement Training	4,715	1,832	61%
Functional Family Therapy	3,819	738	81%
Multi-Systemic Therapy	451	58	87%
Family Integrated Transitions	11	24	na
Coordination of Services	141	469	na
Juvenile Rehabilitation Administration			
Aggression Replacement Training	1,218	308	75%
Family Integrated Transitions	131	54	59%
Functional Family Therapy	237	84	65%
Multi-Dimensional Treatment Foster Care	59	12	80%

Eligibility and the number of eligible participants who were served were obtained from the respective agencies via email correspondence (April & August 2010): the Department of Corrections, the Administrative Office of the Courts, and the Juvenile Rehabilitation Administration.

[23] 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.

Appendix C

Screen Shot of the WSIPP Sentencing-Programming Portfolio Application

Main Elements on Screen

Run the Model: Clicking launches the application.

Number of runs for Monte Carlo simulation: User selects the number of times the model is run when it is launched. The default value is 10,000 runs.

Capital costs: User selects whether to include capital costs in the calculation of taxpayer spending or saving.

Local government costs. User selects whether to include local government benefits in the calculation of taxpayer spending or saving.

Prison Average Daily Population (ADP) Change: User enters the magnitude of a sentencing policy's change on average daily prison population.

Elasticity and Adjustments: User enters parameters.

Percentage of initial taxpayer savings, stemming from prison ADP change, to spend on evidence-based programming. User enters the percentage (values: 0 to 1.0).

Percentage of state fiscal benefits from initial purchases to buy additional evidence-based programming. User enters the percentage (values: 0 to 1.0).

Selection of individual evidence-based programs for the portfolio. User enters the percentage of the total portfolio to spend on each program (values: 0 to 1.0). The total portfolio percentage must equal 1.0.

Results window.

Appendix D
Technical Documentation of the Benefit-Cost Model

The technical description of the WSIPP sentencing tool is presented in two parts. In Appendix D1, we describe the computational procedures used to estimate the net crime effects of different portfolios of sentencing and programming policy changes. In Appendix D2, we describe the computations and procedures in WSIPP's benefit-cost model used to estimate the monetary benefits of programs that reduce crime.

While the two models are discussed separately, they are part of one overall benefit-cost application. We have constructed software that allows users to enter the necessary parameters, run the model, and test results. In both Appendices D1 and D2, we show screen shots from the software to indicate where users enter information, and how the application can be run. Thus, these two appendices serve two functions: (a) to describe the methods and computational routines we have adopted to compute benefits and costs, and (b) to provide documentation on how users can load information and run the application. The inputs currently loaded into the model are, except where noted, Washington State inputs we have entered. Users in other jurisdictions should enter inputs reflective of their state. To take just one example, we have entered the average sentence length received by an adult offender convicted of robbery in Washington. This value, which will be different in other jurisdictions, is just one of the many factors that the model uses to compute system implications of crime changes.

Appendix D1: The WSIPP Sentencing and Programming Portfolio Model.

The WSIPP sentencing/programming model analyzes the effects of two types of evidence-based crime fighting policy options available to a legislature: sentencing-related policies and offender programming policies. As we indicate, there is evidence that both types of policies can reduce crime and both, of course, cost taxpayers money. The model is designed to examine how changes in the mix of these two resources can affect at the state level: (a) the number of crime victimizations, and (b) taxpayer costs.

Appendix C provides a screen shot of the main sentencing/programming portfolio model. The screen is divided into three main sections.

1. **Inputs: Prison-Crime Elasticity Estimates.** This section displays the inputs, described below, that collectively estimate the degree to which prison average daily population is expected to affect crime levels in a state. The user enters the estimates of prison-crime elasticities and related adjustments. As we note below, there is uncertainty in all of these parameters. As a result, the model employs user-supplied low, modal, and high estimates of each of the key parameters. These are then combined in a Monte Carlo simulation to calculate the probability distribution of the expected effectiveness of prison average daily population on crime levels. The first section of the screen allows the user to enter these values and then see the resulting distribution of elasticities the parameters produce. The specific values of the input parameters chosen by WSIPP are discussed below.

2. **Inputs: Evidence-Based Program Portfolio.** The second section on the screen displays the pre-loaded information on the effectiveness of various types of correctional programming on crime. We have chosen a selection of programs, for both adult offenders and juvenile offenders, for which we have found credible evidence that they can reduce crime. The screen shows the key summary statistics for each program available to be included in a portfolio. When running the application, the user selects a portfolio and also selects the portion of savings to be applied to funding the chosen portfolio. Each of these steps is explained below.

3. **Results: Net Impacts on Crime Victimizations and Taxpayer Costs.** The third section of the screen displays key statistics summarizing the impacts of the sentencing and programming policies choices.

The WSIPP sentencing and programming portfolio model implements a five-step computational process. First, the effect of prison ADP changes on crime levels is estimated. Second, the fiscal effect stimulated by these crime changes is estimated. Third, the benefits and costs of evidence-based crime programs are estimated focusing on their ability to affect crime outcomes and related taxpayer net savings. Fourth, the results (on victimizations and taxpayer costs) of an overall portfolio of sentencing and programming resources are tallied. Fifth, we describe the Monte Carlo approach to simulation.

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

The analytical task for Step 1 is to estimate the change in the number of crimes that a state can expect to see if incarceration rates are changed. The public policies considered with WSIPP's tool are those sentencing-related policies that affect the overall incarceration rate in a state. The incarceration rate is simply the number of offenders in prison at any point in time divided by a statewide population total (such as total population, or all adults over the age of 18).

Public policies that affect the incarceration rate can be sentencing laws that determine or affect the probability that convicted offenders go to prison, as well as policies that govern the length of sentences. They can also be laws that allow the executive

or judicial branch discretion to shorten or, in some cases, lengthen sentences. Since the current population in prison is determined by how many people go to prison and for how long, then all of these sentencing-related public policies collectively affect a state's overall incarceration rate at any point in time. There are other public policies that affect the incarceration rate; for example, early childhood education has been shown to reduce crime and, as a result, can be expected to affect future incarceration rates.[24] For Step 1, however, the focus is on those sentencing-related public policies that directly affect the incarceration rate.

The types of sentencing policy changes may affect the sentences of particular types of offenders, or the policies may affect all offenders. For example, sentencing policy changes may be specifically targeted for drug offenders, or they may be focused on the early release of lower-risk offenders, or they could be general changes that apply to all of those sentenced to prison regardless of offense, criminal history, or risk level. In terms of the expected effect on crime, these are important considerations. We note below that the user can adjust inputs to the model to better approximate differential sentencing policies.

There is a fairly large research literature on the effect of incarceration rates on crime.[25] Many of the studies addressing this relationship in the United States construct models using state-level data over a number of years to estimate the parameters of an equation of this general form:

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

In this typical type of model, crime C in state s and year y is estimated to be a function of a state's overall average daily prison population, ADP, a vector of control variables, X, and an error term, e. Crime is most frequently measured with data from the FBI's Uniform Crime Reporting (UCR) system. The variables are usually 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. Several authors have also observed that the state-level time series data often used to estimate equation (1) are likely have unit roots.[26] 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. As noted below, there is also considerable concern in the research literature on the econometric implication of the possible simultaneous relationship between the variables of interest in equation (1): crime may be a function of ADP, but ADP may also be a function of crime. This simultaneous relationship can cause statistically biased estimates if not dealt with.

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

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

In equation (2), the change in crime is estimated with E, the crime-prison elasticity obtained from coefficient b of the typical log-log estimation of equation (1); UCR, the reported crime rate (explained below); ADP, the incarceration rate (explained below), and $RRate$, the reporting rate to police by crime victims (also explained below). The marginal effects are sometimes calculated either at the mean values for ADP-UCR-$RRates$ or, more to the point for policy purposes, at the most recent values for ADP-UCR-$RRates$. The log-log estimation of the constant elasticity E implies diminishing returns when E is less than one and incarceration rates are raised. Similarly, an elasticity less than one coupled with reduced ADP implies increasing returns.

The dependent variable: crime. In the studies estimating these types of equations, crime is most often measured with data from the FBI's UCR. These data count the number of crimes reported to police. Some studies estimate a model of total UCR crime reported to police, while other studies estimate two equations, one for violent crime reported to police, and another for property crime reported to police. Still other studies break the analysis down further and estimate equations for the seven major types of "Part 1" crimes 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, thus, is not included in the UCR data. Accordingly, most authors, in drawing conclusions from their analyses, use information from the federal 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, as depicted in equation (2).

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[24] S. Aos, R. Lieb, J. Mayfield, M. Miller, A. Pennucci (2004). *Benefits and Costs of Prevention and Early Intervention Programs for Youth*, Olympia: Washington State Institute for Public Policy, Document No. 04-07-3901.
[25] 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.* Marvell's paper will be published in the *Handbook on the Economics of Crime*, Edited by Bruce L. Benson and Paul R. Zimmerman, Edward Elgar Publishing, September 2010.
[26] See, for example, Marvell, 2009. See also, W. Spelman (2008). Specifying the relationship between crime and prisons, *Journal of Quantitative Criminology, 24*, 149-178.

One significant problem with the "Part 1" UCR crime data is that they do not match directly how some states, including Washington, define felony crimes. In Washington, this applies to two types of crimes in particular: felony sex crimes and theft/larceny. The UCR sex offense data only count rapes of females over the age of 12. In addition to this obvious limitation in the UCR data, there are other felony sex crimes (e.g., child molestation), 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 in Appendix D.2, we make adjustments for these two crime types, since the policy focus of Washington's sentencing laws is felony crime as defined in Washington.

The policy variable: average daily prison population. In virtually all studies in the research literature, the policy variable of interest is prison average daily population. In most studies, this is measured by counting the total number of inmates at the beginning of a year, or the end of a year, and dividing by a state's population aggregate to obtain an overall incarceration rate. Measuring ADP with the total number of offenders—as opposed to more refined categories of offenders convicted of violent, property, or drug offenses, or defining offenders based on an actuarial risk assessment as high risk, moderate risk, or lower risk offenders—is necessary in cross-state analyses, because total ADP is usually the only information available.

