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Prison, Police, and Programs: Evidence-Based Options that Reduce Crime and Save Money

Summary

Since the 1990s, the Washington State legislature has directed the Washington State Institute for Public Policy to identify policies with an "evidence-based" track record of improving certain public policy outcomes. Outcomes of interest have included, among others, education, child welfare, crime, and mental health.

This report updates and extends WSIPP's list of well-researched policies that reduce crime. We display our current tabulation of evidence-based prevention, juvenile justice, and adult corrections programs, and we include our initial reviews of prison sentencing and policing.

As with our previous lists, we find that a number of public policies can reduce crime and are likely to have benefits that exceed costs. We also find credible evidence that some policies do not reduce crime and are likely to have costs that exceed benefits. The legislature has previously used this type of information to craft policy and budget bills. This updated list is designed to help with subsequent budgets and policy legislation.

Since the 1990s, the Washington State legislature has directed the Washington State Institute for Public Policy (WSIPP) to identify "evidence-based" policies that can improve particular outcomes.

The goal of these legislative assignments has been straightforward: to provide Washington policymakers and budget writers with a list of well-researched public policies that can—with a high degree of certainty—lead to better statewide outcomes coupled with a more efficient use of taxpayer dollars.

Crime reduction has been a particular focus of the legislative study directives. Initially, in the mid-1990s, WSIPP was asked to examine policy options that reduce juvenile crime.[1] Subsequent legislation directed WSIPP to study adult correction programs,[2] certain sentencing policies,[3] and prevention strategies designed to stop crime before it happens.[4] Additionally, in 2011, WSIPP's Board of Directors approved a study, funded by the MacArthur Foundation, to extend the list of crime control options to include policing.

This report provides our updated list of evidence-based policy options that reduce crime. We display prevention, juvenile justice, and adult corrections programs, and we include our initial reviews of prison sentencing and policing. We also provide an apples-to-apples assessment of the benefits and costs of each option from the perspective of Washington citizens and taxpayers.

In essence, this report is similar to an investment advisor's "buy-sell" list. It contains current information on policy options that can give taxpayers a good return on their crime fighting dollars (the "buys") as well as those well-researched strategies that apparently cannot reduce crime cost-effectively (the "sells"). The benefit-cost information can be used by policymakers to help write budgets identifying a portfolio of evidence-based options able to reduce crime and save money.

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[1] Aos, S., Barnoski, R., & Lieb, R. (1998). *Watching the bottom line: Cost-effective interventions for reducing crime in Washington* (Doc. No. 98-01-1201). Olympia: Washington State Institute for Public Policy.
[2] Aos, S., Phipps, P., Barnoski, R., & Lieb, R. (2001). *The comparative costs and benefits of programs to reduce crime* (Doc. No. 01-05-1201). Olympia: Washington State Institute for Public Policy.
[3] Drake, E., Barnoski, R., & Aos, S. (2009). *Increased earned release from prison: Impacts of a 2003 law on recidivism and crime costs, revised* (Doc. No. 09-04-1201). Olympia: Washington State Institute for Public Policy.
[4] Aos, S., Lieb, R., Mayfield, J., Miller, M., & Pennucci A. (2004). *Benefits and costs of prevention and early intervention programs for youth* (Doc. No. 04-07-3901). Olympia: Washington State Institute for Public Policy.

General Research Approach

When WSIPP carries out assignments from the legislature to identify what works (and what does not), we implement a three-step research approach.

Step 1: What Works? What Doesn't?

In the first research step, we estimate the probability that various public policies and programs can achieve desired outcomes, such as crime reduction. We carefully analyze all high-quality studies from the United States and elsewhere to identify policy options that have been tried, tested, and found to either achieve or not achieve improvements in outcomes. We look for research studies with strong evaluation designs and exclude studies with weak research methods. Our empirical approach then follows a meta-analytic framework to assess systematically all credible evaluations we can locate on a given topic. Given the weight of the evidence, we calculate an average expected effect of a policy on a particular outcome of interest, as well as an estimate of the margin of error for that effect.

Step 2: What Makes Economic Sense?

Next, we insert benefits and costs into the analysis by answering two questions:

- ✓ How much would it cost Washington taxpayers to produce the results found in Step 1?
- ✓ How much would it be worth to people in Washington State to achieve the improved outcome (for example, reduced crime)?

That is, in dollars and cents terms, what are the costs and benefits of each policy option?

To answer these questions, we developed, and continue to refine, an economic model that assesses benefits and costs. The goal is to provide an internally consistent monetary valuation so that policy options can be compared on an apples-to-apples basis. Our benefit-cost results include standard financial statistics: net present values, benefit-cost ratios, and rates of return on investment.

We present these monetary estimates from three distinct perspectives: (a) the benefits and costs that accrue solely to program participants; (b) those received by taxpayers; and (c) those received by other people in society (for example, crime victims).

The sum of these three perspectives provides a "total Washington" view on whether a policy or program produces benefits that exceed costs. We also designed our model so that it can be restricted to focus solely on the taxpayer perspective, which can be useful for fiscal analyses and state budget preparation.

Step 3: What is the Risk in the Benefit-Cost Findings?

Any tabulation of benefits and costs involves some degree of risk about future performance. This is expected in any investment analysis, whether in the private or public sector. To assess the riskiness of our conclusions, we perform a "Monte Carlo simulation" in which we vary the key factors in our calculations. The purpose of the risk analysis is to determine the odds that a particular policy option will at least break even.

Thus, for each option analyzed, we produce two "big picture" findings: an expected benefit-cost result and, given our understanding of the risks involved, the odds that the policy will at least have benefits that are greater than the costs. The best policies are able to achieve a high expected return on investment with relatively low investment risk. Next, for all of the options analyzed, we arrange the information into a *Consumer-Reports*-like list of what works and what does not, ranked by the benefit-cost statistics and measure of investment risk.

Readers interested in an in-depth description of WSIPP's research methods for these three steps can find a Technical Manual available on WSIPP's website and, for prison and policing, in the Technical Appendix at the end of this report.[5]

New in this Report: Prison and Police

WSIPP has previously published benefit-cost results for prevention, juvenile justice, and adult corrections programs.[6] In Exhibit 1 of this report, we provide a current listing of our bottom-line findings for these programs.

We also add two new policy topics to our list of evidence-based crime reduction policy options:

(1) Changes to certain adult sentencing policies that affect prison average daily population, and

(2) Policies that affect the level and deployment of policing resources in the state.

With the addition of these topics, we can now analyze a wider array of evidence-based policies that can influence the number of crimes in the state. This information can allow policymakers and budget writers to consider a broad portfolio of evidence-

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[5] Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf

[6] Lee, S., Aos, S., Drake, E., Pennucci, A., Miller, M., & Anderson, L. (2012). *Return on investment: Evidence-based options to improve statewide outcomes, April 2012* (Doc. No. 12-04-1201). Olympia: Washington State Institute for Public Policy.

based strategies—prison, police, and programs—to reduce crime and save taxpayer money.

Limitation: our results apply to Washington State. The estimates provided in this report are calibrated to Washington State. Users of this information from other states should be cautious in interpreting these results for their states. This cautionary note applies to all resources listed in Exhibit 1, but is particularly relevant to our results for prison and police. These two resources are susceptible to diminishing returns, and the findings shown here reflect Washington's current rates of incarceration and police per capita relative to Washington's crime rates. Other states have different rates and, accordingly, the economics of these resources in other states will not be the same as those listed for Washington in Exhibit 1.

Limitation: our results pertain to avoiding future crimes, not applying justice for prior crimes. An equally important limitation is that our benefit-cost estimates for the incarceration policies shown in Exhibit 1 measure only one of two broad goals of the state's criminal justice system. Specifically, we quantify the degree to which prison affects current and future crime levels—one of the two goals of criminal justice policy. Our estimates, however, do not address the second overall policy goal of the criminal justice system: using prison to punish offenders for crimes for which they have been convicted.

That is, our estimates in Exhibit 1 pertain to policies that further the goal of using prison, police, and programs to avoid crime in the future. They do not provide information on the degree to which different policy options provide justice to offenders for previous criminal activity. Criminal justice policies are often selected to address both goals while our estimates only pertain to the goal of reducing future crime. This limitation needs to be kept in mind when interpreting the results shown in this report.

The November 2013 Findings

Exhibit 1 summarizes our latest results for a number of evidence-based options that can help policymakers reduce crime in Washington. We display the information in five broad groupings of programs and policies:

- Correctional interventions for adult offenders,
- Prison sentencing options,
- Police resources,
- Correctional interventions for juvenile offenders, and
- Prevention programs.

Within each grouping we rank the evidence-based options by a key benefit-cost summary statistic: net present value (benefits minus costs).

We have prepared the information using an internally consistent approach so that options can be compared to one another. It is important to recognize, however, that the options serve different populations with different characteristics and in different settings. Thus, the purpose of the list is to assist the legislature in drafting policy and budget bills to assemble an overall portfolio of evidence-based options that, together, reduce crime and save money. Readers can find more information about each of the policies and programs on WSIPP's website.[7]

[7] www.wsipp.wa.gov

Highlights

As with our previous evidence-based lists, we find that a number of public policies and programs can reduce crime and are likely to have benefits that exceed costs. We also find credible evidence that some policies do not reduce crime and are likely to have costs that exceed benefits. Both types of information—what works and what does not work—can be useful for legislative policy formulation.

Correctional Interventions for Adult Offenders. Our updated list of adult correctional interventions continues to indicate that there are a number of intervention programs for adult offenders where benefits exceed costs.

To highlight two well-researched results, we find that community supervision of high and moderate risk offenders using the "Risk, Need and Responsivity" approach produces almost five dollars of crime-reduction benefits per dollar of costs. On the other hand, intensive supervision, where the focus is solely increased surveillance of offenders, does not reduce recidivism and is a poor investment.

Prison Sentencing Policies. For illustrative purposes, in this report we analyze the benefits and costs of three hypothetical prison-related topics.

In recent sessions, the Washington legislature has considered bills that would have affected the length of stay in prison for certain offenders. Therefore, for our three hypothetical prison policy options, we examined the benefits and costs of policies that would lower the length of stay by three months for lower, moderate, and high risk-to-reoffend inmates. For each of these three illustrative options, we modeled the effect that would result in a statewide decrease of 250 prison beds—roughly the equivalent of closing a wing of a state prison.

It needs to be stressed that our three hypothetical options are not recommendations by WSIPP. Rather, we selected these options to illustrate how benefits and costs can be used to analyze different policies considered by the legislature. During a legislative session, the WSIPP benefit-cost model can be used to analyze a variety of specific policy proposals that affect the level of state incarceration.

How to Read Exhibit 1

To illustrate our findings, we summarize results for a juvenile justice program called Functional Family Therapy (FFT). The program is designed for juveniles on probation, and the program is listed under the topic of correctional interventions for juvenile offenders in Exhibit 1. FFT was originally tested in Utah; Washington began to implement the program in the mid-1990s. The legislature continues to fund FFT, and it is now used by many juvenile courts in Washington.

We reviewed all research we could find on FFT and found eight credible evaluations that have investigated whether it reduces crime. We find that the program can be expected to reduce recidivism rates by about 13 percentage points, with a margin of error of about 4 percentage points. In Exhibit 1, we show our estimate of the total benefits of FFT per participant (in 2012 dollars). These benefits spring primarily from reduced crime, but also include labor market and health care benefits due to increased probability of high school graduation.

