A Welfare Analysis of Medicaid and Crime

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Abstract

We calculate conservative estimates for the marginal value of public funds (MVPF) associated with providing Medicaid to inmates exiting prison. Our MVPF estimates, which measure the ratio between the benefits associated with the policy (measured in terms of willingness to pay) and its costs net of fiscal externalities, range between 3.44 and 10.61. A large proportion of the benefits that we account for are related to the reduced future criminal involvement of exiting inmates who receive Medicaid. Using a difference-in-differences approach, we find that Medicaid expansions reduce the average number of times a released inmate is reimprisoned within a year by about 11.5%. We use this estimate along with key values reported elsewhere (e.g., victimization costs, data on victimization and incarceration) to calculate specific benefits from the policy. These include reduced criminal harm due to reductions in reoffenses; direct benefits to former inmates from receiving Medicaid; increased employment; and reduced loss of liberty due to fewer future reimprisonments. Net-costs consist of the cost of providing Medicaid net of changes in the governmental cost of imprisonment; changes in the tax revenue due to increased employment; and changes in spending on other public assistance programs. We interpret our estimates as being conservative, because we err on the side of under-estimating benefits and over-estimating costs when data on specific items are imprecise or incomplete. Our findings are largely consistent with others in the sparse literature investigating the crime-related welfare impacts of Medicaid access, and suggest that public health insurance programs can deliver sizeable indirect benefits from reduced crime in addition to their direct health-related benefits.

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I. Introduction

The ineffectiveness of imprisonment in deterring crime combined with the high costs associated with incarceration has caused policy researchers to seek alternatives to law enforcement in combatting crime (Mungan, 2021). One of the surprising results obtained in recent scholarship investigating such alternatives is that increased access to public health insurance leads to a reduction in crime (Wen, Hockenberry, and Cummings, 2017; Vogler, 2020; He and Barkowski, 2020; Aslim et al., 2022). Although the precise mechanism that leads to such reductions needs to be further examined, there is some evidence suggesting that mental health and substance use disorder treatments can reduce self-control problems, and thereby reduce the impulsive commission of crimes (Aslim et al., 2022). Because these problems are particularly prevalent among exiting inmates who rejoin society (Chamorro et al., 2012; Bronson and Berzofsky, 2017), policies extending public health insurance access to these individuals can carry large social benefits. However, to date, there are few rigorous attempts at measuring these benefits against the cost of such policies where Jácome (2020) and Aslim et al. (2022) are the only exceptions of which we are aware.

Here, we add to this literature by estimating the marginal value of public funds (henceforth 'MVPF') (Hendren and Sprung-Keyser, 2020; Finkelstein and Hendren, 2020) devoted towards providing exiting inmates increased access to public health insurance. To do so, we estimate the social benefits associated with such policies, which consist of the direct benefits from health insurance in addition to reduced criminal harm and reduced loss of liberty due to incarceration as well as increased employment. We then measure these against the costs of supplying health insurance net of additional fiscal externalities (e.g., changes in the governmental cost of imprisonment, tax revenue generated through employment, and spending on public assistance programs). Overall, our analysis suggests conservative estimates of the MVPF associated with these policies ranging between 3.44 and 10.61. Our MVPF ratios are comparable but slightly narrower than those reported by Jácome (2020), which range between 1.77 and 14.96. These ratios can be compared to those reported by Hendren and Sprung-Keyser (2020) for various social insurance programs.[1] For example, the MVPF for providing Medicaid coverage to low-income single adults in the Oregon Health Insurance Experiment is 1.16 (see, also, Finkelstein, Hendren, and Luttmer 2019), whereas expanding Medicaid coverage to young children pays for itself (see, e.g., Brown, Kowalski, and Lurie 2020).

To conduct this analysis, we first estimate the impact of providing an exiting inmate with public health insurance on the number of times they are reimprisoned after their release. We use administrative data on prison admissions and releases from the National Corrections Reporting Program (NCRP). Exploiting the variation in Medicaid expansions across states and over time in a difference-in-differences (DID) framework, we find that Medicaid expansions reduce the average number of times a released inmate is reimprisoned within a year by 11.5%. Combining this estimate with other key values obtained from the existing literature (e.g., average victimization costs for different types of crimes from Cohen and Piquero 2009 and Miller et al. 2021), we estimate the components described above to calculate the MVPF associated with providing exiting inmates increased access to public health insurance.