The typical research study only includes a measure of total ADP and, thereby, only measures the average effect on crime of the average offender sentenced to prison. However, the criminal propensities of different types of offenders—for example, sex offenders or property offenders—are quite heterogeneous in terms of the amount and types of crime committed. For example, among offenders in Washington's current average daily population, there are some very high and lower risk offenders.[27] Thus, the "average offender" findings from typical research studies limit the practical policy relevance in crafting specific sentencing policies.

Given trends in sentencing policies in the United States, the "average offender" limitation poses at least three empirical problems. First, the average mix of offenders in prison has changed over time. 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.[28] 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). 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 policy selectivity in which types of offenders are released early. Much more often, a legislature will adjust sentencing statutes for particular types of crimes, rather than adopt across-the board changes.

The third very important reason why a policy adjustment needs to be made to the average elasticity estimates is that not all policies that affect prison ADP have an equal effect on crime. Durlauf and Nagin (2010) provide a very useful review and analysis of the research literature on the two sentencing factors that determine a state's ADP: the probability of a sentence to prison given a conviction, and the severity of the sentence in terms of length of prison stay.

Each of these sentencing parameters—the certainty of punishment and the severity of punishment—are affected by different sentencing policies. Yet, as Durlauf and Nagin found, the research literature indicates that the two types of policies are likely to have quite different effects on crime. They conclude:

> *The key empirical conclusion of our literature review is that there is relatively little reliable evidence of variation in the severity of punishment having a substantial deterrent effect but that there is relatively strong evidence that variation in the certainty of punishment has a large deterrent effect.*[29]

Thus, when using the WSIPP model to measure how a change in ADP affects crime, via the estimated elasticities discussed above, it is likely to matter a lot if the policy affecting ADP is based on a change to the certainty or severity of punishment. Using the Durlauf and Nagin results, one would conclude that the mean ADP elasticity for a sentencing policy that affects the certainty of punishment would be higher. Conversely, the mean ADP elasticity for a sentencing policy that affects the length of prison stay would be lower.

While the state of research may not allow a clear delineation of the magnitude of these differential effects, the direction seems clear based on the findings of Durlauf and Nagin. Therefore, the WSIPP model allows the user to enter low, modal, and high

[27] 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.
[28] Ibid.
[29] Durlauf & Nagin, 2010.

ADP policy adjustments to modify the overall elasticities obtained from studies estimating models of the type shown in equation (1).

This means that the coefficients obtained from equations such as (1) above can be thought of as only rough guides for the effectiveness of average sentencing changes. The coefficients obtained from these equations need to be adjusted to better estimate the specific policy choices available to legislatures. Adjustments need to reflect: (a) the wide heterogeneity of criminal propensities among offenders, (b) that legislatures usually adjust sentencing policies differentially for different types of crimes, and (c), that the type of sentencing policy is likely to affect crime differentially depending on whether the policy changes the certainty or severity of punishment. Our approach attempts to account for, even if crudely, some of these necessary policy adjustments.

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 in many of the studies that the use of prison is affected by crime.[30] This simultaneous relationship, if not accounted for, will probably bias the coefficient in a model like equation (1) downward. If a legislature's willingness to provide prison cells is motivated by changes in crime levels, then the observed relationship between prison and crime can be measuring both prison supply decisions and criminal response to prison levels. Therefore, an observed effect of prison on crime is likely to be 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.[31] 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 are hard to find so there are many more estimates that do not account for simultaneity than that do. The model we constructed allows the user to enter different estimates of this ostensibly important effect.

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 number of crimes that a state will add or subtract if sentencing policies alter ADP.

An estimate of the total current level of crimes, C_T, in a state is computed with Equation (3a). Reported UCR crimes for each type of crime c are multiplied by any adjustment to the UCR crime series for each crime type, and summed. This total is divided by the weighted average reporting rate for crimes to compute the estimated total crimes. Since the focus of the model is changes to current levels of crime stemming from changes of current levels of incarceration, the current level is computed for the most recent UCR data available.

$$(3a) \quad C_T = \frac{\sum_{c=1}^{Ct}(UCR_c \times UCRAdj_c)}{RRateAdj_T}$$

Since the computation of marginal effects for equation (2) is designed for one unit changes in ADP, and since the model may be used to estimate the effects of large changes in ADP, the computation of the total marginal crime effect is estimated iteratively, one ADP at a time. Equation (3b) implements this iterative process. The model sums the (absolute value) of a total sentencing change, ΔADP. Equation (3b) is similar to equation (2) with additional parameters to explicitly address the issues raised above. For a policy that raises or lowers total prison ADP, 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 adopted by a legislative body. S_T is likely to be greater than one while A_T is likely to be less than one if a sentencing-related policy change is selectively applied by a legislature 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 product of these three terms by total Crimes at each iteration of the total ADP change. This product is then divided by total ADP at each iteration for the total ADP change. If ADP is increased by a policy change, then ADP increases (+) by one unit for each iteration a; if ADP is decreased by a policy change, then ADP decreases (-) by one unit for each iteration a.

$$(3b) \quad \Delta C_T = \sum_{a=1}^{|\Delta ADP_T|} \frac{(E_T \times S_T \times A_T) \times [C_T - \sum_{i=1}^{a}(\Delta C_{T(i-1)})]}{(ADP_T \pm a)}$$

For example, for a 100 unit change in ADP, equation (3b) is estimated 100 times, each time substituting a one unit difference in ADP and the new level of the UCR variable after the previous delta crime has been computed.

[30] Marvell, 2009.
[31] S. D. Levitt (1996). The Effect of Prison Population Size on Crime Rates: Evidence From Prison Overcrowding Litigation. *The Quarterly Journal of Economics*, *111*, 319-51. W. Spelman (2005). Jobs or Jails? The Crime Drop in Texas. *Journal of Policy Analysis and Management*, *24*(1), 133-165.

For use in Step 2 of WSIPP's sentencing model, we are interested in the change in reported crimes, not total crimes. This is given by equation (3c).

$$(3c) \quad \Delta RC_T = \Delta C_t \times RRateAdj_t$$

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.

$$(4) \quad \Delta C_V = \sum_{a=1}^{|\Delta ADP_T|} \frac{(E_V \times S_V \times A_V) \times \left[C_V - \sum_{i=1}^{a}(\Delta C_{V(i-1)})\right]}{(ADP_T \pm a)}$$

$$(5) \quad \Delta C_P = \sum_{a=1}^{|\Delta ADP_T|} \frac{(E_P \times S_P \times A_P) \times \left[C_P - \sum_{i=1}^{a}(\Delta C_{P(i-1)})\right]}{(ADP_T \pm a)}$$

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

Elasticity Estimates. As noted, there is a fairly sizable research literature that has attempted to estimate the effect of average incarceration on crime. Marvell (2009) recently surveyed the entire literature and summarized the estimates.[32] The chart below summarizes the result of Marvell's review of 22 elasticity estimates of how ADP affects the total crime rate (21 of the estimates are from previously published research studies, one of the 22 estimates was Marvell's new original analysis, as reported in his 2009 review).[33] The findings from the studies shown on this chart did not account for the simultaneity issues discussed above; these studies, which form the existing knowledge base, measure the effect of total prison ADP on total UCR crime. The average elasticity estimate for this group of estimates is -0.11 (the median was also -0.11) with a standard deviation of 0.05. Using these results, we entered in the WSIPP sentencing tool the following parameters for a triangular probability distribution: a modal elasticity of -.11 with a minimum crime reduction elasticity of -.02 and maximum crime reduction elasticity of -.23.[34] This range seems to fairly well reflect the current consensus on prison-crime elasticities. It is important to reiterate, however, that these estimates are likely to be biased downward, because they do not reflect the likely simultaneity effect that exists between prison and crime—therefore, we apply a simultaneity adjustment (see below) to these base elasticity estimates.[35]
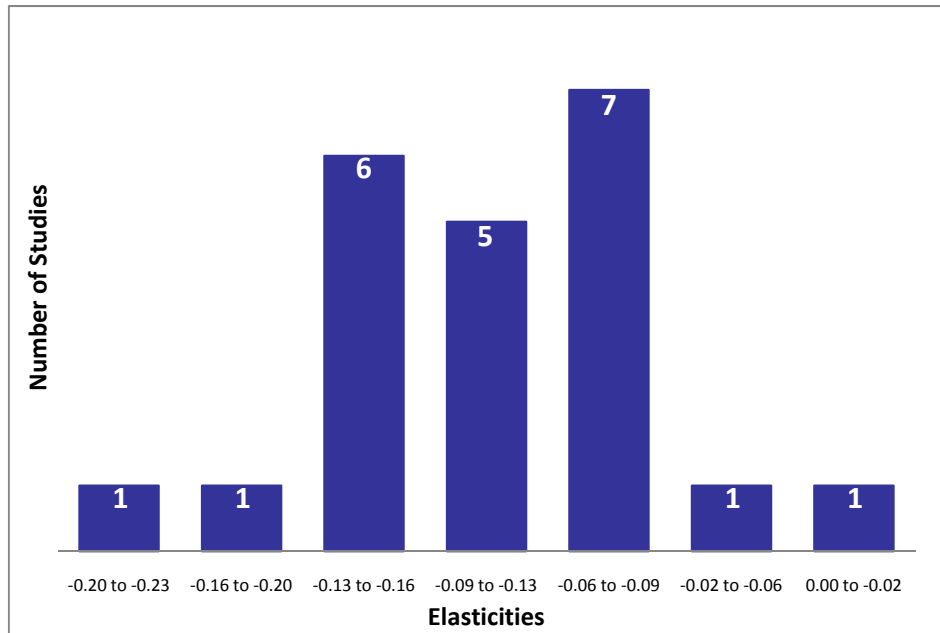
---

[32] Marvell, 2009.
[33] We did not include the results of the national level analyses summarized in Marvel; this summary only includes the results of studies using state or local data sets.
[34] See the screen shot in Appendix C.
[35] Spelman, 2008, pg. 168.