- Of the total benefits of $37,587, Exhibit 1 shows that we expect $9,510 to be received by taxpayers and $28,077 to accrue to others, including people who were not victimized.
- The Exhibit also shows our estimate of the cost per participant to deliver the program in Washington, $3,333.
- The three columns on the right-hand side of Exhibit 1 display our benefit-cost summary statistics for FFT. We show the net present value (benefits minus costs), $34,254, and the benefit-to-cost ratio (benefit divided by costs), $11.28 of benefits per dollar of cost. Finally, we show the results of our risk analysis—the odds that the program will at least generate benefits equal to the costs, 99%, after accounting for the risk we anticipate in our estimates.

Based on our bottom-line findings for FFT, we conclude that FFT is an evidence-based program that reduces crime and achieves a favorable return on investment, with a small chance of an undesirable outcome.

Exhibit 1

Monetary Benefits and Costs of Evidence-Based Public Policies That Affect Crime

Estimates as of November 2013

Topic Area/Program	Last Updated	Monetary Benefits			Costs	Summary Statistics		
Benefits and costs are life-cycle present-values per participant, in 2012 dollars. The programs are listed by major topic area, although some programs achieve benefits in multiple areas. Also, some programs achieve benefits that we cannot monetize; see Technical Appendix I for program-specific details.		Total Benefits	Taxpayer	Non-Taxpayer		Benefits Minus Costs (net present value)	Benefit to Cost Ratio [1]	Odds of a Positive Net Present Value
Correctional Interventions for Adult Offenders								
Offender Re-entry Community Safety Program (dangerously mentally ill offenders)	Apr. 2012	$57,765	$19,087	$38,677	($32,924)	$24,840	$175	93%
Electronic monitoring (radio frequency or global positioning systems)	Apr. 2012	$23,085	$5,617	$17,468	$1,093	$24,178	n/e	100%
Therapeutic communities for offenders with co-occuring disorders	Dec. 2012	$26,842	$7,321	$19,520	($3,628)	$23,213	$7.40	99%
Drug Offender Sentencing Alternative (for drug offenders)	Apr. 2012	$23,441	$6,068	$17,373	($1,574)	$21,867	$14.89	99%
Correctional education (basic or post-secondary) in prison	Apr. 2012	$22,539	$5,875	$16,664	($1,149)	$21,390	$19.62	100%
Vocational education in prison	Apr. 2012	$21,131	$5,585	$15,546	($1,599)	$19,531	$13.21	100%
Risk Need & Responsivity supervision (for high and moderate risk offenders)	Apr. 2012	$23,822	$6,624	$17,198	($4,854)	$18,968	$4.91	100%
Outpatient/non-intensive drug treatment (incarceration)	Dec. 2012	$18,452	$4,797	$13,655	($589)	$17,863	$31.34	100%
Mental health courts	Apr. 2012	$20,211	$5,522	$14,689	($2,995)	$17,217	$6.75	100%
Inpatient/intensive outpatient drug treatment (incarceration)	Dec. 2012	$17,900	$4,748	$13,152	($1,208)	$16,692	$14.82	100%
Case management: swift & certain/graduated sanctions for substance abusing offenders	Dec. 2012	$19,385	$5,430	$13,955	($4,834)	$14,551	$4.01	97%
Drug Offender Sentencing Alternative (for property offenders)	Dec. 2012	$11,775	$3,126	$8,649	($1,572)	$10,203	$7.49	71%
Drug courts	Apr. 2012	$14,459	$3,795	$10,663	($4,276)	$10,183	$3.38	100%
Cognitive behavioral treatment (for high and moderate risk offenders)	Apr. 2012	$10,364	$2,677	$7,687	($419)	$9,945	$24.72	99%
Therapeutic communities for chemically dependent offenders (community)	Dec. 2012	$11,494	$3,171	$8,323	($2,463)	$9,031	$4.67	99%
Work release	Apr. 2012	$7,550	$2,012	$5,538	($675)	$6,875	$11.19	96%
Therapeutic communities for chemically dependent offenders (incarceration)	Dec. 2012	$10,794	$3,323	$7,471	($4,359)	$6,435	$2.48	98%
Employment training/job assistance in the community	Apr. 2012	$5,949	$1,502	$4,447	($138)	$5,811	$43.26	99%
Outpatient/non-intensive drug treatment (community)	Dec. 2012	$6,390	$1,669	$4,721	($589)	$5,802	$10.85	92%
Correctional industries in prison	Apr. 2012	$6,859	$1,931	$4,929	($1,447)	$5,412	$4.74	98%
Intensive supervision (surveillance & treatment)	Apr. 2012	$12,619	$4,150	$8,469	($8,031)	$4,588	$1.57	78%
Case mgmt for offenders with SA	Dec. 2012	$8,528	$2,144	$6,384	($4,757)	$3,770	$1.79	91%
Inpatient/intensive outpatient drug treatment (community)	Dec. 2012	$3,746	$1,050	$2,696	($945)	$2,801	$3.96	79%
Case management: not swift and certain for substance abusing offenders	Dec. 2012	$4,059	$1,614	$2,446	($4,841)	($781)	$0.84	45%
Intensive supervision (surveillance only)	Apr. 2012	($2,494)	($93)	($2,401)	($4,220)	($6,714)	($0.59)	10%
Domestic violence perpetrator treatment	Apr. 2012	($6,137)	($1,370)	($4,767)	($1,390)	($7,527)	($4.41)	19%
Adult criminal justice programs for which we have not calculated benefits and costs (at this time):								
Adult boot camps			See previous WSIPP publications for past findings.					
Jail diversion for mentally ill offenders			See previous WSIPP publications for past findings.					
Life skills education programs			See previous WSIPP publications for past findings.					
Restorative justice for lower-risk offenders			See previous WSIPP publications for past findings.					
Sex offender community notification and registration			See previous WSIPP publications for past findings.					
Sex offender treatment			See previous WSIPP publications for past findings.					
Prison								
For lower risk offenders, decrease prison average daily population by 250, by lowering length of stay by 3 months	Oct. 2013	($1,301)	($517)	($783)	$5,642	$4,341	$4.34	98%
For moderate risk offenders, decrease prison average daily population by 250, by lowering length of stay by 3 months	Oct. 2013	($5,433)	($1,044)	($4,389)	$5,633	$200	$1.04	52%
For high risk offenders, decrease prison average daily population by 250, by lowering length of stay by 3 months	Oct. 2013	($10,213)	($1,681)	($8,533)	$5,641	($4,573)	($0.55)	17%
Police (results are per-officer)								
Deploy one additional police officer with hot spots strategies	Oct. 2013	$648,535	$70,018	$578,517	($92,597)	$555,938	$7.00	100%
Deploy one additional police officer with statewide average practices	Oct. 2013	$573,700	$61,637	$512,063	($88,310)	$485,390	$6.50	100%

Exhibit 1 *(continued)*

Monetary Benefits and Costs of Evidence-Based Public Policies That Affect Crime

Estimates as of November 2013

Topic Area/Program Benefits and costs are life-cycle present-values per participant, in 2012 dollars. The programs are listed by major topic area, although some programs achieve benefits in multiple areas. Also, some programs achieve benefits that we cannot monetize; see Technical Appendix I for program-specific details.	Last Updated	Monetary Benefits: Total Benefits	Monetary Benefits: Taxpayer	Monetary Benefits: Non-Taxpayer	Costs	Summary Statistics: Benefits Minus Costs (net present value)	Summary Statistics: Benefit to Cost Ratio[1]	Summary Statistics: Odds of a Positive Net Present Value
Correctional Interventions for Juvenile Offenders								
Functional Family Therapy (youth in state institutions[2])	Apr. 2012	$61,374	$12,982	$48,392	($3,332)	$58,043	$18.42	99%
Aggression Replacement Training (youth in state institutions)	Apr. 2012	$57,364	$11,940	$45,423	($1,543)	$55,821	$37.19	90%
Functional Family Therapy (youth on probation)	Apr. 2012	$37,587	$9,510	$28,077	($3,333)	$34,254	$11.28	99%
Aggression Replacement Training (youth on probation)	Apr. 2012	$35,329	$8,727	$26,602	($1,540)	$33,788	$22.94	86%
Multidimensional Treatment Foster Care	Apr. 2012	$39,094	$8,875	$30,218	($8,059)	$31,035	$4.85	80%
Family Integrated Transitions (youth on probation)	Apr. 2012	$38,556	$10,221	$28,335	($11,469)	$27,087	$3.36	86%
Multisystemic Therapy	Apr. 2012	$34,067	$7,700	$26,367	($7,522)	$26,545	$4.53	93%
Multidimensional Family Therapy (MDFT) for substance abusers	Dec. 2012	$21,125	$5,725	$15,400	($5,835)	$15,289	$3.62	74%
Family Integrated Transitions (youth in state institutions)	Apr. 2012	$26,420	$6,503	$19,917	($11,483)	$14,937	$2.30	75%
Multisystemic Therapy for substance abusing juvenile offenders	Sept. 2013	$22,235	$4,286	$17,949	($7,528)	$14,708	$2.95	71%
Drug court	Apr. 2012	$14,692	$3,810	$10,882	($3,154)	$11,539	$4.66	93%
Multisystemic Therapy for juvenile sex offenders	Sept. 2013	$17,831	$4,561	$13,271	($7,526)	$10,305	$2.37	85%
Functional Family Parole (with quality assurance)	Jan. 2013	$14,593	$3,481	$11,112	($4,425)	$10,168	$3.30	77%
Coordination of Services	Apr. 2012	$6,445	$1,684	$4,762	($403)	$6,043	$16.01	78%
Therapeutic communities for chemically dependent juvenile offenders	Dec. 2012	$9,150	$2,326	$6,824	($4,522)	$4,628	$2.02	64%
Victim offender mediation	Apr. 2012	$4,271	$1,159	$3,113	($589)	$3,682	$7.25	89%
Other chemical dependency treatment for juveniles (non-therapeutic communities)	Dec. 2012	$4,105	$1,382	$2,723	($3,157)	$948	$1.30	56%
Scared Straight	Apr. 2012	($12,932)	($3,259)	($9,673)	($66)	($12,998)	($195.61)	1%
Juvenile justice programs for which we have not calculated benefits and costs (at this time):								
Cognitive Behavioral Therapy (general)		See previous WSIPP publications for past findings.						
Diversion Programs		See previous WSIPP publications for past findings.						
Juvenile Boot Camps		See previous WSIPP publications for past findings.						
Sex Offender Treatment for Juvenile Offenders		See previous WSIPP publications for past findings.						
Supervision for Juvenile Offenders		See previous WSIPP publications for past findings.						
Team Child		See previous WSIPP publications for past findings.						
Teen Courts		See previous WSIPP publications for past findings.						
Wilderness Challenge Programs		See previous WSIPP publications for past findings.						
Prevention								
Nurse Family Partnership for low-income families	Apr. 2012	$26,743	$9,463	$17,281	($9,788)	$16,956	$2.73	76%
Early childhood education for low income 3- and 4-year olds	Apr. 2012	$24,094	$7,657	$16,437	($7,653)	$16,441	$3.15	100%

Notes to Exhibit 1

[1] Benefit to cost ratios cannot be computed in every case; we list "n/e" for those that cannot be reliably estimated.

[2] Institutions = state institutionalized juvenile justice populations

To produce the estimates for prison and policing, we followed our usual three-step research approach. We reviewed the growing body of credible research that measures the effect of prison and police on crime. While there remain significant gaps in the state of knowledge about how prison and police affect crime, it is possible to assemble information to assist current public policy in Washington. In the Technical Appendix, we provide the details of our formal meta-analyses of these research literatures.

In addition to our review of other research studies, we conducted our own empirical analysis, also reported in the Appendix, on how prison and police levels affect crime in Washington. We found results for Washington consistent with the typical findings from studies conducted elsewhere.

We find that, on average, both prison incarceration and the overall level of police employment affect the amount of crime in a state.

In recent years, criminologists and economists have been attempting to peer inside the policy "black box" to identify how specific sentencing policies and police deployment strategies affect crime.[8] These newer studies can help identify the specific policy options that state and local governments can use to reduce crime. That is, rather than looking at overall incarceration rates and police levels, these more recent and policy-relevant studies examine how apprehension and punishment certainty—versus severity—affects crime and how particular deployment strategies increase the effectiveness of policing. As described in the Appendix, we use these results to inform our analysis of particular options for Washington State.

For lower risk, moderate risk, and high risk offenders, we show the benefits and costs of policies that would lower length of prison stay by three months and result in a decrease in state incarceration by 250 average daily population.

The economics of these three alternatives for Washington look very different. For lower risk offenders, the benefits of the fiscal savings outweigh the increased costs of new crimes from the policy. As a result, the benefit-to-cost ratio is $4.34 of benefits per dollar of costs for lower risk offenders.

For high risk offenders, on the other hand, the costs of new crimes for a three-month reduction in length of stay outweigh the benefits such that the benefit-to-cost ratio is only 55 cents of benefits per dollar of costs, and the risk is high. Specifically, the odds of a benefit-cost ratio of 1 or greater is only 17%.

For moderate risk offenders, the average benefit-cost ratio is neutral (about one dollar of benefits per dollar of costs), but the measure of investment risk indicates that this strategy would pay off only about 52% of the time.

Again, we wish to emphasize that these prison policy options are illustrative only. The WSIPP benefit-cost model can be used during legislative sessions to analyze specific legislative proposals.

Police Resources. We analyzed two topics related to policing. One topic is the effect on crime of adding a police officer and deploying the officer with routine practices. The second is to add a police officer and deploy the officer using a "hot spots" practice, where data-driven crime mapping is used to allocate police deployment. We find that additional police officers, especially when dispatched with a hot-spots deployment strategy, reduce crime and generate six to seven dollars of benefits per dollar of cost.[9] The finding that policing is effective in reducing crime is consistent with other recent reviews of the national research literature.[10] Our analysis of the economics of policing is described in the Technical Appendix to this report.

Correctional Interventions for Juvenile Offenders. Our current list of juvenile justice programs shows that a number of options for juvenile offenders can generate benefits well in excess of costs, with low investment risk. The Washington legislature has used this information for more than a decade to fund a portfolio of programs near the top of this list. As an example, the sidebar on page 4 highlights the results of one such program, Functional Family Therapy.

Prevention Programs. For illustrative purposes, we show the results of two early childhood programs that have demonstrated a direct effect on preventing crime and that are currently operating in Washington:

- Nurse Family Partnership program, which uses nurses to provide home visitation to single, young, low-income, first-time mothers; and
- Early childhood education for low-income three- and four-year olds.

Along with reduced crime outcomes, these two programs improve education outcomes and reduce child abuse. The economic analysis shown for these programs includes our evaluation of the benefits of these other outcomes, in addition to the benefits of crime reduction. Both programs generate benefits that exceed costs.

In addition to these two prevention programs, we have found other policy options for young people that prevent crime, not shown in Exhibit 1.[11]

[8] See, for example, these excellent reviews: Nagin, D. (2013). Deterrence in the twenty-first century: A review of the evidence. *Crime and Justice: A Review of Research*. Chicago, IL: University of Chicago Press. Durlauf, S. N., & Nagin, D. S. (2010). The deterrent effect of imprisonment. In P. Cook, J. Ludwig, J. & J. McCrary (Eds.), *Controlling crime: Strategies and tradeoffs* (pp. 43-94). Chicago, IL: University of Chicago Press. Downloaded from: www.nber.org/chapters/c12078

[9] Our estimates for policing resources are expressed on a per-officer basis, unlike our estimates for programming, which are expressed on a per-program participant basis. To compare these two types of resources, the benefit-cost ratio is a better statistic than the net present value metric.

[10] Nagin (2013).

[11] See, e.g., Lee, S., Aos, S., Drake, E., Pennucci, A., Miller, M., & Anderson, L. (2012). *Return on investment: Evidence-based options to improve statewide outcomes, April 2012* (Doc. No. 12-04-1201). Olympia: Washington State Institute for Public Policy.

Portfolio Analysis

Exhibit 1 can be used as a guide to help policymakers in Washington State. In our benefit-cost model, we also developed the additional capability to analyze a portfolio—that is, a combination—of the policy options in Exhibit 1. WSIPP's model is able to project the effects of a portfolio of policies and programs on current and future crime rates and prison beds in Washington.

The main body of this report provides a list (see Exhibit 1) of three general types of evidence-based public policy options that can affect the number of crimes in Washington: prisons, police, and programs. In this context, "programs" refer to a broad classification of options that includes prevention programs designed to stop crime before it happens, as well as intervention programs for juvenile and adult offenders intended to reduce the likelihood that new crimes will be committed.

In this Technical Appendix, we provide a description of our research approach for two of these three types of policy options— prison and policing. We have previously described our methods for crime prevention and intervention programs; readers interested in a technical description can find a Technical Manual available on WSIPP's website.[12] Here, we limit our discussion to the two new topics for our review: policies that change the level of state incarceration or the level and deployment of commissioned police officers in a state.

As noted in the main body of the report, WSIPP carries out a three-step research approach to estimate the benefits and costs of a variety of policies and programs that attempt to reduce crime. First, we review the available research literature on "what works" (and what does not) to lower crime. Second, we estimate the costs to implement a particular policy or program, and we monetize the benefits from the crime reduction. Third, we calculate the overall risk in our bottom-line estimates to determine the likelihood that a program or policy will at least break even. With this information calculated on a consistent basis for a variety of public policies, we assemble a list of options, ranked by net present value, that can be used by policymakers in Washington State to help craft policy and budget bills.

For police and prison, we follow these same steps. Our first analytical task is to conduct a meta-analytic review of the research literature from the United States and beyond to determine if prison and police are effective at reducing crime rates. Broadly, we review two bodies of research. First, we examine studies that have measured how prison average daily population or the number of police officers affects current crime rates. Second, for incarceration-related policies, we review studies that measure how prison affects the post-release criminal recidivism rate of specific offenders. We use both of these two bodies of research to estimate the benefits and costs of specific policies that affect prison average daily population. For our analysis of the economics of policing, we use results from the first body of research, along with a meta-analytic result on "hot spots" policing to examine the benefits and costs of policing levels and deployment.

This Technical Appendix is organized as follows. In Section 1, we describe the methods we use to analyze the results from the first body of research addressing the following question: does the overall level of prison or the overall number of police officers affect current crime rates? We also describe the procedures we use to deal with the particular empirical limitations in this research when estimating the marginal effects on crime of specific policies that affect average daily prison population and police deployment strategies. In Section 2, we discuss the second body of research that addresses the following question: Does a prison sentence and prison length of stay affect the recidivism rates of specific offenders? In Section 3, we discuss the benefit-cost summary statistics for policies that affect prison average daily population. We list the citations to the studies included in the meta-analyses in Section 4. In Section 5 we describe a separate study we conducted of the prison-crime relationship and the police-crime relationship for Washington State using panel data from Washington's 39 counties from 1982 to 2011.

Section 1: Do Prison Incarceration Rates and Police Per Capita Affect the Current Level of Crime?

Section 1.1 General Considerations

There is research literature on the effect of incarceration rates on crime.[13] 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:

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

In this typical model, crime, *C,* of type, *t,* 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*, often including state and year fixed effects, and an error term, *e*. Some studies use this type of model to estimate total reported crime, while others examine types of crime such as violent crime or property crime.

[12] Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf

[13] See, for example, Marvell, T. B. (2010). *Prison population and crime. Handbook on the economics of crime*, B. L. Benson & P. R. Zimmerman (Eds.). Cheltenham, UK: Edward Elgar Publishing.

There is similar research literature on the effect of the number of police officers on crime rates.[14] Many of these studies use data at the city or county level to estimate the parameters of an equation of this form:

$$(1b) \quad C_{tcy} = a + b(POL_{cy}) + c(X_{cy}) + e$$

In a typical police model, crime, *C,* of type, *t,* in city or county, *c,* and year, *y,* is estimated to be a function of the size of a city's or county's overall commissioned police force, *POL*, a vector of control variables, *X*, often including city/county and year fixed effects, and an error term, *e*.

In the research literature we reviewed, these models are almost always estimated with a log-log functional form, at least for the dependent and policy variables. Several authors have observed that the panel time series often used to estimate equations (1a) and (1b) likely have unit roots, especially with state level data.[15] Thus, to help avoid estimating spurious relationships, some authors estimate equations (1a) and (1b) in first-differences since the time series typically do not exhibit unit roots after differencing once.

As noted later, there is considerable concern in the research literature on the econometric implications of possible simultaneous relationships between the variables of interest in equations (1a) and (1b) and in omitted variables bias.[16] Simultaneity can occur because crime may be a function of *ADP* or *POL*, but *ADP* and *POL* may also be a function of crime. Failure to account for these simultaneous relationships, as well as failure to address omitted control variables in regressions, can cause statistically biased estimates. In recent years, much of the discussion and debate in the research literature has focused on ways to address statistical bias from simultaneity and omitted control variables.

The dependent variable: crime. In the American studies estimating equations (1a) and (1b), crime is most often measured with data from the Federal Bureau of Investigation's Uniform Crime Reports (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.

Most studies in our review also recognize that not all crimes are reported to police. Accordingly, most authors, in drawing conclusions from their analyses, use information from the annual National Crime Victimization Survey (NCVS) to obtain estimates about how often crime victims say they report crimes to police.[17] Reporting rates are then used to adjust the coefficients estimated with equations (1a) and (1b) to produce estimates on how the total amount of crime changes as prison population or policing levels are altered.

One particular problem with the "Part 1" UCR crime data is that they do not align directly with 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 include rapes of females over the age of 12. In addition to this obvious limitation in the UCR data, other felony sex crimes (e.g., child molestation) are defined by the Revised Code of Washington and are not included in the UCR rape category. Similarly, the UCR data include some types of theft crimes that are below the threshold of felony theft in Washington. Therefore, in order to draw policy conclusions from research estimating equations (1a) and (1b) with UCR data, it is necessary to adjust the estimates to account for these limitations in the UCR data.

The policy variables: average daily prison population and the number of police officers. In virtually all studies in these two research literatures, the policy variable analyzed is either average daily prison population or the number of police officers. In the prison studies, ADP is often measured by counting the total number of inmates at some point during a year. Similarly, for the policing studies, the policy variable is usually measured with counts of commissioned police officers also taken at some point during a year.

Measuring prison ADP with the total number of offenders is necessary in cross-state analyses because total ADP is usually the only consistent information available to researchers. In lieu of the "average" prison population, however, it would be more useful to measure policy-relevant categories of offenders such as those 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.

It would also be better if the studies measured the two ways that policies can influence total prison ADP: the probability of going to prison given a conviction and the length of stay in prison given a prison sentence. As noted later, these separate policies are likely to have substantially different effects.