**Summary of the Number of Elasticity Estimates Reported in
the Literature Review of Marvell (2009)**

```
Number of Studies

7 ┤                                          7
6 ┤                   6
5 ┤                         5
  │
  │
  │
  │
1 ┤   1     1                          1     1
  └──────────────────────────────────────────────
   -0.20   -0.16   -0.13   -0.09   -0.06   -0.02   0.00
   to      to      to      to      to      to      to
   -0.23   -0.20   -0.16   -0.13   -0.09   -0.06   -0.02

                   Elasticities
```

In addition to examining the results of Marvell's 2009 literature review, we also estimated our own econometric model of the crime-prison relationship for Washington State. Our model estimates an equation similar to equation (1), except that we used county-level data from 1982 to 2008 for Washington's 39 counties. For this analysis, we ran models with total statewide average daily prison population in Washington (expressed as a rate by dividing by the 18- to 49-year-old population) and total county-level UCR crime (expressed as a rate by dividing by total Washington population). In keeping with the functional forms reviewed in the Marvell study, we estimated a model for the log of county total UCR crime rate and the log of the total statewide ADP prison rate. We also controlled for the log of the local county jail incarceration, the log of county-level police employment, the county unemployment rate, and the log of county real per capita income. The model includes county-level fixed effects. White standard errors are reported. When the log-log model is run in levels, the resulting elasticity is -.07, which is in the range of those observed in the Marvell review.

Dependent Variable: LOG(CR_RATETOT)

Method: Panel Least Squares

Date: 08/30/10   Time: 17:27

Sample (adjusted): 1983 2008

Periods included: 26

Cross-sections included: 39

Total panel (balanced) observations: 1014

White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.13445	1.414325	9.993774	0.0000
LOG(ADP_TOTAL1049(-1))	-0.074764	0.081799	-0.914001	0.3609
LOG(ADP_JAIL1849MOD(-1))	0.004265	0.005725	0.745031	0.4564
LOG(POLICEEMP1049(-1))	-0.474798	0.096142	-4.938509	0.0000
E_UR	0.077093	0.391337	0.197000	0.8439
LOG(E_PCIR(-1))	-0.518642	0.148012	-3.504053	0.0005

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.767389	Mean dependent var	8.334487
Adjusted R-squared	0.757078	S.D. dependent var	0.417188
S.E. of regression	0.205620	Akaike info criterion	-0.283151
Sum squared resid	41.01121	Schwarz criterion	-0.069588
Log likelihood	187.5574	Hannan-Quinn criter.	-0.202037
F-statistic	74.42002	Durbin-Watson stat	0.516363
Prob(F-statistic)	0.000000		

We then tested for unit roots in the crime and prison ADP variables. The county total UCR crime rate data did not exhibit unit roots; the Im-Pesaran-Shin panel unit root test produced a p-value of .034, thus rejecting the null hypothesis of a unit root. We then tested the prison ADP variable and we found a strong indication of a unit root with a Im-Pesaran-Shin p-value of 1.0, thus clearly not rejecting the presence of a unit root series. Since the ADP variable is a statewide rate applied to all counties, we also tested the single statewide series from 1982 to 2008 with an Augmented Dickey Fuller test, and we also did not reject a unit root (p-value = .94). With a trend and an intercept, the p-value of the Augmented Dickey Fuller test remained non-significant .74. In first differences, on the other hand, the Augmented Dickey Fuller test had a p-value of .02 and the Im-Pesaran-Shin panel unit root test produced a p-value of .000. Thus a first difference model is indicated based on the ADP variable. The need to use a first difference estimation of the prison-crime relationship is consistent with the recommendation in Marvell (2009) and Spelman (2008). Additional research is warranted with this Washington county level data set to test for possible cointegration.

The results of a first difference specification of the logged variables is shown below. Here the prison elasticity is larger, at -.33. This is in line with some estimates that have been produced when simultaneity is accounted for with instrumental variables. As noted by Spelman (2008), it is possible that by using county level data within a particular state (Washington, in this case), the data may not require accounting for simultaneity. Washington also had an arguably close-to-exogenous change in ADP in the 1980s when it adopted a new form of adult sentencing. When this new system went into effect, the incarceration rate was lowered as a matter of policy; this trend was later reversed by subsequent sentencing policy actions, but for a few years this seemingly exogenous policy change probably allowed a cleaner delineation of the true prison-crime relationship. This may be why the -.33 estimate in the first difference model is close to the estimates obtained by other studies when simultaneity is accounted for.

Dependent Variable: CR_RATETOT_FDL
Method: Panel Least Squares
Date: 08/30/10   Time: 17:21
Sample (adjusted): 1984 2008
Periods included: 25
Cross-sections included: 39
Total panel (balanced) observations: 975
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000920	0.005504	-0.167186	0.8673
ADP_TOT1049_FDL(-1)	-0.326227	0.111908	-2.915149	0.0036
POLICEEMP1049_FDL(-1)	-0.165927	0.068704	-2.415085	0.0159
ADP_JAIL1849MOD_FDL(-1)	0.000695	0.006330	0.109770	0.9126
E_UR-E_UR(-1)	-0.406372	0.481598	-0.843800	0.3990
E_PCIR_FDL(-1)	-0.303863	0.146536	-2.073633	0.0384

R-squared	0.029606	Mean dependent var		-0.014413
Adjusted R-squared	0.024599	S.D. dependent var		0.143917
S.E. of regression	0.142136	Akaike info criterion		-1.057935
Sum squared resid	19.57626	Schwarz criterion		-1.027889
Log likelihood	521.7433	Hannan-Quinn criter.		-1.046501
F-statistic	5.912732	Durbin-Watson stat		2.198526
Prob(F-statistic)	0.000022			

The Marvell (2009) review provides the basis for the estimated range of elasticities we include in the WSIPP sentencing model. The evidence from the regression results for Washington appear to align with Marvell's findings. Additional exploration of the Washington county-level data may provide further insights.

Simultaneity Adjustment. In addition to the studies reported above, Marvell (2009) also reviewed the few studies that have been done using instrumental variables to control for simultaneity bias. The median elasticity estimate for total crime of the three studies that controlled for simultaneity is -.28, compared to the -.11 estimate from the 22 studies that did not control for simultaneity. A simply ratio of these estimates produces a multiple of 2.58; that is, accounting for simultaneity could raise the average elasticity 2.58 times. We use this ratio as a modal, multiplicative simultaneity adjustment in the WSIPP sentencing model. We bound this rough estimate on the high side with the OLS and IV estimates reported in the well-known study by Levitt (1996). Levitt used a common dataset and method and produced IV elasticities that were 3.69 times higher than his OLS elasticity estimates where he did not control for simultaneity. We use this ratio as our high simultaneity adjustment. For the low simultaneity adjustment, we simply take the difference between 2.58 and 3.69 and subtract it from 2.58. These three multiplicative simultaneity adjustments, 1.47, 2.58, and 3.69, are then used in a triangular probability density distribution to adjust the basic elasticity estimate discussed above. We entered these three parameters in the WSIPP model as shown in Appendix C.

Average Policy Adjustment. As noted previously, policymakers are not likely to apply uniform sentencing practices for offenders with varying risk levels. For example, if a legislature were to consider lowering prison sentences, it probably would draw some distinction between high risk sex offenders and lower-risk drug offenders. The empirical studies that estimate how a change in ADP affects crime, however, do not consider this type of differential change in APD; instead, nearly all studies estimate the effect of total ADP on crime. The WSIPP model is designed to allow users to enter parameters that scale the elasticities to better reflect the selective policy adjustments legislatures are likely to consider.

The Combined Effect of the Range of Elasticity Estimates, Simultaneity Adjustments, and Policy Adjustments. The WSIPP model is designed to be run as a Monte Carlo simulation since there is a great deal of uncertainty in some of the key parameters in the model. The true effect of prison on crime, as measured by the elasticity, is a major source of uncertainty. The effect can be broken down into the component parts and then combined multiplicatively, and in equation 3(b). Once the user has entered low, modal, and high parameters for each of the three factors, triangular probability density distributions are created. Then, in Monte Carlo simulation, each of the three parameters is drawn randomly from the triangular distribution and

the joint product is computed. The chart shown in Appendix C displays a distribution of elasticity estimates after a 10,000 case Monte Carlo run, given the parameters shown in the first section of the screen shot.

Uniform Crime Report Adjustments. Not all UCR reported crime categories align with felony conviction data as defined by the Revised Code of Washington. We describe the procedures we use to adjust the UCR data in Appendix D2.3.

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 D2.3.

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

There can be two related fiscal effects that stem from the results of Step 1. If ADP is lowered or raised by a sentencing policy change, then there should be a fiscal effect on state budgets. For example, we have estimated that a one-unit change in ADP can be expected to change state prison operating costs by about $13,921 (in 2009 dollars) for Washington State. As we explain in Appendix D2, 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 user can elect to include capital costs in all calculations. If this option is selected (see the input screen), then the user-supplied annualized capital cost is added to this estimate. For Washington, we have estimated that the annual taxpayer capital payment for a prison bed is about $8,308; the derivation of this estimate is also discussed in Appendix D2. Thus, the first fiscal effect from a change in prison ADP is the budgetary effect on state prison budgets (with or without capital costs included).

The second fiscal effect stemming from a change in prison ADP has to do with other fiscal costs that can be expected to change to the degree that a change in prison ADP affects the crime rate in a state. If sentencing policies 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 and this will cost taxpayers money. These increased costs will offset the immediate prison fiscal savings from the ADP reduction.

If, on the other hand, changed sentencing policies result in increased incarceration rates, and if this results in a decrease in crime, then other fiscal costs can be expected to be reduced as crime drops. In this case, increased costs associated with the increased ADP will be offset by expected reductions in other fiscal costs as crime goes down.

WSIPP's model estimates both of these fiscal effects.

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 T, 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 UCR data and adjustments (as described in equation (3a)).

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

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

The Washington data sources for equations (6) and (7) are described in Appendix D2. Equations (6) and (7) describe the process for the average prison or jail sentence probability for total felony crimes, *T*. Similar equations, not shown, can be calculated for the violent crime or property crime subcategories.

Average Length of Stay in Prison or Jail. The calculation of fiscal effects for total felony crime *T* 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 (8) and (9) are described in Appendix D2.

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

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

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 D2. The two equations estimate the weighted probabilities for total felony crimes *T*.

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

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

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 D2. The two equations estimate the weighted length of stays for total felony crimes *T*.