Unfortunately, because these more detailed categories are not available consistently across states, the typical study only includes a measure of total ADP and, thereby, only measures the average effect on crime of the average offender sentenced

[14] See, for example, Lim, H., Lee, H., & Cuvelier, S.J. (2010). The impact of police levels on crime rates: A systematic analysis of methods and statistics in existing studies. *Asia Pacific Journal of Police & Criminal Justice, 8*(1), 49-82.
[15] See, for example, Marvell, (2010). See also, W. Spelman (2008). Specifying the relationship between crime and prisons. *Journal of Quantitative Criminology, 24*, 149-178.
[16] Durlauf, S.N., & Nagin, D.S. (2010). *The Deterrent Effect of Imprisonment* NBER 5/07/10, downloaded from: www.nber.org/chapters/c12078
[17] Bureau of Justice Statistics, United States Department of Justice, NCVS http://www.bjs.gov/index.cfm?ty=dcdetail&iid=245

to prison from the average policy change that affects ADP. Thus, without adjustment, the overly general findings from the typical research studies implementing equation (1a) limits the practical policy relevance in analyzing the types of specific sentencing policies frequently advanced by policymakers.[18]

Two adjustments to address the "average offender" and "average policy" limitations. These limitations pose at least two problems that limit the usefulness of models like equation (1a) to inform actual policy choices facing legislatures.

First, policy decisions to raise or lower ADP are not usually across-the-board or "average" decisions applied to all offenders. 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 in some states). A legislature will more often adjust sentencing statutes for particular types of crimes or for different offender risk levels, rather than adopt across-the board changes. For example, if a legislature allows executive agencies to grant early release from prison, the policy will most often be limited to offenders with certain types of criminal history or for offenders with particular risk-for-reoffense levels.

Fortunately, additional information can be obtained about the criminal propensities of different types of offenders, the types of crimes they commit, and their overall risk level for committing crimes. As noted later, we use this information to make an adjustment to address, at least partially, the policy relevance of the "average offender" limitation in the current level of research.

The second significant reason why an adjustment needs to be made to the prison or police average estimates is that not all policies that affect prison ADP or policing levels appear to have an equal effect on crime. Nagin (2013) notes that ADP "is not a policy variable per se; rather, it is an outcome of the sanction policies dictating who goes to prison and for how long—namely, the certainty and severity of punishment."[19]

Durlauf and Nagin (2010) provide a useful review 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. And, 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 state:

> *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.*[20]

Thus, when estimating how a specific policy proposal to change ADP affects crime with the estimated coefficients from equation (1a), it is likely to matter if the policy being analyzed affects ADP based on a change to the certainty or severity of imprisonment. Using the Durlauf and Nagin results, one would conclude that ADP's "average" elasticity from (1a) for a sentencing policy that affects the certainty of punishment would be higher than the elasticity for a sentencing policy that affects the length of prison stay. While the current state of research may not be settled on the magnitude of these effects, the direction is clear based on the review of the literature by Durlauf and Nagin. Therefore, to make the results of the literature more relevant for policy purposes, we make an adjustment, described later, to the coefficients from equation (1a) to deal with this "average policy" limitation in the current research literature.

In summary, these two factors—the "average offender" and "average policy" limitations—imply that the coefficients obtained from equations such as (1a) can be thought of as only rough guides for the effectiveness of 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 heterogeneity of criminal propensities among offenders and that legislatures usually adjust sentencing policies differentially for different types of crimes, and (b), that the type of sentencing policy is likely to affect crime differentially depending on whether total prison ADP is achieved with policy changes affecting the certainty or the severity of punishment. Our modeling approach attempts to account for these necessary policy adjustments.

These limitations that affect the prison research literature also apply to the policing literature in that the research studies typically measure policing levels with a simple count of the total number of officers, not by type of officer employed or how they are deployed in the community. We address this limitation, discussed below, in the policing literature by incorporating recent meta-analyses of police "hot spots" and "pulling levers" deployment strategies.[21]

Simultaneity. Another major empirical difficulty, observed by many, in providing credible estimates from models such as those in equations (1a) and (1b) is related to the likely nature of the relationship between crime levels and prison or policing levels. Crime may be affected by prison or police, but there is also evidence in many studies that the level of prison or police

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[18] Durlauf & Nagin, (2010).
[19] Nagin, D. (2013). Deterrence in the twenty-first century: A review of the evidence. *Crime and Justice: A Review of Research*. Chicago, IL: University of Chicago Press.
[20] Durlauf & Nagin, (2010), page 45 of the NBER draft chapter.
[21] Braga, A., Papachristos, A., & Hureau, D. (2012). Hot spots policing effects on crime. *Campbell Systematic Reviews* 2012:8.
Braga, A., Weisburd, D. The effects of "pulling levers" focused deterrence strategies on crime. Campbell Systematic Reviews 2012:6.

is affected by crime.[22] This simultaneous relationship, if not accounted for, will probably bias the coefficient in equations (1a) or (1b) downward. If a legislature's decision to provide prison beds 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. In the research literature on prison and police, there have been several attempts to measure the magnitude of this simultaneous relationship.[23] Technically, these models require an exogenous source of variation—an instrumental variable, a discontinuity around some arbitrary sentencing cut-off level, or a unique change to policing levels stimulated by a random event—that affects the use of prison or police but is probably otherwise unrelated to the error term in equations (1a) or (1b). These instrumental variables or natural experiments are hard to find in practice so many more estimates do not account for simultaneity than do. In our meta-analytic literature reviews we separate the studies for both prison ADP and policing levels into those studies that account for simultaneity and those that do not.

Section 1.2 Meta-Analysis on the Relationship Between Current Crime Levels and Prison and Police Levels

To provide an evidence-based assessment of the degree to which changes in prison and policing levels affect the current crime level, we systematically reviewed the relevant research literatures and performed a random effects meta-analysis. We identified studies for inclusion in the literature reviews primarily by examining the citations cited in major papers that have been published in academic journals or on websites such as the National Bureau of Economic Research or the European Institute for the Study of Labor. Fortunately, there have also been some major narrative reviews of these literatures in recent years, and these reviews allowed us to identify many of the relevant papers.[24] We also searched the internet with Google and Google Scholar to identify other papers that might not have been cited in the published papers.

Methodological Screening. We screened studies for methodological rigor. We assessed the degree to which a study accounted for unobserved variables bias and simultaneity. Durlauf and Nagin (2010) described three distinct waves of studies on prison and policing research, where "first wave" studies did not address unobserved or simultaneity issues or attempts to isolate the effects of certainty from severity, while later waves of research have employed more sophisticated methods to attempt to measure these factors.[25] In our final meta-analyses, we only included studies that met the more rigorous standards of evidence. At a minimum, all studies included in our reviews attempted to address omitted variables bias and some of the studies also attempted to account for simultaneity. Citations to the specific studies included in our meta-analyses are included in Section 4 of this Appendix.

The Effect Size Metric: Elasticity. Most of the studies in these literatures (prison ADP and policing levels on current crime levels) are econometric in nature; that is, they use regression techniques econometricians often use to consider unobserved variables bias or simultaneity. The metric used in almost all of these economic studies to summarize results is an elasticity—how a percentage change in either prison or police levels affects the percentage change in crime levels. This is a standard metric in studies conducted by economists. Accordingly, for each prison or police study we included in our meta-analyses, we coded the author's preferred finding. For those few primary studies that did not estimate elasticities directly, we computed the elasticity from the author's preferred regression coefficient taken at the study's mean values for crime and prison or police. Thus, the effect size for these prison and policing meta-analyses is an elasticity, rather than the other effect size metrics (Cohen's d or D-cox effect sizes) used when we conduct meta-analyses of programs. Apart from the effect size metric, all of the other meta-analytic computations follow the procedures as described in WSIPP's report on our methods.[26]

Meta-Analytic Results. Exhibit TA1 displays the results of our meta-analyses. The results are shown for both prison and police policy variables and their estimated effects on total crime, violent crime, and property crime. Additionally, because of the importance of dealing with simultaneity in these two literatures, we provide separate meta-estimates for those studies without and with simultaneity adjustments. The results indicate, first, that there are many more studies that have estimated prison and police effects that have not addressed simultaneity than there are those that have addressed simultaneity. Second, as predicted, the elasticities are uniformly larger for studies that have addressed simultaneity. Because of the importance of addressing simultaneity,[27] in our benefit-cost computations described in this Section we use the simultaneity-adjusted elasticities, along with their standard errors.

[22] See, Durlauf & Nagin, (2010) and Marvell, (2010).
[23] See, for example: 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. Johnson, R. & Raphael, S. (2012). How much crime reduction does the marginal prisoner buy? *Journal of Law and Economics*, *55*(2) 275-310. Levitt, S. D. (2002). Using electoral cycles in police hiring to estimate the effects of police on crime: Reply. *The American Economic Review, 92(*4), 1244-1250. Evans, W. N., & Owens, E. G. (2007). COPS and crime. *Journal of Public Economics, 91*(1-2), 181.
[24] See, for example, Marvell (2010) and Lim, et al. (2010).
[25] Durlauf & Nagin, (2010).
[26] Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf
[27] See, for example, Durlauf & Nagin, (2010).

Exhibit TA1
Meta-Analytic Results: Prison ADP and Police Levels on Current Crime Levels

Policy topic & outcome		Simultaneity not addressed			Simultaneity addressed		
Topic	Dependent variable: Type of crime	Elasticity	Standard error	Number of studies	Elasticity	Standard error	Number of studies
Prison: average daily population	Total	-0.180	0.032	30	-0.350	0.079	7
	Violent	-0.092	0.031	25	-0.323	0.058	5
	Property	-0.164	0.039	23	-0.280	0.030	5
Police: number of officers	Total	-0.167	0.041	18	-0.495	0.173	9
	Violent	-0.181	0.070	12	-0.796	0.095	7
	Property	-0.166	0.051	12	-0.513	0.264	7

Notes: All results are from random effects meta-analyses estimated with the methods described in Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf

Section 1.3 Computation of Marginal Crime Effects from the Elasticities

In order to compute benefit-cost estimates, the meta-analyzed elasticities reported in Exhibit TA1 need to be converted into the number of crimes avoided or incurred with a particular change in prison or policing levels. Additionally, to address the aforementioned limitations in the policy-relevance of the overall elasticities, we implement two adjustments.

To begin, the usual calculation of marginal effects from the elasticities of log-log crime models is obtained with equation (2a) for the effect of prison on crime, and equation (2b) for the effect of police on crime.

$$(2a)\ \Delta C_t = \frac{E_t \times \left(\frac{C_t}{ADP}\right)}{RR_t} \qquad (2b)\ \Delta C_t = \frac{E_t \times \left(\frac{C_t}{POL}\right)}{RR_t}$$

In equations (2a) and (2b), the change in the number of crimes, *ΔC,* for a particular type of crime, *t,* is estimated with: (a) *E,* the crime-prison elasticity or the crime-police elasticity for a particular type of crime, *t,* obtained from the relevant meta-analysis reported in Exhibit TA1; (b) the reported level of crime, *C,* for a particular crime type, *t;* (c) the incarceration rate, *ADP,* or the level of police employment, *POL;* and (d) the reporting rate to police by crime victims, *RR*, for a particular type of crime, *t.* In many studies, the marginal effects are often calculated at the mean values for *ADP, POL*, C_t, and RR_t over the time series. For policy purposes, however, it is more relevant to use more recent values for these variables.