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

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

Change in Prison Costs. The change in the present value of prison costs for the change in all types of felony crime *T*, given the above equations, 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 change in reported crime from the change in prison ADP is computed from equation (3c). The variable *dis* is the discount rate used in the overall benefit-cost analysis, and is entered by the user on the WSIPP model screen. The variable for prison costs, *Prison$*, is the calculated figure discussed above and represents changed operating and capital costs (if the user has selected the capital cost inclusion option).

Change in Jail Costs. The change in the present value of jail costs for the change in all types of felony crime *T*, given the above equations, 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 change in reported crime from the change in prison ADP is computed from equation (3c). The variable *dis* is the discount rate used in the overall benefit-cost analysis, and is entered by the user on the WSIPP model screen. The variable for jail costs, *Jail$*, is the calculated operating costs estimate and capital costs if the user has selected the capital cost inclusion option.

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 D2.

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 D2.

Change in Police Costs. The change in police costs is computed by first developing a weighted average per-arrest police cost. Equation (18) computes this estimate for all types of crime *T*. This model assumes one arrest per prison or jail sentence.

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

$$(19) \ \Delta Police\$_T = \Delta RC_T \times (PrisonProb_T + JailProb_T) \times Police\$_T$$

The data source for Washington State for the variables in (18) and (19) are described in Appendix D2.

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

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

$$(21) \ \Delta Court\$_T = \Delta RC_T \times (PrisonProb_T + JailProb_T) \times Court\$_T$$

The data source for Washington State for the variables in (20) and (21) are described in Appendix D2.

Change in State Government Fiscal Costs

$(22) \ \Delta StateFiscal\$ =$
$\Delta Prison\$_T \times PrisonStatePct + \Delta PostPrisonCS\$_T \times PostPrisonStatePct + \Delta Jail\$_T \times JailStatePct + \Delta PostJailCS\$_T \times PostJailCSStatePct + \Delta Police\$_T \times PoliceStatePct + \Delta Court\$_T \times CourtStatePct$

Change in Local Government Fiscal Costs

$(23) \ \Delta LocalFiscal\$ = \Delta Prison\$_T \times (1 - PrisonStatePct) + \Delta PostPrisonCS\$_T \times (1 - PostPrisonStatePct) + \Delta Jail\$_T \times (1 - JailStatePct) + \Delta PostJailCS\$_T \times (1 - PostJailCSStatePct) + \Delta Police\$_T \times (1 - PoliceStatePct) + \Delta Court\$_T \times (1 - CourtStatePct)$

Inputs to Step 3 (of 5): Estimating the Effect of a Portfolio of Evidence-Based Programs That Reduce Crime.

The logic behind WSIPP's sentencing tool is that if a state decides to change its average daily prison incarceration rate, then two things will happen initially: crime levels will change as will net taxpayer costs. Steps 1 and 2 describe the procedures we use to estimate these initial values from a sentencing policy change. The third step in WSIPP's approach then estimates the crime and fiscal effects if a portion, or all, of the net taxpayer savings (from Step 2) is used to fund a portfolio of evidence-based programming resources.

This section describes the inputs needed to create the portfolio of evidence-based crime-reduction programs. It draws on the on-going work of WSIPP, as described in Appendix D2. There are three steps to WSIPP's programming portfolio model.

Review of the Evidence on What Works (and What Does Not). The first step 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 have not). Our empirical approach for this first task is to assess systematically, using a meta-analytic framework, the research literature on a given topic. We have found that a meta-analytic approach is particularly helpful in a "real world" policy environment, because it considers all available

evidence, not just one or two selected studies. A well done meta-analysis produces an expected effect of a public policy option (and standard error), given the weight of all the evidence. For this analysis, we have examined programs that have achieved reduction in crime outcomes. We report here the results of various types of programs for adult and juvenile offenders. There is also evidence that some prevention programs, such as early childhood education, can reduce crime. We do not show the results of the prevention programs in this document; we are updating reviews of this prevention literature at the present time.

Compute the Economics (Costs and Benefits) of Specific Policy Options. The product of the meta-analyses reveals whether a given programming 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 D2. 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: the direct participants in policy options; a taxpayer-only perspective; and the non-taxpayer perspective of people who are not the direct program recipient. In the case of crime outcomes, the later perspective is that of crime victims. If crime is reduced, then there is value to people who do not become the victims of crime. If crime is increased, then victimization costs are incurred. The combination of these three perspectives enables a "total state" perspective. For crime outcomes, the taxpayer perspective if further divided into state taxes and local taxes; this information is used in the model.

Create a Portfolio of Programs Available for Selection. For the sentencing model, we use our benefit-cost model to create a set of programs that includes adult corrections programs and juvenile justice programs. In the table below, we report the results of our crime model. These results are also displayed on the software input screen as shown in Appendix C. The table displays the number of program evaluations (from the meta analysis) used to draw conclusions about program effectiveness in reducing crime. The table also shows the estimated program cost per participant in 2008 dollars. These costs are on an "intent-to-treat" basis, to be consistent with how we compute crime outcomes. That is, we count both the average costs and the average crime effects of people who start a program, not just those who finish a program. This is done to help avoid the statistical selection bias that can otherwise cloud the causal interpretation of program effectiveness.

We then show the results, per average program participant, of the mean victimizations avoided (and standard error) estimated from the program effect size and other parameters. This process is described in Appendix D2. We then divide the mean victimizations avoided by program costs to show the victimization avoided per dollar of cost. The benefit-cost model described in Appendix D2 estimates the monetary value of the avoided crimes in terms of reduced criminal justice system spending. These results are shown on the table for both mean values and associated standard errors (computed with Monte Carlo simulation after varying a number of parameters). We also compute and report the estimated state portion of the taxpayer benefits. Finally, we indicate the monetary values we compute for the avoided victimization costs.

Portfolio of High Return-on-Investment Adult Offender and Juvenile Offender Programs to Reduce Crime
Results from WSIPP Benefit-Cost Analysis (August 2010), 2008 Dollars

Program Name	Number of Studies Meta Analyzed	Program Cost Per Program Participant	Victimizations Avoided Per Program Participant			Taxpayer Benefits Per Program Participant			Victim Benefits Per Program Participant
			Mean	Standard Error	Per $/1000 Program Cost	Mean	Standard Error	State Percent of Benefits	
Adult Programs									
Vocational Education in Prison	4	$1,296	0.26	0.05	0.20	$2,965	$610	47%	$7,070
Education in Prison (basic or post-secondary)	17	$1,055	0.22	0.08	0.21	$2,525	$922	47%	$5,961
Cognitive Behavioral Programs in Prison	27	$517	0.19	0.07	0.36	$2,080	$722	47%	$5,100
Correctional Industries in Prison	4	$457	0.16	0.03	0.36	$1,907	$374	47%	$4,592
Drug Treatment in Prison	21	$1,758	0.16	0.06	0.09	$1,883	$649	47%	$4,592
Drug Treatment in Community	6	$629	0.14	0.06	0.23	$2,000	$867	42%	$4,804
Drug Courts (adults)	67	$4,792	0.09	0.02	0.02	$2,044	$382	44%	$4,376
Juvenile Programs									
Multi-dimensional Treatment Foster Care	3	$7,418	0.76	0.30	0.10	$7,363	$2,994	50%	$24,068
Family Integrated Transitions	1	$10,795	0.40	0.24	0.04	$3,867	$2,307	50%	$13,050
Coordination of Services	14	$379	0.07	0.05	0.19	$723	$534	45%	$2,135
Functional Family Therapy	7	$3,134	0.68	0.19	0.22	$6,692	$1,858	45%	$20,623
Aggression Replacement Training	4	$1,449	0.32	0.16	0.22	$3,195	$1,565	45%	$9,731
Multi-systemic Therapy	10	$7,076	0.36	0.12	0.05	$3,641	$1,258	45%	$11,027

A user can then select any of these resources to be elements of an overall portfolio. For example, a user could designate 50 percent of the portfolio into cognitive behavioral therapy (CBT) for adult offenders; 25 percent into the juvenile justice program Functional Family Therapy; and 25 percent into the juvenile justice program Aggression Replacement Therapy. The weighted average portfolio effect on crimes avoided (and standard error) as well as the weighted average portfolio cost and taxpayer and victim savings are then computed. The portfolio standard error on the crimes avoided assumes no correlation among the programs selected for the portfolio. The results of a sample portfolio are displayed on the screen shot shown in Appendix C.

Step 4 (of 5): Combinations of Policies

At this stage, the user has identified a prison ADP change and elasticity assumptions (Step 1); calculated the initial change in criminal justice system costs or benefits from the ADP change's effect of crime (Step 2); and selected a portfolio of evidence-based programs to purchase (Step 3). In Step 4, the user decides on the percentage of taxpayer savings from Step 2 to apply to buying high return on investment program "slots."

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 the initial purchases of evidence-based programming, *InitialPctProgramming.* The user enters this programming percentage in the model as shown on the screen shot in Appendix C. 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. The source of the net fiscal savings is dependent upon whether the user has chosen to decrease or increase prison ADP. For example the net fiscal savings for an ADP reduction results from the direct change in prison expenditures. Alternatively, the net fiscal savings for an increase in ADP derives from the changed costs of criminal justice system if the user has negative elasticities in the model.

$$(24)\ InitialSlotsPurchased = \frac{(\Delta NetFiscal\$ \times InitialPctProgramming)}{AvgCostofPortfolioPrograms}$$

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 D2.

$$(25)\ InitialTaxpayerBenefits = IntialSlotsPurchased \times AvgTaxpayerBenefitofPortfolio$$

Cost of Additional Slots Purchased. The expected taxpayer benefits from the initial purchase of evidence-based programs can allow a state to purchase additional evidence-based program slots. The user also enters the parameter for *AdditionalPctProgramming*. The total number of any additional slots is given by:

$$(26)\ AdditionalSlotsPurchased = \frac{(InitialTaxpayerBenefits \times AdditionalPctProgramming)}{AvgCostofPortfolioPrograms}$$

Total Slots Purchased. Equation (27) then sums the initial and additional evidence-based portfolio slots purchased to arrive at the total number of slots purchased, *TotalSlotsPurchased*.

$$(27)\ TotalSlotsPurchased = InitialSlotsPurchased + AdditionalSlotsPurchased$$

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*.

$$(28)\ AvoidedCrimes = TotalSlotsPurchased \times AvgCrimesAvoidedPerSlot$$

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).

$$(29)\ CrimeChange = \Delta C_t - AvoidedCrimes$$

As 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. We will investigate whether it is possible to enhance the model to contain this capability.

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 typically wants to know the expected gain of an investment along with a measure of 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 WSIPP tool produces include the expected change in taxpayer spending for a portfolio of policy options, along with the risk that the mix of options could lead to more crime, not less.

We estimate the known uncertainty surrounding many of the inputs to the model. We implement a Monte Carlo simulation approach in Microsoft Excel to vary the following key inputs in the model.   Each time the model is run (the default is 10,000 cases per run), the model draws randomly from the user-specified probability distributions for the variables shown in the following table.

Parameters Allowed to Vary in Monte Carlo Simulation of the Model

Model Parameter Allowed to Vary	Type of Probability Distribution *
Crime-Prison Elasticity and Adjustments	
UCR Crime-Prison Elasticity	Triangular
Drug Conviction-Prison Elasticity	Triangular
UCR Crime-Prison Simultaneity Adjustment	Triangular
Drug Conviction-Simultaneity Adjustment	Triangular
UCR Crime-Policy Adjustment	Triangular
Drug Conviction- Policy Adjustment	Triangular
Portfolio Program Effectiveness Estimates	
Victimization Avoided Per Program Portfolio Slot	Normal
Taxpayer Savings Per Program Portfolio Slot	Normal
Additional Indirect variation on Program Portfolio Slots	
Program Effect Size	Normal
Victimization Costs	Triangular
Operating Criminal Justice System Costs	Triangular
Discount Rate	Triangular

* The specific parameters for these distributions are selected by the user. We show WSIPP's values on the screen shot in Appendix C.

Appendix D2: Benefit and Costs of Crime Prevention—Computational Procedures and Monetary Valuation

This section of the Appendix describes WSIPP's benefit-cost model that estimates the monetary value to taxpayers and victims of programs that reduce crime. In this Appendix, we describe the methods, data sources, and estimation procedures.

The current version of WSIPP's model approaches the crime valuation question from two perspectives. We compute the value to taxpayers if a crime is avoided. We also estimate the costs that can be avoided by people who would otherwise have been a victim of a crime, had the crime not been averted.[36] 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 uses 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. This section begins by describing these four data sources and then turns to the computational procedures that produce the avoided costs of reduced crime.

D2.1 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.[37] 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 D2.1a shows a screen shot, taken from WSIPP's benefit-cost model, that displays an array of per-unit costs for the 12 sectors and seven types of crime modeled. The estimates for each row in Exhibit D2.1a are described below.

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

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

WSIPP Benefit-Cost Model: Version 1.0

| Enter Sector Inputs | Enter Program Inputs | Run Models & View Reports |

Per Unit Costs | Resource Use | Offender Populations | Victimization | Program Participation | Sentencing

General
Economic
Crime
Education
Child Welfare
Mental Health
Substance Use (ATOD)
Teen Birth
Public Assistance
Public Health
Housing
Outcomes & Links

	Marginal Operating Costs									Capital Costs			Misc.
	Murder	Felony Sex Crimes	Robbery	Aggravated Assault	Felony Property	Felony Drug	Misdemeanor	Year of Estimate	Real Escalation Rate	Capital Cost Per Unit	Year of Estimate	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	13,921	13,921	13,921	13,921	13,921	13,921	13,921	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%
Adult State Prison	13921	13921	13921	13921	13921	13921	13921	2009	0.003	113339	2007	25	1

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.

Cost Variance for Per Unit Criminal Justice and Victim Costs

	Low Variance	High Variance
Criminal Justice System Costs	-0.1	0.1
Crime Victim Costs	-0.2	0.1

Instructions:
To reflect variation in per unit cost estimates, enter a low and high percentage change variance, which is used during the monte carlo sensitivity analysis. Low percentage change must be entered as a negative value and high variance must be a positive value.

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 D2.1a.

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, as of winter 2010, 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.[38] 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 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.

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

Aggregating thus allowed for a more consistent cost-arrest data series for the years in our study. 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.

Exhibit D2.1b
Average Police Costs Per Arrest, 2009 Dollars
Calendar Years 1999 to 2007

$y = 112.92x + 3617.5$
$R^2 = 0.9113$
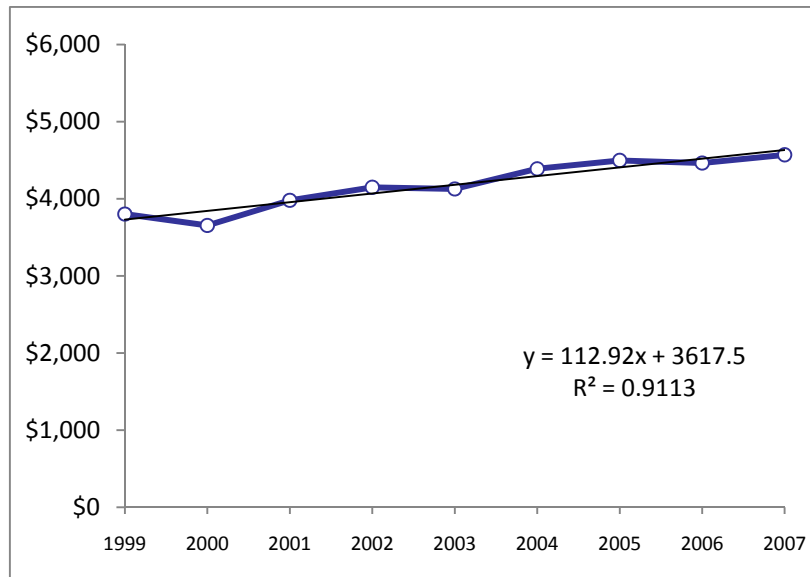
Over the entire 1999 to 2007 timeframe, the average statewide cost is $4,182 per arrest, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in 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 D2.1a.

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.[39] 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 D2.1a. The sum of the arrest lags is $670. An identical model, but without including a right-hand side dependent variable, produced quite similar results.

Exhibit D2.1c

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		

[39] 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 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 D2.1a, along with an assumed five-year 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 D2.1a.

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, as of winter 2010, 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.

Exhibit D2.1d
Average Court Costs Per
Conviction, 2009 Dollars
Calendar Years 1994 to 2008

$$y = 131.03x + 5489.2$$
$$R^2 = 0.724$$
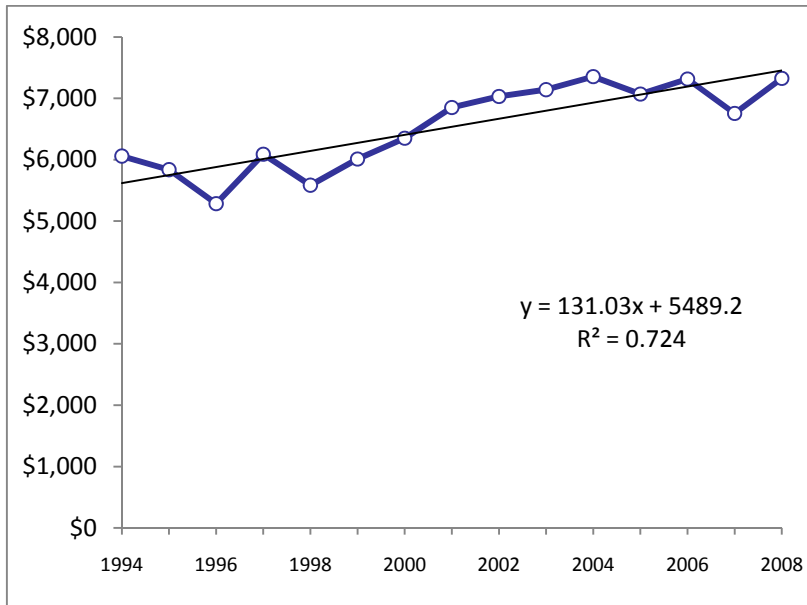
Over the entire 1994 to 2008 timeframe, the average statewide cost is $6,557 per conviction, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown 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 D2.1a.

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.[40] 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.

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[40] Ibid., p. 636.

Exhibit D2.1e

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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 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 D2.1a, 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 D2.1a. 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, as of winter 2010, 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.

Exhibit D2.1f
Average County Jail ADP Costs, 2009 Dollars
Fiscal Years 1993 to 2008

$$y = 608.62x + 23267$$
$$R^2 = 0.7161$$
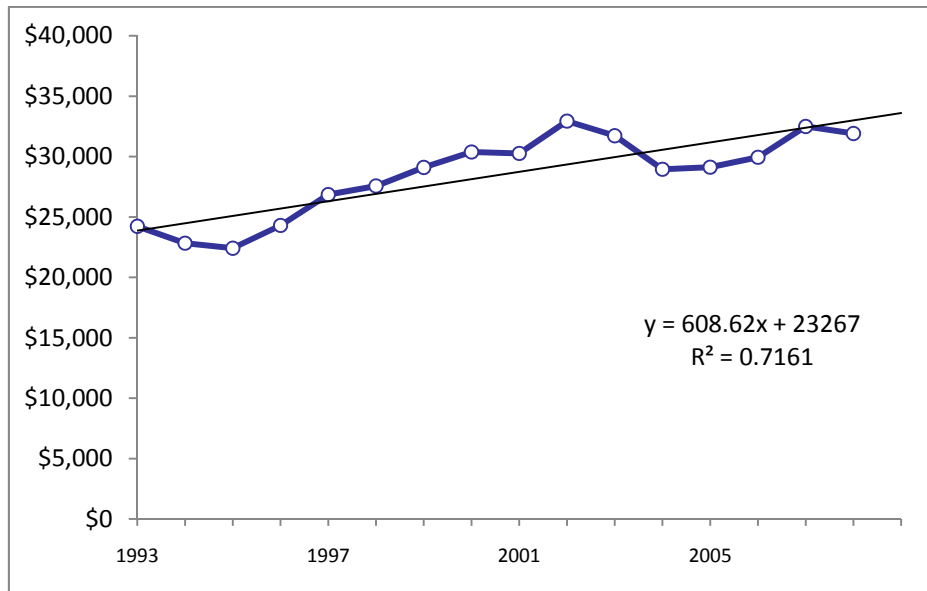
Over the entire 1993 to 2008 timeframe, the average statewide cost is $28,900 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown of the 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 D2.1a.