As noted earlier, the UCR definition of Part 1 crimes may not match a state's current definition of felony crimes (see Section 1.1). Therefore, we make adjustments to the reported UCR crimes for two types of crimes, sex offenses and larceny/theft, to more closely align the UCR definitions with current law definitions in Washington.[28]

$$(3)\ C_t = UCR_t \times UCRAdj_t$$

In this analysis, we implement equations (2a) and (2b) for two types of crime: violent crime and property crime. Further, we make two adjustments to the meta-analyzed elasticities, E_t, as reported in Exhibit TA1. Therefore, we modify equations (2a) and (2b) as follows:

$$(4a)\ \Delta C_v = \frac{(E_v \times R_v \times P_v) \times \left(\frac{C_v}{ADP}\right)}{RR_v} \qquad (4b)\ \Delta C_v = \frac{(E_v \times R_v \times P_v) \times \left(\frac{C_v}{POL}\right)}{RR_v}$$

$$(5a)\ \Delta C_p = \frac{(E_p \times R_p \times P_p) \times \left(\frac{C_p}{ADP}\right)}{RR_p} \qquad (5b)\ \Delta C_p = \frac{(E_p \times R_p \times P_p) \times \left(\frac{C_p}{POL}\right)}{RR_p}$$

Two adjustments for risk and policy. These equations for violent and property crimes modify the basic elasticities to account for how a particular sentencing policy change being analyzed may be focused on offenders with different risk classifications, *R.* Additionally, for incarceration policies we make an adjustment for how a specific policy being analyzed, *P*, may influence average ADP through its effect on the certainty or severity of punishment. For policing, the policy adjustment, *P*, pertains to decisions on how police are deployed in the community. As noted above, both *R* and *P* are likely to be important in estimating the effect of prison or police on crime, yet the studies used in the meta-analytic determination of *E*

[28] Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf

only measure average effects. Without adjustment, the average elasticity effect, measured by *E*, masks important factors that specific sentencing or policing policies try to achieve.

1. The Risk Adjustment, *R*. The first adjustment factor is designed to modify *E* to account for how particular policy proposals may be designed for offenders with different risk-for-reoffense probabilities. For example, some sentencing policy changes might be focused on early prison release policies for lower-risk offenders. The basic elasticity, *E*, however, was estimated from research studies that measure all offenders that make up total prison ADP. If the models had been able to use "lower-risk" ADP instead of total ADP in the estimations, then *E* would have been different (particularly if the main effect being measured is the incapacitation of specific offenders, rather than general deterrence). The multiplicative adjustment factor, *R*, provides a way to model this likely result.

To estimate *R*, we report in Exhibit TA2 the recidivism rates of offenders released from prison in Washington State. These data were obtained from WSIPP's criminal history database, which is a synthesis of criminal conviction data from the Administrative Office of the Courts (AOC) and the Department of Corrections (DOC). This comprehensive database can be used to determine an offender's criminal history or to calculate recidivism. We analyzed the recidivism rates of offenders who were released from prison during Fiscal Years 2002 to 2004.

Washington State uses an actuarial-based risk assessment that predicts the probability of recidivism. This assessment is used in Washington to classify offenders in prison, in terms of recidivism risk, as lower risk, moderate risk, higher risk for non-violent recidivism, and higher risk for violent recidivism.[29]

From the recidivism rates for all offenders and for those same offenders separated by risk levels, we compute simple ratios of recidivism rates. The ratios indicate the relative likelihood of recidivism for different risk levels, compared to all offenders as a group. These ratios are then used as the risk adjustment multipliers, R, in equations (4a-5b). Since there is risk around these risk adjustment multipliers, we use a triangular probability density distribution for the Monte Carlo simulation with minimum and maximum multiplicative values to account for within-group variation. We use the ratio relative to all offenders in Exhibit TA2 as the mean value and 90% of the mean ratio as the minimum and maximum values.

Exhibit TA2
Three–Year Recidivism Rates of Offenders Released from Prison in Washington State, Fiscal Years 2002 to 2004

		Recidivism for a Violent Felony Offense		Recidivism for a Property Felony Offense	
Risk for re-offense category	Number of offenders	Recidivism rate	Ratio: relative to all offenders	Recidivism rate	Ratio: relative to all offenders
All offenders	14,459	12.8%	1.00	16.2%	1.00
Lower-risk	2,018	3.6%	0.28	2.7%	0.16
Moderate-risk	2,743	8.1%	0.63	9.3%	0.57
High-risk, non-violent	5,167	9.3%	0.72	22.2%	1.37
High-risk, violent	4,531	23.9%	1.86	19.6%	1.21

Note: Recidivism is defined as a new felony reconviction in the State of Washington within three years of release from prison, where the most serious conviction is either for a violent or property offense. For the purposes of this Exhibit, other offenses, such a drug offenses, are not included in this definition.

2. The Policy Adjustment, *P*. In the WSIPP model, we incorporate a policy adjustment, *P*, to better estimate the degree to which a specific policy proposal affects outcomes differently than the average effect estimated with the elasticity, *E*. For incarceration-related topics, the policy adjustment measures the degree to which a specific policy affects the certainty or severity of punishment. For policing-related topics, the policy adjustment measures whether the specific policy affects how police are deployed in the community.

2a. The incarceration policy adjustment. As noted earlier, there are two ways policies can affect total incarceration ADP: the probability of going to prison given a conviction and the length of stay given a prison sentence. The first factor implies punishment certainty while the second more closely reflects punishment severity. These two factors are likely to have different effects on crime, yet the overall elasticity, *E*, estimated with current research using total ADP, is unable to distinguish the separate effects. Therefore, equations (4a) and (5a) implement a second multiplicative adjustment, *P*, to account at least partially for this limitation in the current state of incarceration research. Without adjustment, simply using E to estimate how a change in prison length of stay affects crime would most likely over-estimate the effect.

Our goal was to be able to adjust for policies that affect the length of prison stay, since these policies have been ones of particular interest to the Washington State legislature in recent years. Additionally, because Nagin (2013) and Durlauf & Nagin (2010) have found that changing length of stay is likely to have a smaller effect than changing the probability of punishment, we developed a procedure to provide a plausible adjustment to the overall prison-crime elasticity measured with the studies we include in the meta-analytic results displayed in Exhibit TA1.

[29] Barnoski, R. & Drake, E. (2007). *Washington's offender accountability act: Department of Corrections' static risk instrument.* (Doc. No. 07-03-1201). Olympia: Washington State Institute for Public Policy.

To do this, we implement the computational procedure displayed in Exhibit TA3. To inform how length of stay policies affect current crime levels through incapacitation, we use our meta-analytic results measuring how length of stay affects the future recidivism rates of specific offenders. If the effect of prison ADP on crime is primarily incapacitation rather than general deterrence, then studies of the effect of prison length of stay on the future recidivism rate of specific offenders provides useful estimates of how current crime levels change when length of stay changes. We estimate an elasticity metric for the literature estimating how prison length of stay affects the recidivism rate of specific offenders. From 1986 to 2009 in the United States, prison length of stay increased by about 4 months, or about 17%, according to the US Department of Justice. We estimate that the 17% increase in length of stay resulted in roughly a 2% decrease in recidivism rates, as described computationally in Exhibit TA3. This produces an elasticity of -0.119. Since the simultaneity-adjusted elasticity for total UCR crime from our meta-analysis reported in Exhibit TA1 is -0.350, a simple policy multiplier to use to analyze length of stay policy changes with equations (4a) and (5a) is 0.339 (-0.119 / -0.350). Thus, when using the equations to analyze sentencing options that affect the length of prison stay on current crime levels, we use a mean multiplicative value of 0.339 to modify the overall elasticities reported in Exhibit TA1 that measure both the probability or prison as well as the length of incarceration. The adjustment is rather crude (if data allowed, it would be better to estimate separate effects for violent and property crimes), but it does provide a first order approximation that is likely to be closer than simply using *E* as the effect. Since there is risk and uncertainty around this estimate, in Monte Carlo simulation we model a triangular probability density distribution with lower and higher values in addition to the modal value of 0.339.

Exhibit TA3
Calculation of WSIPP Policy Adjustment Multiplier for Changes in Average Daily Prison Population Obtained by Changing the Length of Stay (rather than the probability of incarceration)

Step		Total crime
(1)	Number of months change in prison length of stay, United States, 1986 to 2009[1]	+4
(2)	Percent change in length of stay[1]	+16.67%
(3)	Effect size for change in recidivism, per month of prison length of stay[2]	-0.006
	Standard error	0.007
(4)	Effect size for observed change in length of stay[3]	-0.024
(5)	Base recidivism rate[4]	50%
(6)	Recidivism rate after change in length of stay[5]	49%
(7)	Percent change in recidivism rates[6]	-1.98%
(8)	Elasticity: percent change in recidivism rate per percent change in length of stay[7]	-0.119
(9)	Overall Prison/Crime elasticity[8]	-0.350
(10)	Policy multiplier[9]	0.339

Notes:

1) Bureau of Justice Statistics, U.S. Department of Justice, National Corrections Reporting Program, First Releases from State Prison, annual reports from 1986 to 2009. The mean length of stay increased from 24 to 28 months between 1986 and 2009.
2) Calculated from our meta-analysis of the effect of a one month increase in incarceration length of stay of criminal recidivism. The result is reported in Exhibit TA5 in this report.
3) We assume a linear effect size and multiply the effect size from step (3) times the number of months change from step (1).
4) This is roughly the long-term (15-year) recidivism rate of adults released from prison in Washington State, where recidivism is defined as a reconviction for a felony offense in Washington.
5) The recidivism rate after applying the Dcox effect size from step (4) to the base recidivism rate from step (5).
6) Step (6) / Step (5) - 1.
7) Step (7) divided by Step (2).
8) From Exhibit TA1, the simultaneity adjusted elasticity for overall UCR crime.
9) Step (8) / Step (9).

2b. The policing policy adjustment. A growing body of research indicates that the way in which police are deployed in the community has a significant effect of crime rates. For example, Nagin's (2013) review of the literature found that "hot spots" and "pulling levers" policing deployment strategies have been shown to produce larger effects than traditional deployment strategies, while rapid response or thorough investigation strategies do not increase the effectiveness of policing on crime.[30] Thus, specific deployment policies are likely to have differential effects on crime, yet the overall elasticity, *E*, estimated with current research using total policing levels, is unable to distinguish additional effects. Therefore, equations (4b) and (5b) implement a second multiplicative policy adjustment, *P*, to account at least partially for this limitation in the current state of policing research.

The steps we use to estimate a policing policy adjustment multiplier are listed in Exhibit TA4 and follow this computational process:

$$(6)\quad PM_t = \frac{ME_t + \dfrac{(HSES_t \times SD_t \times \overline{POP})}{\overline{\overline{POL}}}}{ME_t}$$

[30] Nagin, D. (2013). Deterrence in the twenty-first century: A review of the evidence. *Crime and Justice: A Review of Research*. Chicago, IL: University of Chicago Press.

We begin by computing the average marginal effect, *ME,* for crime type *t*, from our meta-analyses of the policing literature, described above. We then use the meta-analyzed effect size for hot spots policing, *HSES*, for crime type *t*, reported in the meta-analysis by Braga, et al. (2012). The effect size measures, at the policing jurisdiction level, the effect of hot spots policing, in standard deviation units of crime, compared to non-hot spots jurisdictions. We use Washington State jurisdiction-level UCR data for 2011 in Washington's cities and county sheriff's offices for mean crime rates and the associated standard deviation in jurisdiction-level crime rates, SD, for crime type *t*. From the UCR data, we also include mean policing levels per jurisdiction, *POL*, and mean population per jurisdiction, *POP.* The resulting policy level multiplier estimates the degree to which policing following a hot spots deployment approach increases policing effectiveness relative to average effects, *E*. For example, a policy multiplier of 1.11 would indicate that hot spots deployed police are, on average, 11% more effective that police deployed with a routine strategy. We estimate an error term for the policy multiplier by running a Monte Carlo simulation, using the standard error from the Braga et al., (2012) meta-analysis.