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.[41] 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.

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[41] Ibid., p. 636.

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Since the two series have unit roots, we tested to determine if the two series together are cointegrated.[42] We used two versions of a panel cointegration test in EVIEWS. Both the Pedroni Engle-Granger test (p-value .000) and the Kao Engle-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.[43]

Exhibit D2.1g

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.

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[42] Ibid., p. 639.
[43] We also ran the preferred model shown above, but without the error correction. The coefficients from the three ADP variables 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 D2.1a.

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, as of winter 2010. The Auditor's data for the expenses include 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.

Exhibit D2.1h
Average Local Juvenile Detention ADP Costs,
2009 Dollars, Fiscal Years 2003 to 2006

$$y = 3200.7x + 49881$$
$$R^2 = 0.9882$$
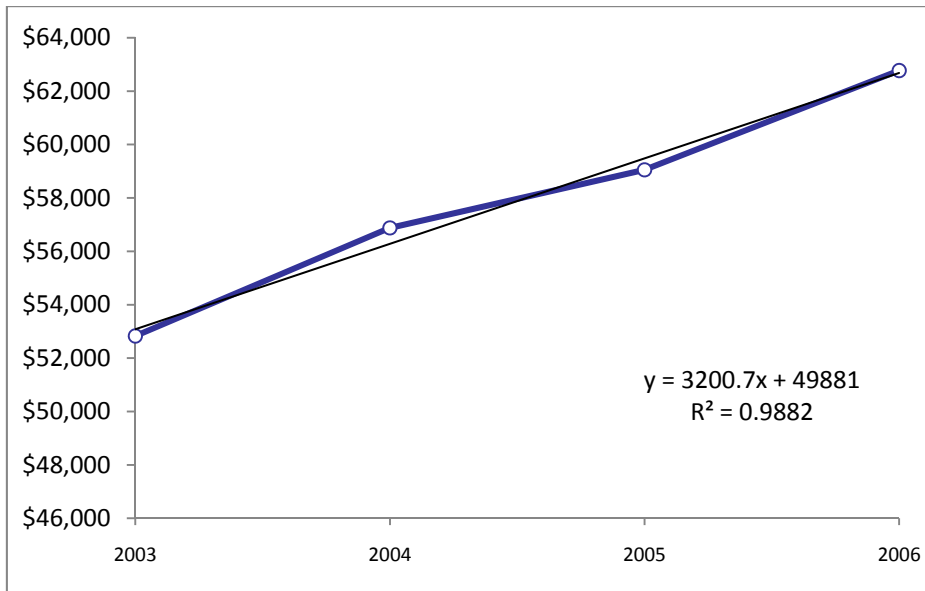
Over the 2003 to 2006 timeframe, the average annual cost is $57,727 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) 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 D2.1a. 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.

Exhibit D2.1i

```
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.[44] 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

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

expenditures for juvenile probation for the state was $29,203,723 for 2008. Again, this figure does not include Snohomish County.

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.[45]

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 D2.1a.

### 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 D2.1a.

Institutional Operating Costs. For an estimate of the marginal operating costs 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 Exhibit D2.1j.

[45] 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.

Exhibit D2.1j
Average JRA Institution ADP Costs, 2009 Dollars
Fiscal Years 1974 to 2009

$$y = 802.5x + 37432$$
$$R^2 = 0.461$$
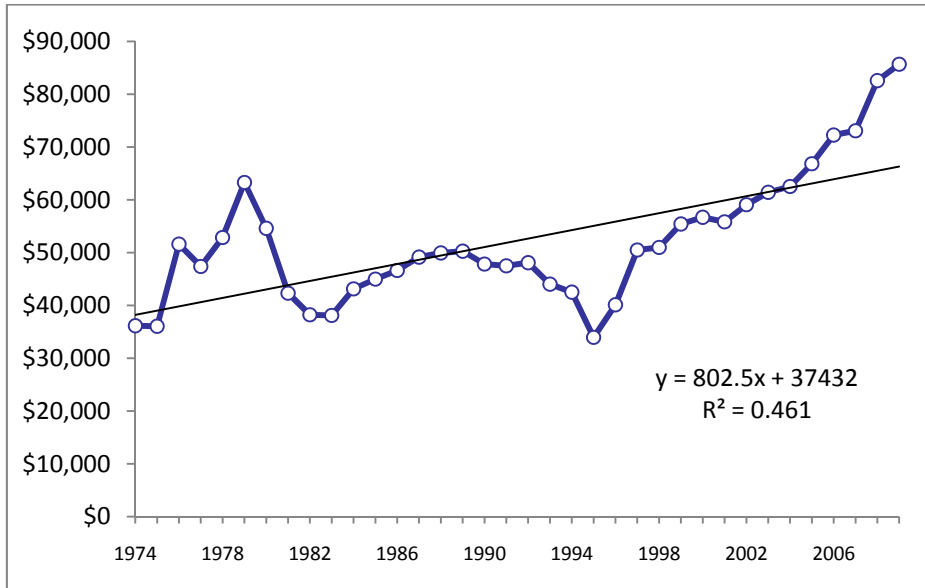
Over the entire 1974 to 2009 timeframe, the average cost is $51,716 per ADP, in 2009 dollars. Over these years, there has been an upward trend in the inflation-adjusted costs. We computed an estimate of the average annual real escalation rate in costs by estimating a linear line (shown in the chart) for this series. From this line, we computed the predicted values for 1974 ($38,274) and 2009 ($66,379) 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 D2.1a. 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 of 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.[46] 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.[47] 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.

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[46] Wooldridge, p. 636.
[47] Ibid., p. 639.

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

Exhibit D2.1k

```
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 was $36,743, in 2009 dollars. This is our estimate of the marginal operating cost of an annual JRA bed.[48] 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: $43,004,688 (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 $7,847, 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 $7,847 by .50 provides an estimate, $3,923 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 D2.1a.

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[48] 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.

Exhibit D2.1I
Average DOC ADP Prison Costs, 2009 Dollars
Fiscal Years 1982 to 2009

$$y = 87.23x + 29798$$
$$R^2 = 0.0562$$
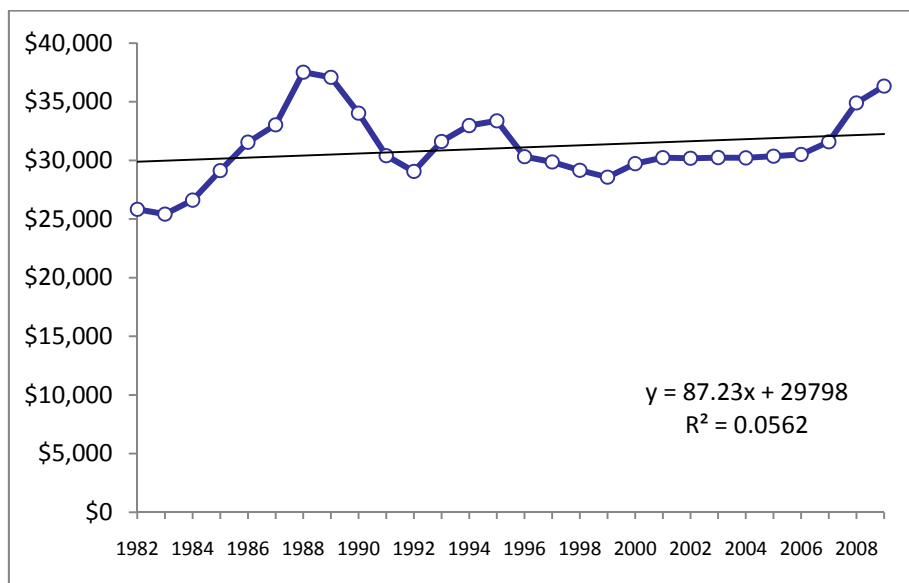
Over the entire 1982 to 2009 timeframe, the average cost is $31,446 per ADP, in 2009 dollars. Over these years, there has been a slight upward trend in the inflation-adjusted per-unit costs, as revealed by the linear regression line shown in the Exhibit. To compute an estimate of the long-run growth rate in real cost per average daily population, we calculated the predicted values from the regression line for 1982 ($29,915) and 2009 ($32,266) 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 D2.1a.

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.[49] We tested for unit roots with an Augmented Dickey-Fuller (ADF) test.

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[49] Wooldridge, p. 636.

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- 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.

- 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.[50]

Assuming the two series have unit roots, we tested to determine if the two series together are cointegrated.[51] 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.

Exhibit D2.1m

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.[52] 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 short-run marginal cost from the regression is the first lag term ($4,495).

The sum of the four DOCADP distributed lags (the long-run multiplier) is $13,921. This figure, $13,921 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 D2.1a.[53]

[50] Ibid., p. 643.
[51] Ibid., p. 639.
[52] Ibid., p. 643.
[53] 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).

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 D2.1a. 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 average community supervision cost over the 1998 to 2009 period is $3,657.

Exhibit D2.1n
Average DOC Average Daily Community Supervision Costs,
2009 Dollars, Fiscal Years 1998 to 2009

$$y = 237.49x + 2161.1$$
$$R^2 = 0.9487$$
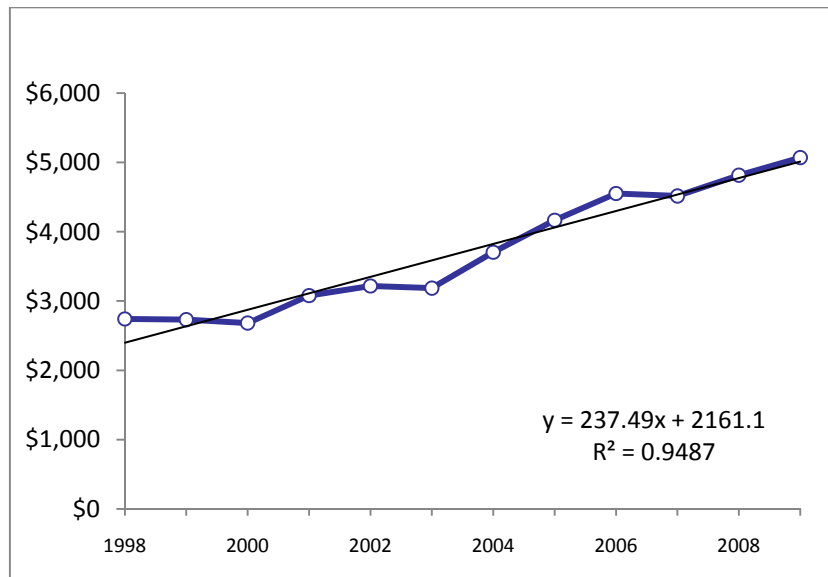
Over the 1998 to 2009 period, there was a significant upward trend in the inflation-adjusted per-unit costs, as revealed by the linear regression line shown in the Exhibit. To compute an estimate of the long-run growth rate in real cost per average daily population, we calculated the predicted values from the regression line for 1998 ($2,399) and 2009 ($4,773) 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 D2.1a. This estimate seems high, and it will be useful to monitor actual expenditure trends in the years ahead.