Exhibit TA4
Calculation of WSIPP Policy Adjustment Multiplier for Hot Spots Police Deployment

Step	Violent crime	Property crime
(1) Marginal effect of a police officer deployed with an average strategy, on annual UCR crime[1]	-2.19	-6.7
(2) Effect size of "Hot Spots" policing, compared to traditional deployment, jurisdiction level[2]	-0.175	-0.084
Standard error of the effect size	0.058	0.048
(3) Mean per-capita UCR crime rate in Washington policing jurisdictions[3]	0.00215	0.03147
Standard deviation in per capita crime rates	0.00177	0.01986
(4) Change in mean jurisdictional per-capita crime rate from hot spots deployment[4]	-0.000310	-0.001668
(5) Change in mean jurisdictional crimes from hot spots deployment[5]	-9.253	-49.794
(6) Change in crimes per officer from hot spots deployment[6]	-0.237	-1.278
(7) Mean Policy Adjustment Multiplier[7]	1.11	1.19
Washington State Statistics		
Mean number of commissioned police officers per jurisdiction[8]	38.97	
Average population per jurisdiction[8]	28,852	

Notes:
1) Marginal effect (E*C/POL) calculated with an elasticity, E, times the current statewide level of violent or property UCR crimes, C, divided by the current statewide level of commissioned police officers. The elasticity E measures the average officer deployed in an average practice manner. The elasticities for the WSIPP analysis are reported in Exhibit TA1.
2) From Table 10.4 of the meta-analysis by Braga, et al. (2012). Braga, A., Papachristos, A., & Hureau, D. *Hot spots policing effects on crime*. Campbell Systematic Reviews 2012:8. Standard errors calculated from the confidence intervals reported in their Table 10.4.
3) Calculated from all reporting city and county sheriff's offices in Washington UCR data for 2011, with data reported on the website of the FBI.
4) The effect size from Braga, et al. (2012) times the standard deviation in crime rates for Washington jurisdictions.
5) The factor in footnote 4, times the average population per Washington policing jurisdiction, reported in this table.
6) Change in crimes per jurisdiction, divided by the mean number of officers per jurisdiction, reported in this table.
7) The sum of the marginal effect per officer (note one), plus the change in crimes per officer due to hot spots (note 6), divided by the marginal effect per officer.
8) Calculated for Washington police jurisdictions from UCR data and population data from the Washington State Office of Financial Management for 2011.

Estimating large changes in ADP or POL. Since the computation of marginal effects from equations (4a), (4b), (5a), and (5b) is designed for small unit changes in ADP or POL, and since the results will typically be used in practice to estimate the effects of larger policy changes in ADP or POL, the computation of the total marginal crime effect is estimated iteratively, one ADP or POL at a time. Equations (7a), (7b), (8a), and (8b) implement this iterative process for violent and property crime marginal effects. The equation sums the change in crimes for the absolute value of a total sentencing change or police change. For a policy that raises or lowers total prison ADP_T or total police levels POL_T, the change in crime by type, ΔC_V *or* ΔC_p, is calculated with the estimate of the adjusted elasticity for that type of crime, *E* times *R* times *P*, multiplied by the total crime of each type after each unit iteration of the total ADP or POL 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*.

$$(7a)\ \Delta C_v = \frac{\sum_{a=1}^{|\Delta ADP_T|} (E_v \times R_v \times P_v) \times \frac{[C_{v(a)} + (\Delta C_{v(a-1)})]}{(ADP_T \pm a)}}{RR_v} \qquad (7b)\ \Delta C_v = \frac{\sum_{a=1}^{|\Delta POL_T|} (E_v \times R_v \times P_v) \times \frac{[C_{v(a)} + (\Delta C_{v(a-1)})]}{(POL_T \pm a)}}{RR_v}$$

$$(8a)\ \Delta C_p = \frac{\sum_{a=1}^{|\Delta ADP_T|} (E_p \times R_p \times P_p) \times \frac{[C_{p(a)} + (\Delta C_{p(a-1)})]}{(ADP_T \pm a)}}{RR_p} \qquad (8b)\ \Delta C_p = \frac{\sum_{a=1}^{|\Delta POL_T|} (E_p \times R_p \times P_p) \times \frac{[C_{p(a)} + (\Delta C_{p(a-1)})]}{(POL_T \pm a)}}{RR_p}$$

For a number of the benefit-cost calculations that follow, we are interested in total violent or property crime effects as described with equations (7a), (7b), (8a), and (8b). Total crime changes are used, for example, in computing the victim costs of crimes incurred or the victim benefits of crime avoided when policies change. For some calculations, however, we are only interested in computing the taxpayer costs of the criminal justice system and, hence for these calculations we are only interested in crimes reported to police. Equations (9) and (10) set these reported-crime estimates, ΔRC_v and ΔRC_p.

$$(9)\ \Delta RC_v = \Delta C_v \times RR_v$$

$$(10)\ \Delta RC_p = \Delta C_p \times RR_p$$

Modeling risk in the marginal crime effects. For the key inputs in equations (7) and (8), we model risk using a Monte Carlo process. For the elasticity parameter, *E*, we use the standard errors from the meta-analyses reported on Exhibit TA1. We also use low, modal, and high parameters for the risk, *R*, and policy, *P*, adjustments. In Monte Carlo simulation, these parameters are used to randomly draw from a normal probability density distribution (for the elasticity estimate, *E*) and triangular probability density distributions (for the risk and policy adjustments, *R* and *P*). We run the Monte Carlo process 10,000 times and compute the mean-adjusted elasticity along with its standard deviation from the 10,000 Monte Carlo runs.

Section 1.4 Estimating the Monetary Value of Changes in Current Crime from Prison and Police Changes

The process described above produces estimates of the number of crimes avoided or incurred when a prison or policing policy is changed. The direction of the change in crimes depends, of course, on the policy being analyzed and the sign on the elasticities in Exhibit TA1. The monetary valuation of the change in the number crimes centers on two types: victim costs or benefits and taxpayer costs or benefits.

Victim Costs or Benefits. The victim costs or benefits are estimated with:

$$(11)\ \Delta Victim\$ = \Delta C_v \times VictimPerUnit\$_v + \Delta C_p \times VictimPerUnit\$_p$$

The change in the total value of victim costs, *ΔVictim$,* is the sum of the change in the number of violent and property victimizations from equations (7) and (8), ΔC_v *and* ΔC_p times, respectively, the marginal victim cost per violent and property victimization, $VictimPerUnit\$_v$ *and* $VictimPerUnit\$_p$. The per unit costs are denominated in a common base year's dollars used for all monetary valuations in the benefit cost analyses. In Monte Carlo simulation, a triangular probability density distribution is used to model uncertainty in the per unit victim costs. The source for the per unit victim costs are described in a separate WSIPP document.[31]

Criminal Justice System Costs or Benefits. When crime is increased or reduced, taxpayers can expect to pay more or less, respectively, from the policy change. The calculation of these amounts are done for police expenses; court-related expenses including court staff, prosecutor and defender staff; jail sanction costs; prison costs; and community supervision costs for jail-based or prison-based sentences. The following equations are used to calculate the change in expenses for each part of the criminal justice system.

$$(12)\ \Delta Police\$ = \Delta RC_v \times \frac{Arrest_v}{RC_v} \times PolicePerArrest\$_v + \Delta RC_p \times \frac{Arrest_p}{RC_p} \times PolicePerArrest\$_p$$

$$(13)\ \Delta Court\$ = \Delta RC_v \times \frac{Conviction_v}{RC_v} \times CourtPerConviction\$_v + \Delta RC_p \times \frac{Conviction_p}{RC_p} \times CourtPerConviction\$_p$$

$$(14)\ \Delta Jail\$ = \Delta RC_v \times \frac{JailLOS_v}{RC_v} \times JailPerYear\$_v + \Delta RC_p \times \frac{JailLOS_p}{RC_p} \times JailPerYear\$_p$$

$$(15)\ \Delta Prison\$ = \Delta RC_v \times \frac{PrisonLOS_v}{RC_v} \times PrisonPerYear\$_v + \Delta RC_p \times \frac{PrisonLOS_p}{RC_p} \times PrisonPerYear\$_p$$

$$(16)\ \Delta JailCS\$ = \Delta RC_v \times \frac{JailCSLOS_v}{RC_v} \times JailCSPerYear\$_v + \Delta RC_p \times \frac{JailSuperLOS_p}{RC_p} \times JailCSPerYear\$_p$$

[31] Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf

$$(17)\ \Delta PrisonCS\$ = \Delta RC_v \times \frac{PrisonCSLOS_v}{RC_v} \times PrisonCSPerYear\$_v + \Delta RC_p \times \frac{PrisonCSLOS_p}{RC_p} \times PrisonCSPerYear\$_p$$

For each segment of the criminal justice system, the change in expenses is the sum the change in the number of reported violent and property victimizations from equations (9) and (10), *ΔRC_v and ΔRC_p* times, respectively, the probability that a reported crime uses resources in each criminal justice segment, times the marginal cost of that segment per violent and property victimization. For jail and prison length of stay and for the length of stay on community supervision for jail-based and post-prison-based segments, the parameters are conditional on the probability of a conviction given a reported crime. The per unit costs are denominated in a common "base" year's dollars used for all monetary valuations in the benefit cost analyses. In Monte Carlo simulation, a triangular probability density distribution is used to model uncertainty in the marginal per unit criminal justice costs. The sources for all of the parameters in these equations are described in a separate WSIPP document.[32]

Equation (18) sums up the total change in crime-related costs from equations (11) to (17) and measures the effect of a policy change on current crime related costs or benefits.

$$(18)\ \Delta CurrentCrime\$ = \Delta Victim\$ + \Delta Police\$ + \Delta Court\$ + \Delta Jail\$ + \Delta Prison\$ + \Delta JailCS\$ + \Delta PrisonCS\$$$

Section 2: Do Prison Incarceration Rates Affect the Recidivism Rates of Offenders?

Section 2.1 General Considerations

In Section 1, we analyzed research studies that address how prison ADP affects current crime levels through some combination of incapacitation and general deterrence. In Section 2, we discussed a second body of empirical research that can be utilized to estimate the crime related impacts of sentencing policy changes. The second strand of research estimates how prison may influence the future crime rates of the specific offenders after they are released from incarceration.

Broadly, we examine two research literatures on specific deterrence. First, we meta-analyze studies that measure the effect of prison sentences, compared to non-prison sentences, on the recidivism rates of offenders. The typical model in these studies implements an equation similar to (19). Second, we analyze studies the measure the effect of longer or shorter prison lengths of stay on the recidivism rate of offenders who receive prison sentences. The typical model for these studies is similar to equation (20).

$$(19)\ C_o = a + b(PrisonYes/No) + c(X) + e$$

$$(20)\ C_o = a + b(PrionLOS|Prison) + c(X) + e$$

As was the case in the research literatures described in Section 1, there are known statistical issues with studies that estimate equations (19) or (20). Primarily the concern is with omitted variable bias; namely, that the observed control variables, X, in the equations may not fully capture all of the unobserved factors that influence recidivism, and that these unobserved (to the researcher) factors may be correlated with the two policy variables. If this is the case, then the coefficients on the policy variables may be biased. The potential for omitted variable bias would seem to be much greater for studies implementing equation (19) since decision to imprison may reflect many factors not observed by the researcher. Much of the discussion and debate in the research literature on these two topics has focused on statistical approaches to address the potential bias from omitted control variables. In particular, in more recent years some researchers have attempted to find natural experiments and regression discontinuity conditions in order to estimate causal effects.