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.[54] 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.[55] 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.[56] This point estimate is included as a parameter in the crime model, as shown in Exhibit D2.1a. The three ADP variables are jointly significant with a p-value on the f-test of .0042.

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[54] Wooldridge, p. 636.
[55] Ibid., p. 639.
[56] 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.

Exhibit D2.1o

```
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.

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.[57] 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).[58]

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

[57] 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.
[58] T. R. Miller, M. A. Cohen, & B. Wiersema (1996). *Victim Costs and Consequences: A New Look*. Research Report. Washington DC: National Institute of Justice.

Washington State; convictions for homicide are not misclassified as other crimes in the Washington system. See section D2.3 of this 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 D2.1a.

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 D2.1p 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 D2.1p are described below.

Probability of Resource Use. The first block of information in Exhibit D2.1p 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.[59]

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

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.[60]

Juvenile Local Supervision. The average length of stay on probation was also estimated from the same survey of juvenile courts conducted by WSIPP.[61]

Juvenile State Institution. The average length of stay in a juvenile state institution was estimated using data obtained from the Sentencing Guidelines Commission.[62]

Juvenile State Supervision. The average length of stay on juvenile parole was estimated using information obtained from the Juvenile Rehabilitation Administration.[63]

Adult Jail, With Local Sentence. The average length of stay in jail for local sentences was estimated using data from the Sentencing Guidelines Commission.[64]

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.[65]

Adult Community Supervision and Adult Post Prison Supervision. These numbers were obtained from the Sentencing Guidelines Commission.[66]

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 D2.1p shows the average prison length of stay, which is computed in the model

[59] 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.
[60] R. Barnoski & M. Burley (1997). *Washington State Juvenile Courts: Workloads and Costs.* Olympia: Washington State Institute for Public Policy, Document No. 97-04-1201.
[61] Ibid.
[62] Received via email on March 10, 2010.
[63] Received via phone conversation on April 18, 1997.
[64] SGC 2009, Table 1.
[65] Received via phone conversation on November 7, 1996.
[66] Received via email on April 6, 2010.

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.

Exhibit D2.1p

WSIPP Benefit-Cost Model: Version 1.0

Enter Sector Inputs | Enter Program Inputs | Run Models & View Reports

Per Unit Costs | **Resource Use** | Offender Populations | Victimization | Program Participation | Sentencing

Total current prison average daily population (ADP): 18400

	Felony Violent & Property Crime Categories					Other		Sums		Year of Data
---	Murder	Felony Sex Crimes	Rob-bery	Aggrav ated Assault	Felony Propert y	Felony Drug	Misdem eanor	Total Violent	Total Violent & Prop-erty	
Probability of Resource Use										
Juvenile State Institution	0.86	0.46	0.68	0.34	0.15	0.14	0.02	0.43	0.24	2009
Adult State Prison	0.96	0.71	0.72	0.39	0.35	0.30	0.00	0.49	0.41	2009
Juvenile Local Supervision	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	
Juvenile State Supervision (Parole)	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	
Adult Community Supervision Post-Jail	1.00	0.85	0.89	0.69	0.17	0.73	0.00	0.73	0.38	2008
Adult Community Supervision Post-Prison	0.99	0.96	0.98	0.81	0.29	0.96	0.00	0.87	0.61	2008
Adult State Prison	0.959	0.708	0.715	0.394	0.352	0.3	0	0.49	0.409	2009
Number of Years of Use Per Resource										
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	0.39	0.29	2009
Adult Jail, with Prison Sentence	1.08	0.48	0.44	0.37	0.32	0.28	0.00			2009
Adult Community Supervision, Jail Sentence	2.00	2.50	1.01	0.82	0.24	0.90	0.50	1.17	0.92	2008
Adult Prison	14.84	6.06	3.95	2.64	1.65	1.35	0.00	4.35	2.99	2009
Adult Community Supervision, Post-Prison	3.91	3.70	2.94	1.67	0.51	1.06	0.00	2.40	2.00	2008
Adult Prison	14.84	6.06	3.95	2.64	1.65	1.35	0	4.35	2.99	2009
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			
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			

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.

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 August 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 D2.1p 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 D2.1p as representative of the typical decisions made pursuant to current Washington State law.

D2.2 Criminological Information for Different Populations

To estimate the long-run impacts of evidence-based programs on crime, WSIPP combines program effect sizes with crime information from various populations in Washington State. To do this analysis, we calculate 15-year recidivism trends for an offender cohort; for non-offender populations, we calculate the probability of obtaining a conviction over the life-course (35 years).

Offender Populations. 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 from adult or juvenile court.[67] In addition to the 15-year follow-up period, a one-year adjudication period is added to allow for court processing of any offenses that occur at the end of the follow-up period. Crime parameters are calculated using WSIPP's criminal history database, which is a synthesis of criminal conviction information for all individuals in Washington State.[68]

We collected recidivism data on five general offender populations 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.

We further break down the general offender populations into various offense and risk for reoffense categories. Offense categories are based on the most serious current offense for which the offender was convicted prior to the 15-year follow-up period. Risk for reoffense is calculated using criminal history data to determine offenders' probability of future reoffense, and then grouped into low, moderate, and high risk categories.[69]

Using the five general populations and nine offender categories described below, we, thus, calculate separate crime distributions for 45 populations. The nine offender categories include:

1) The general population of offenders (i.e., DOC offenders who release 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

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[67] R. Barnoski (1997). *Standards for Improving Research Effectiveness in Adult and Juvenile Justice*. Olympia: Washington State Institute for Public Policy, Document No. 97-12-1201, pg. 2.

[68] Criminal history data are from the Administrative Office of the Courts and the Department of Corrections.

[69] 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.

Non-Offender Populations. To determine the impact of prevention programs on future crime, we calculate the probability of obtaining a conviction over the life-course for a given birth cohort.

From WSIPP's criminal history database, we select felony and misdemeanor offenders who were born in 1974 (n=78,517) to determine how many people were convicted at age 8, age 9, age 10, and so on. The 1974 birth cohort gives us the longest follow-up period (36 years) possible using Washington State criminal records data.

Next, using Office of Financial Management state population data, we abstract the number of people living in Washington State, and 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.

Finally, we calculate the average size of the 1974 cohort each follow-up year weighted by crime propensity.

Crime Parameters. We calculate the following information for each of the offender and non-offender populations:

1) <u>Conviction Rate</u>. The percentage of the cohort convicted of a felony or misdemeanor in Washington during the follow-up period.

2) <u>Crime Probability</u>. For people who do commit crimes during the follow-up period, we calculate the probability of being convicted for a certain type of crime using a ranked order of seriousness. The mutually exclusive categories from most serious to least serious include: murder, sex, robbery, assault, property, drug, and misdemeanor.

3) <u>Trips Through the System</u>. We calculate the total number of adjudications, defined as the number of "trips" through the criminal justice system, during the follow-up period. We also determine the average number of trips per offender during the follow-up period.

4) <u>Volume of Offenses</u>. 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, as well as the average number of offenses per adjudication. Adjudications and offenses are broken into the following categories: murder, sex, robbery, assault, property, drug, and misdemeanor.

5) <u>Timing</u>. For those persons convicted, we compute a probability density distribution for each of the offender and non-offender populations using exponential, lognormal, polynomial (second order), or power distributions, which indicate when convictions are likely to happen over the follow-up period.

Exhibit D2.1q

D2.3 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 D2.1r 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 D2.1r are described below.

Exhibit D2.1r

WSIPP Benefit-Cost Model: Version 1.0

Enter Sector Inputs | Enter Program Inputs | Run Models & View Reports

General | Economic | Crime | Education | Child Welfare | Mental Health | Substance Use (ATOD) | Teen Birth | Public Assistance | Public Health | Housing | Outcomes & Links

Per Unit Costs | Resource Use | Offender Populations | Victimization | Program Participation | Sentencing

	Murder	Rape	Robbery	Aggravated Assault	Burglary	Theft	Motor Vehicle Theft	Year of Data
Number of statewide crimes reported to police	191	2664	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	6420	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	20912	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 number of counts, adult and juvenile	328	3338	1277	7223	24627		
Average number of offenders per victim	1	1	1	1	1		
Statewide estimated felony-type crimes	191	20912	9672	21767	195804		
Percent of other crimes per conviction	0.64	0.2	0.2	0.2	0.2		
Estimated victimizations per convicted offender	1	4.08	3.64	2.28	4.96		

Variance in ratios of victimizations per convicted offender

Low Percent	High Percent
-0.2	0.2

	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 attributed 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[70] and other sexual assaults.[71] 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.[72]

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[70] US Department of Justice, (2008). *Criminal Victimization in the United States, 2006 Statistical Tables* (NCJ 223436), Table 2. Washington, DC.
[71] Ibid., Table 1.
[72] 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.[73]

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.[74]

Statewide number of convictions, adult and juvenile. Adult and juvenile felony conviction data are obtained from the Administrative Office of the Courts.[75]

Average number of offenders per victim. Many victimizations are committed by groups of offenders, thus we estimate the average number of offenders per victimization using data from the National Incident Based Reporting System (NIBRS).[76] We use the offender sequence number in the NIBRS data, which indicates the number of offenders for each incident, and we determine the average number of offenders for each broad offense category.

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.

D2.4 Procedures to Estimate Criminal Justice System and Victimization Events

In this section of the technical appendix, we describe how the inputs from the previous sections are used to calculate victimizations and costs avoided. In some instances, we also count the quantity of criminal justice events, such as prison beds, avoided.

Criminal Justice System Resources.

For each criminal justice resource, as seen on Exhibit D2.1p, we estimate costs avoided using the following equation:

$$(3) CjsResource\$_{ry}$$
$$= \sum_{c=1}^{C} \sum_{t=1}^{ceiling(T_c)} \sum_{f=1}^{F} [CjsEvent_{yctf} \times CrimePr_c \times CjsResourcePrW_{rc} \times TripPr_{ct} \times TimetoRecid_f$$
$$\times RelRisk_y \times CjsResourceCost_{rc}] \times RecidRate$$

We also count Average Daily Population prison beds avoided. We do this using equation 3 above however; we do not multiply by the *CjsResourceCost_{rc}*.

Variable Definitions. Below are definitions and calculations for the variables used in Equation 3.

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[73] Criminal Victimization in the United States, NCJ 223436, Table 100.
[74] Criminal Victimization in the United States, NCJ 223436.
[75] 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.
[76] United States Department of Justice. Federal Bureau of Investigation. National Incident-Based Reporting System, 2008 [Computer file]. ICPSR27647-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2010-05-03. doi:10.3886/ICPSR27647

C – The number of crime types modeled, ranked from most serious crime category to least serious. For example, we use seven crime types ranked in the following order: murder, sex offenses, robbery, aggravated assault, property, drug, and misdemeanors.

F – The number of years in the recidivism follow-up.

Y – The at-risk year following treatment.

T – The number of trips (adjudications) through the system rounded up. For example, prison offenders, whose most serious reoffense is a sex offense, have an average number of 1.08 trips in a 15-year follow-up period. Thus, the total possible number of trips through the system is two with the probability of the second trip being less than .08. See also *TripPr$_{ct}$*.

CjsEvent$_{yctf}$ – Variable indicating if and when a criminal justice resource is used and, if so, how much of the resource is used during the at-risk year. Criminal justice resources are shown in Exhibit D2.1p. The Visual Basic Programming language for *CjsEvent$_{yctf}$* is shown in Exhibit D2.1s.

CrimePr$_c$ – Among those who re-offend, the probability that the most serious offense occurring during the follow-up period is of type *c*. The data for populations are show in Exhibit D2.1q.

CjsResourcePrW$_{rc}$. – The probability that a criminal justice resource will be used for a specific type of crime. See Exhibit D2.1p. For example, not all offenders who are convicted of a crime will necessarily receive a prison sentence. The *CjsResourcePrW$_{rc}$* for police and courts is 1.

TripPr$_{ct}$ – The probability that a trip, a criminal justice event resulting in an adjudication during the follow-up period, occurs for crime c for trip t as show in Exhibit D2.1q. The probability of a trip occurring is 1. Once a whole trip has been used, then we use the remaining probability of the trip. For example, prison offenders whose most serious reoffense is a sex offense have an average number of 1.08 trips in a 15-year follow-up period. Thus, there is a probability of 1 trip occurring and a probability of .08 remaining trips.

TripSpaces$_c$ – The number of years in the follow-up period divided by the number of *Trips$_c$*. This estimate enables us to distribute the total number of adjudications over the 15-year period.

TimetoRecid$_f$ – Among those who re-offend during the recidivism follow-up period *f*, the probability that the recidivism event happens in year *f*. The sum of TimetoRecidf = 1.0

RelRisk$_y$ – The change in the relative risk in crime outcomes in year y. Equation 4 shows how we calculate *RelRisk$_y$*.

$$(4) RelRisk_y = \left[\frac{\left(\frac{(e^{ES \times 1.65} \times RecidRate)}{(1 - RecidRate + RecidRate \times e^{(ES \times 1.65)})} \right)}{RecidRate - 1} \right]$$

> *ES* – The estimated effect size on crime outcomes for the program. The value is computed as a standardized mean difference effect size, approximated for dichotomous outcomes with the Dcox transformation.

CjsResourceCost$_{rc}$ – The per unit marginal costs of each criminal justice resource as estimated in section D.2 of this appendix and as shown in Exhibit D2.1a

RecidRate – The percentage of offenders who have a Washington state court legal action during the recidivism follow-up period F for that specific offender population as shown in Exhibit D2.1q. Different recidivism base rates are used depending on the specific population that receives a given program. See Exhibit D2.1q.

Exhibit D2.1s

Visual Basic Programming Code Used to Calculate *CjsEvent*$_{yctf}$