Section 2.2 Meta-Analysis of the Effect of a Prison Sentence and Prison Length of Stay on Recidivism

To provide an evidence-based assessment of the degree to which changes in the use of prison sentences or the length of prison stay given a prison sentence affects recidivism, we surveyed the relevant research literatures and performed a random effects meta-analysis. We identified studies for inclusion in the literature reviews primarily by examining the citations cited in the major papers that have been published in academic journals. There have also been some recent narrative reviews of these literatures that allowed us to identify many of the relevant papers.[33] We also searched the internet with Google and Google Scholar to identify other papers that might not have been cited in the main published papers.

[32] Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf
[33] Durlauf & Nagin (2010).

Methodological Screening. We screened the studies for methodological rigor. For these two research literatures, we particularly focused on the degree to which a study accounted for possible unobserved variables bias in equations (19) and (20). In our final meta-analyses, we only included recent studies that met the more rigorous standards of evidence. For our meta-analysis of the literature, we separately analyzed the studies that use a natural experiment or regression discontinuity approach since these approaches offer an improved ability to detect cause-and-effect relationships. Citations to the studies in our meta-analyses are included in Section 4 of this report.

The Effect Size Metric: Recidivism as a Dichotomous Outcome. We coded an effect size for each study from the author's preferred estimates. Since nearly all of the studies in our review estimated equations with a dichotomous dependent variable measuring criminal recidivism, we calculated a D-cox effect size metric. A few studies estimate continuous crime outcomes and for these studies we computed a Cohen's d effect size. For the topic on the effect of prison length of stay on recidivism, we standardized the "dosage" of the length of stay increase of one month. Then, when necessary, we scaled the author's preferred estimate to a one-month increase in LOS. We used our standard meta-analytic computations, following the procedures described in WSIPP's report on methods.[34]

Meta-Analytic Results. Exhibit TA5 displays the results of our meta-analyses. The results are shown for both topics and their estimated effects on total crime. Additionally, because of the particular concern about omitted variable bias, we separately analyzed the correlational studies based on observed variables from the natural experiment and regression discontinuity studies.

Exhibit TA5
Meta-Analytic Results: Specific Deterrence for Prison Policies on Recidivism

Policy topic & outcome		Correlational studies			Natural experiment or regression discontinuity studies			All studies		
Topic	Type of crime	Effect size	Standard error	Number of studies	Effect size	Standard error	Number of studies	Effect size	Standard error	Number of studies
Prison sentences compared to non-prison sentences	Any recidivism	.145	.077	8	-.014	.026	4	.082	.050	12
One month increase in prison length of stay	Any recidivism	-.002	.008	6	-.020	.014	3	-.006	.007	9

Notes: All results are from random effects meta-analyses estimated with the methods described in Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf

Section 2.3 Computation of Marginal Crime Effects and Monetary Valuation from the Change in Recidivism

The effects reported in Exhibit TA5 are expressed in the standard D-cox or Cohen's d effect size metric used in WSIPP's general analysis of benefits and costs. The computation of marginal effects from these effect sizes can be found in a separate WSIPP Technical Manual.[35] Similarly, the procedures used to monetize victim and criminal justice system benefits and costs follow the same procedures described in the Technical Manual.

Section 3: Summary Benefit-Cost Measures for the Prison Incarceration Topics

For prison incarceration-related topics, the calculation of benefit-cost summary measures—net present values, benefit-cost ratios, and internal rates of return—follows a two-step process. The first step, described in Section 1 of this Technical Appendix, calculates the degree to which prison affects the *current* crime rate during the period in which an offender is incarcerated. The second step, described in Section 2 of this Appendix, estimates the degree to which prison affects the *future* recidivism rates of offenders once they are released. These two steps are entered by the user of the WSIPP benefit-cost model as separate outcomes of incarceration-related topics. The benefit-cost model then sums the two effects to obtain the overall benefit-cost summary statistics reported in Exhibit 1 in this report.

[34] Washington State Institute for Public Policy (2013), Benefit-Cost Technical Manual, available at: www.wsipp.wa.gov/rptfiles/BCTechnicalManual.pdf
[35] Ibid.

Section 4: Studies Used in the Meta-Analyses

Police Per Capita (studies with estimates that address simultaneity)

Draca, M., Machin, S., & Witt, R. (2011). Panic on the streets of London: Police, crime, and the July 2005 terror attacks. The *American Economic Review, 101* (5), 2157-2181.

Evans, W. N., & Owens, E. G. (2007). COPS and crime. *Journal of Public Economics, 91* (1-2), 181.

Klick, J., & Tabarrok, A. (2005). Using terror alert levels to estimate the effect of police on crime. *Journal of Law and Economics, 48* (1), 267-279.

Levitt, S. D. (2002). Using electoral cycles in police hiring to estimate the effects of police on crime: Reply. *The American Economic Review, 92* (4), 1244-1250.

Lin, M. (2009). More police, less crime: Evidence from US state data. *International Review of Law and Economics, 29* (2), 73-80.

McCrary, J. (2002). Using electoral cycles in police hiring to estimate the effect of police on crime: Comment. *The American Economic Review, 92* (4), 1236-1243.

Shi, L. (2009). The limit of oversight in policing: Evidence from the 2001 Cincinnati riot. *Journal of Public Economics, 93* (1), 99-113.

Worrall, J. L., & Kovandzic, T. V. (2010). Police levels and crime rates: An instrumental variables approach. *Social Science Research, 39* (3), 506-516.

Police Per Capita (studies with estimates that do not address simultaneity)

Benson, B. L., Rasmussen, D. W., & Kim, I. (1998). Deterrence and public policy: Trade-offs in the allocation of police resources. *International Review of Law & Economics, 18* (1), 77-100.

Chalfin, A. & McCrary, J. (2013). *The effect of police on crime: New evidence from U.S. cities, 1960-2010.* Working paper.

Corman, H., & Mocan, N. (2005). Carrots, sticks, and broken windows. *Journal of Law and Economics, 48 (*1), 235-266.

Donohue, J. J., & Levitt, S. D., (2001). The impact of legalized abortion on crime. *The Quarterly Journal of Economics, 116* (2) 379-420.

Draca, M., Machin, S., & Witt, R. (2011). Panic on the streets of London: Police, crime, and the July 2005 terror attacks. The *American Economic Review, 101* (5), 2157-2181.

Evans, W. N., & Owens, E. G. (2007). COPS and crime. *Journal of Public Economics, 91* (1-2), 181.

Kim, M. (2007). *Reassessing the effects of police manpower changes on crime rates: Evidence from a dynamic panel model.* Doctoral Dissertation, State University of New York at Albany, UMI No. AAT 3293128.

Kovandzic, T. V., & Sloan, J. J. (2002). Police levels and crime rates revisited: A county-level analysis from Florida (1980-1998). *Journal of Criminal Justice, 30* (1), 65-76.

Levitt, S. D. (2002). Using electoral cycles in police hiring to estimate the effects of police on crime: Reply. *The American Economic Review, 92* (4), 1244-1250.

Lin, M. (2009). More police, less crime: Evidence from US state data. *International Review of Law and Economics, 29* (2), 73-80.

Marvell, T. B. (2009). Prison Population and Crime. Presented at the DeVoe Moore Center Symposium on the Economics of Crime at Florida State University. http://ssrn.com/abstract=1452427.

Marvell, T. B., & Moody, C. E. (1996). Specification problems, police levels, and crime rates. *Criminology, 34* (4), 609-646.

McCrary, J. (2002). Using electoral cycles in police hiring to estimate the effect of police on crime: Comment. *The American Economic Review, 92* (4), 1236-1243.

Reyes, J. W., 2007. Environmental policy as social policy? The impact of childhood lead exposure on crime. *The B.E. Journal of Economic Analysis & Policy*, *7* (1).

Vollaard, B., & Hamed, J. (2012). Why the police have an effect on violent crime after all: Evidence from the British Crime Survey. *Journal of Law and Economics, 55* (4), 901-924.

Worrall, J. L., & Kovandzic, T. V. (2010). Police levels and crime rates: An instrumental variables approach. *Social Science Research, 39* (3), 506-516.

WSIPP, 2013, See section 5 of this Technical Appendix

Prison Sentence vs. No Prison Sentence

Bales, W. D., & Piquero, A. R. (2012). Assessing the impact of imprisonment on recidivism. *Journal of Experimental Criminology, 8 (*1), 71-101.

Barnoski, R. P. (2004). *Sentences for adult felons in Washington: Options to address prison overcrowding: Pt. 2 (recidivism analyses)*. (Doc. No. 04-07-1201). Olympia, WA: Washington State Institute for Public Policy.

Berube, D., & Green, D. P., (2007). *The effects of sentencing on recidivism: results from a natural experiment.* Working paper.

Bhati, Avinash Singh, and Alex R. Piquero. (2007). Estimating the impact of incarceration on subsequent offending trajectories: Deterrent, criminogenic, or null effect? *Journal of Criminal Law and Criminology, 98* (1), 207-254.

Helland, E., & Tabarrok, A. (2007). Does three strikes deter? A nonparametric estimation. T*he Journal of Human Resources, 42* (2), 309-330.

Jolliffe, D., & Hedderman, C. (2012). Investigating the impact of custody on reoffending using propensity score matching. *Crime & Delinquency*, DOI: 10.1177/0011128712466007.

Loughran, T. A., Mulvey, E. P., Schubert, C. A., Fagan, J., Piquero, A. R., & Losoya, S. H. (2009). Estimating a dose-response relationship between length of stay and future recidivism in serious juvenile offenders. *Criminology, 47* (3).

Marie, O. (2009). *The best ones come out first! Early release from prison and recidivism: A regression discontinuity approach.* Discussion paper.

Nagin, D. S., & Snodgrass, G. M. (2013). The effect of incarceration on re-offending: Evidence from a natural experiment in Pennsylvania. *Journal of Quantitative Criminology.* DOI: 10.1007/s10940-012-9191-9

Nieuwbeerta, P., Nagin, D. S., & Blokland, A. A. J. (2009). Assessing the impact of first-time imprisonment on offenders' subsequent criminal career development: A matched samples comparison. *Journal of Quantitative Criminology, 25* (3).

Weatherburn, D., (2010). *The effect of prison on adult re-offending.* Sydney: NSW Bureau of Crime Statistics and Research.

Wermink, H., Blokland, A., Nieuwbeerta, P., Nagin, D., & Tollenaar, N. (2010). Comparing the effects of community service and short-term imprisonment on recidivism: A matched samples approach. *Journal of Experimental Criminology, 6* (3), 325-349.

Prison Length of Stay

Barnoski, R. P. (2004). *Sentences for adult felons in Washington: Options to address prison overcrowding: Pt. 2 (recidivism analyses)*. (Doc. No. 04-07-1201). Olympia, WA: Washington State Institute for Public Policy.

Bushway, S. D., & Owens, E. G (2013). Framing punishment: Incarceration, recommended sentences, and recidivism. *Journal of Law and Economics, 56* (2), 301-331.

Drago, F., Galbiati, R., & Vertova, P. (2009). The deterrent effects of prison: Evidence from a natural experiment. *The Journal of Political*

Economy, 117 (2), 257-280.
Drake, E. K., Barnoski, R., & Aos, S. (2009). *Increased earned release from prison: Impacts of a 2003 law on recidivism and crime costs, revised* (Doc. No. 09-04-1201). Olympia: Washington State Institute for Public Policy.
Gottfredson, D. M. (1999). *Effects of judges' sentencing decisions on criminal careers.* Washington, DC: U.S. Dept. of Justice, Office of Justice Programs, National Institute of Justice.
Kuziemko, I. (2013). How should inmates be released from prison? An assessment of parole versus fixed-sentence regimes. *The Quarterly Journal of Economics, 128* (1), 371-424.
Meade, B., Steiner, B., Makarios, M., & Travis, L. (2012). Estimating a dose-response relationship between time served in prison and recidivism. *Journal of Research in Crime and Delinquency,* DOI: 10.1177/0022427812458928.
Oliver, B. E. (2011). *Recidivism: A multi-level explanation.* St. Louis, Mo: University of Missouri--St. Louis.
Snodgrass, G.M., Blokland, A.A.J., Haviland, A., Nieuwbeerta, P., & Nagin, D.S. (2011). Does the time cause the crime? An examination of the relationship between time served and reoffending in the Netherlands. *Criminology, 49* (4), 1149-1194.