```
RowCount = 0
   For c = 1 To CrimeTypes
      For t = 1 To TripsCeiling(c, 1)
         If t <= Trips(c, 1) Then
         TripMultiplier = 1
         Else
         TripMultiplier = Trips(c, 1) - Int(Trips(c, 1))
         End If
         AgeTemp = age + (t - 1) * TripSpaces(c, 1)

         For f = 1 To FollowUpYears
            RowCount = RowCount + 1
            If AgeTemp < AgeofAdultCJS(c, 1) Then GoTo SkipAdult

            For y = 1 To MaxAtRiskYears
               If (f + ((t - 1) * TripSpaces(c, 1))) > y Then
                     CjsEvent(RowCount, y) = 0
               ElseIf Int(CjsResourceLength) + (f + ((t - 1) * TripSpaces(c, 1))) = y Then
                      CjsEvent(RowCount, y) = CjsResourceLength - Int(CjsResourceLength)
               ElseIf y > CjsResourceLength + (f + ((t - 1) * TripSpaces(c, 1))) Then
                     CjsEvent(RowCount, y) = 0
               Else
                     CjsEvent(RowCount, y) = 1
               End If

               CjsResourceAvoided(1, y) = CjsResourceAvoided (1, y) _
                  + CjsEvent(RowCount, y) _
                  * CrimeProbCjs(c, 1) _
                  * CjsResourceProb(c, 1) _
                  * TimeToRecid(f, 1) _
                  * TripMultiplier _
                  * RelativeRisk(f, 1) _
                  * RecidRate _
                  * CjsResourcePerUnitCost(c, 1) _
                  * (1 + CjsResourcePerUnitCost Esc) ^ (y - 1)
            Next y
SkipAdult:
   AgeTemp = AgeTemp + 1
         Next f
      Next t
   Next c
   For y = 1 To MaxAtRiskYears
      CjsResourceAvoided (y, 1) = CjsResourceAvoidedSum(1, y)
   Next y
```

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Victimizations Avoided

Using information from Exhibit D2.1r, we estimate the number of victimizations avoided and victimization costs avoided using the following equation:

$$(5) Victim\$_{ry} = \sum_{c=1}^{C} \sum_{t=1}^{ceiling(Trips_c)} \sum_{f=1}^{F} [VictimEvent_{yctf} \times VictimVolume_{yctf} \times CrimePr_c \times TripPr_{ct} \times_f RelRisk_y \\ \times VictimCost_{rc}] \times RecidRate$$

Variable Definitions. Below are definitions and calculations for the variables used in Equation 5 unless otherwise defined in the aforementioned section, criminal justice system resource variable definitions.

VictimVolume_{ctf}. The volume of victimizations is estimated using a three-step process. First, we estimate the number of victimizations avoided for the most serious offense in the follow-up period. Second, since there are usually other offenses adjudicated at the time of the most serious offense, we calculate the additional offenses and related victimizations. Finally, we calculate the number of victimizations avoided for the trips through the criminal justice system during the remainder of the follow-up period.

F – The number of years in the recidivism follow-up time trips ceiling for that offense type. For example, prison offenders whose most serious reoffense is a sex offense have an average number of 1.08 trips in a 15-year follow-up period. Thus, the ceiling of the total number of trips that need to be modeled are 2.

$$(6) VictimVolume_{cf} = \sum_{c=1}^{C} \sum_{v=c}^{C} \sum_{f=1}^{F} \frac{(MostSeriousTripVic_c + AddVicsMostSeriousTrip_c + RemainingTrips_c)}{Trips_c}$$

Equations 7, 8, and 9 show our calculations for each component of *VictimVolume_{yctf}*. In the following equations, when *c* equals *v*, we estimate the most serious offense using the following formulas. Otherwise, *c*, the most serious crime, is equal to zero.

$$(7) MostSeriousTripVic_c = 1 \times VicsPerConvictedOffender$$

$$(8) AddVicsMostSeriousTrip_c = OffensesPerTrip_c \times VicsPerConvictedOffender_v \times \left(\frac{CrimePr_v}{\sum_{c=1}^{C} CrimePr_c} \right)$$

$$(9) RemainingTrips_c = (Trips_c - 1) \times OffensesPerTrip_c \times VicsPerConvictedOffender_c \times \left(\frac{CrimePr_v}{\sum_{c=1}^{C} CrimePr_c} \right)$$

VictimEvent_{yctf}. A dichotomous variable indicating if a victimization event has occurred during the at-risk year. Victimizations are shown in Exhibit D2.1r. The Visual Basic Programming language for *VictimEvent_{yctf}* is shown in Exhibit D2.1t.

VictimCost_{rc}. The per unit cost of crime to victims as estimated in section D.2 of this appendix and as shown in Exhibit D2.1a.

Exhibit D2.1t

Visual Basic Programming Code Used to Calculate *VictimEvent$_{yctf}$*.

```
For v = 1 To CrimeTypes
   RowCount = 0
     For c = 1 To CrimeTypes
       For t = 1 To TripsCeiling(c, 1)
          If t <= Trips(c, 1) Then
            TripMultiplier = 1
          Else
            TripMultiplier = Trips(c, 1) - Int(Trips(c, 1))
          End If
          For f = 1 To FollowUpYears
            RowCount = RowCount + 1
              For y = 1 To MaxAtRiskYears
                If f + (t - 1) * TripSpaces(c, 1) = y Then
                   VictimEvent(RowCount, y) = 1
                Else
                   VictimEvent (RowCount, y) = 0
                End If
                AvoidedVictims(v, y) = AvoidedVictims(v, y) _
                   + VictimEvent (RowCount, y) _
                   * CrimeProbCjs(c, 1) _
                   * TimeToRecid(f, 1) _
                   * TripMultiplier _
                   * RelativeRisk(f, 1) _
                   * RecidRate _
                   * VictimVolume(RowCount, v)
              Next y
          Next f
       Next t
     Next c
Next v
```

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