Prison Per Capita (studies with estimates that address simultaneity)

Bhati, A. (2007). Estimating the number of crimes averted by incapacitation: An information theoretic approach. *Journal of Quantitative Criminology, 23* (4), 355-375.
Johnson, R., & Raphael, S. (2012). How much crime reduction does the marginal prisoner buy? *Journal of Law and Economics, 55* (2), 275-310.
Levitt, S. D. (1996). The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *The Quarterly Journal of Economics, 111* (2), 319-351.
Spelman, W. (2005). Jobs or jails? The crime drop in Texas. *Journal of Policy Analysis and Management, 24* (1), 133-165.
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Section 5: WSIPP Analysis of Washington State Data

We conducted a study of the prison-crime relationship and the police-crime relationship for Washington State by estimating models similar to equations (1a) and (1b). We included our preferred regression results, discussed below, as a separate study in the meta-analyses reported in Exhibit TA1.

We analyzed the relationships for Washington with a panel of county data. For the dependent variables, we used county-level UCR crime data from 1982 to 2011 for Washington's 39 counties. To align our results with the meta-analyses reported in Exhibit TA1, we estimated separate equations for total UCR crimes, violent UCR crimes, and property UCR crimes. The annual county UCR crime data were expressed as crime rates by dividing by annual county population. We obtained the UCR data from the Washington Association of Sheriffs and Police Chiefs, and we inspected and adjusted the data, year by year and jurisdiction by jurisdiction, to impute crime values when crime was not reported by local agencies. The number of imputations was minor. We obtained the county population data from the Washington State Office of Financial Management.

For the incarceration policy variable, we computed an annual total statewide incarceration rate (STATEADP) for Washington by dividing total average daily incarcerated population for adult prisons and state juvenile facilities by the 10-to-59 year old population in the state. We included state juvenile incarceration because the UCR crime data also include crimes committed by juveniles. For the policing policy variable (POLICE), we divided the total number of commissioned police officers in each county, as reported in the UCR data system, by each county's 10-to-59 year old population. We used the 10-59 age group to more closely align the criminal justice resources, incarceration and police, with the age groups that engage in most criminal activity.

In keeping with the majority of the research literature, we estimated models for the natural log of the county UCR crime rates and the natural log of the total statewide incarceration rate and the natural log of county police rates. We also controlled for the log of local county jail incarceration rates (LOCALJAIL). We included a variable for population density, operationalized with county population divided by the square miles in each county (POPSQMILE), and we included a squared term for this measure of density (POPSQMILE^2). We tested models with county-level fixed effects and, for some models, year fixed effects. White robust standard errors are reported.

We observed in the basic statewide prison-crime relationship a marked change beginning in 2005 and continuing to 2011, the latest date available for this study. Therefore, in some of the models we included separate year dummies for these years. These year dummies are not necessary when we include statewide year fixed effects in the regressions. Unfortunately, for the regressions that include statewide incarceration rates, it is not possible to include year fixed effects. Therefore, in those non-fixed year effects models we used the more focused set of annual dummies for 2005 to 2011.

We tested for unit roots in the crime variables. The county UCR crime rate data did not exhibit unit roots; the Im-Pesaran-Shin panel unit root test produced a p-value of 0.0011 for total UCR crime, a p-value of 0.0000 for violent UCR crime, and a p-value of 0.0009 for property UCR crime. These tests rejected the null hypothesis of a unit root. We also tested the police policy variable for a unit root and it too did not indicate a unit root; the Im-Pesaran-Shin panel unit root test produced a p-value of 0.0000. Thus, the regressions estimating the police-crime relationship were performed in levels.

We then tested the statewide incarceration policy variable and did not reject the presence of a unit root. Since the STATEADP variable used in this study is a statewide rate applied to all counties, we tested the single statewide series from 1980 to 2012 with an Augmented Dickey Fuller test, and we did not reject a unit root (p-value = 0.447). With a trend and an intercept, the p-value of the Augmented Dickey Fuller test remained non-significant 0.544. In first differences, on the other hand, the Augmented Dickey Fuller test had a p-value of 0.019 with a constant term, and a p-value of 0.046 with a constant and time trend terms. Thus, for the incarceration variable, we implemented some models with a first differences estimation to test the sensitivity of the prison-crime findings to the possibility of a unit root in the incarceration variable.

For this study, we did not have instrumental variables to help identify either the prison-crime or the police-crime relationships. As noted by Spelman (2008), however, it is possible that when using county-level data within a particular state (Washington, in this case), the data may not require accounting for simultaneity.[36] Whether this is the case or not, Washington did have an arguably close-to-exogenous change in adult prison ADP in the 1980s when the legislature adopted a new form of adult sentencing (the Sentencing Reform Act of 1984). When this new system went into effect, the incarceration rate was lowered as a matter of policy that was, in part, driven by sentencing reforms unrelated to current crime trends. The motivation for the new sentencing structure was to reduce sentencing disparities among judges. The new sentencing system has been modified by subsequent sentencing policy actions, also arguably unrelated to underlying crime trends. These seemingly exogenous policy changes in Washington probably allow a cleaner delineation of the true prison-crime relationship. As the results of our estimations show, this may be why many of our elasticity estimates for the prison-crime relationship are similar to the national studies that use instrumental variables to account for simultaneity. Nonetheless, we do not claim that our results deal with simultaneity explicitly and, therefore, we include our preferred Washington elasticity estimates for both the prison-crime and police-crime relationships in our meta-analyses of the correlational studies. Nonetheless, the similarity of our preferred results for Washington State to those national studies accounting for simultaneity increase our confidence in identifying the prison-crime relationship for use in our analysis of Washington State incarceration policy options.

[36] Spelman, W. (2008). Specifying the relationship between crime and prisons, *Journal of Quantitative Criminology, 24*, 149-178.

The results of our estimations are shown in Exhibit TA5. Our preferred model is the estimates from Model 7. We think it is important to include both policy variables—state average daily prison population and policing—in the same model because the two factors broadly measure the certainty and severity of punishment described by Durlauf and Nagin (2010). Additionally, we favor the models that account explicitly for the fixed year effects either directly or through the dummies for 2005-2011 when there appears to be a structural change (a shift in the demand curve) taking place in Washington. We note that, for total crime and for property crime, Models 7 through 10 produce roughly similar elasticities for the two policy variables. For violent crime, there is a larger difference for policing when prison is included in the model (Model 7) compared to the model when prison is excluded from the model (Model 9). Our preference for Model 7 reflects our view that Model 9 would likely overestimate the effect of police on violent crime if the effect of prison is excluded. For violent crime, the elasticity for state average daily population for Model 10, which estimates a first-difference model, is about a third lower than our preferred Model 7. Recall that for prison, but not for policing, there is some evidence for a panel unit root. The first difference specification in Model 10 provides virtually the same elasticities as Models 7 and 8 for total crime and property crime, but a smaller elasticity for violent crime (-0.21 vs. -0.29). We think a reasonable case can be made for using the results from Model 7 in the meta-analyses reported on Table TA1.

Exhibit TA5
Regression Results from WSIPP Analysis of Washington State County-Level Data, 1982 to 2011

Outcome: Total UCR Crime										
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Ln(STATEADP)	-0.473	-	-	-	-0.457	-0.483	-0.305	-0.317	-	-0.287
Standard error	0.026	-	-	-	0.027	0.040	0.039	0.038	-	-0.105
Ln(POLICE)	-	-0.239	-0.419	-0.166	-0.155	-0.225	-0.195	-	-0.223	-
Standard error	-	0.044	0.098	0.092	0.095	0.099	0.095	-	0.096	-
Ln(LOCALJAIL)	-	-	-	-	-	Y	Y	Y	Y	Y
POPSQMILE	-	-	-	-	-	Y	Y	Y	Y	Y
POPSQMILE^2	-	-	-	-	-	Y	Y	Y	Y	Y
Dummies: 2005-2011	-	-	-	-	-	-	Y	Y	-	Y
Fixed County Effects	Y	-	Y	Y	Y	Y	Y	Y	Y	-
Fixed Year Effects	-	-	-	Y	-	-	-	-	Y	-
N	1248	1248	1248	1248	1248	1248	1170	1170	1170	1131
Adjusted R^2	0.710	0.021	0.636	0.763	0.712	0.718	0.765	0.764	0.773	0.048
Levels (L) or first differences (FD)	L	L	L	L	L	L	L	L	L	FD
Outcome: Violent UCR Crime										
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Ln(STATEADP)	-0.34	-	-	-	-0.343	-0.464	-0.292	-0.302	-	-0.210
Standard error	0.047	-	-	-	0.046	0.072	0.077	0.078	-	0.302
Ln(POLICE)	-	-0.411	-0.161	-0.063	0.037	-0.17	-0.154	-	-0.331	-
Standard error	-	0.070	0.214	0.217	0.214	0.195	0.193	-	0.185	-
Ln(LOCALJAIL)	-	-	-	-	-	Y	Y	Y	Y	Y
POPSQMILE	-	-	-	-	-	Y	Y	Y	Y	Y
POPSQMILE^2	-	-	-	-	-	Y	Y	Y	Y	Y
Dummies: 2005-2011	-	-	-	-	-	-	Y	Y	-	Y
Fixed County Effects	Y	-	Y	Y	Y	Y	Y	Y	Y	-
Fixed Year Effects	-	-	-	Y	-	-	-	-	Y	-
N	1248	1248	1248	1248	1248	1170	1170	1170	1170	1131
Adjusted R^2	0.547	0.031	0.526	0.588	0.546	0.57	0.582	0.582	0.621	0.019
Levels (L) or first differences (FD)	L	L	L	L	L	L	L	L	L	FD
Outcome: Property UCR Crime										
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Ln(STATEADP)	-0.48	-	-	-	-0.463	-0.48	-0.299	-0.312	-	-0.302
Standard error	0.026	-	-	-	0.027	0.040	0.038	0.037	-	-0.104
Ln(POLICE)	-	-0.237	-0.438	-0.176	-0.171	-0.237	-0.206	-	-0.225	-
Standard error	-	0.056	0.096	0.090	0.093	0.099	0.095	-	0.097	-
Ln(LOCALJAIL)	-	-	-	-	-	Y	Y	Y	Y	Y
POPSQMILE	-	-	-	-	-	Y	Y	Y	Y	Y
POPSQMILE^2	-	-	-	-	-	Y	Y	Y	Y	Y
Dummies: 2005-2011	-	-	-	-	-	-	Y	Y	-	Y
Fixed County Effects	Y	-	Y	Y	Y	Y	Y	Y	Y	-
Fixed Year Effects	-	-	-	Y	-	-	-	-	Y	-
N	1248	1248	1248	1248	1248	1170	1170	1170	1170	1131
Adjusted R^2	0.711	0.764	0.638	0.763	0.713	0.717	0.766	0.764	0.772	0.054
Levels (L) or first differences (FD)	L	L	L	L	L	L	L	L	L	FD

Note: standard errors are White standard errors estimated with EVIEWS 8.

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