Our analysis adds to a small body of literature that similarly estimates the cost effectiveness of health insurance in delivering criminal-justice-related benefits. Among existing scholarship, Jácome (2020) is the most closely related analysis to ours. By exploiting the variation in public insurance eligibility, Jácome (2020) finds that losing access to Medicaid eligibility at age 19 increases the likelihood of incarceration among men by 15% in the following two years. Our analysis complements Jácome (2020) while differing from it in several ways. Most importantly, while Jácome (2020) estimates the impact of losing Medicaid eligibility, we analyze the impact of an expansion in this policy under the Affordable Care Act. Moreover, while Jácome's analysis focuses on male teenagers in South Carolina, we analyze data from 43 states available in the NCRP and for all adults aged 25-54. Aslim et al. (2022) also contains a back-of-the-envelope welfare analysis of Medicaid expansions and finds benefit-to-cost ratios ranging between 25% and 135%.

[1] See the Policy Impacts Library to compare MVPF estimates across policies: https://www.policyimpacts.org.

However, Aslim et al. (2022) analyze a shorter period of time and focus on whether an exiting inmate becomes a multi-time recidivist rather than on the average number of times a released inmate is reimprisoned.[2] In the current paper, our ability to analyze a longer period with more data not only helps improve the precision of the estimates but also allows us to investigate an important question that has not been explored before: do the dynamic effects of Medicaid persist in the long run? We answer this question affirmatively by employing methodologies very recently introduced in the DID literature (see, e.g., Sun and Abraham, 2021; Borusyak, Jaravel, and Spiess, 2021; Gardner, 2021). Moreover, our analysis here incorporates a wider range of considerations (e.g., increased employment, reduced loss of liberty, fiscal externalities) to conduct a more precise MVPF analysis, whereas Aslim et al. (2022) reports preliminary findings from a partial cost-benefit analysis. Thus, our results can be interpreted as lending external validity to existing analyses by revealing results that are consistent with the limited prior scholarship.

II. Empirical Analysis

II.A. Data

We obtain administrative data on prison spells from the National Reporting Corrections Program (NCRP), which is collected by the US Bureau of Justice Statistics. Similar to Aslim et al. (2022), we employ the publicly available version of the NCRP.[3] The data include a unique ID number for each inmate, which allows the prisoners to be linked across prison spells within each state. We observe the following characteristics for each inmate: age at release, gender, race/ethnicity, offense of conviction, time served, sentence length, as well as admission and release type.[4] For each prison spell, there is also information on

[2] This difference in outcomes is particularly important in terms of carrying out a more precise MVPF calculation.

[3] Aslim et al. (2022) demonstrate that exploiting the restricted version of the data, which includes more disaggregated information on inmate characteristics and admission date, yields very similar estimates to those obtained from the publicly available version in the context of Medicaid expansions. The restricted version is not available for general dissemination given the level of information (e.g., last known address) on each offender. See Aslim et al. (2022) for additional details on data.

[4] Due to missing information on highest grade completed in the current version of NCRP employed in this study, we instead exploit data from the American Community Survey (2009-2019) to construct

admission and release year as well as inmate characteristics.

Exploiting the information on prison spells, we define reimprisonments as the number of times a released inmate is reimprisoned within 1-, 2-, and 3-years. To prevent our policy from interacting with other social insurance programs, we use observations from inmates aged 25-54.[5] Following Agan and Makowsky (2018), we also exclude the state of California due to the state's attempt at reducing prison overcrowding through the Public Safety Realignment Act. Overall, our data consist of an unbalanced panel of inmates released in 43 states between the years 2009 and 2019.[6]

Tables A1 and A2 report summary statistics for reimprisonments and inmate characteristics, respectively. A few notable observations are the following. The number of reimprisonments in expansion states declines, on average, in the post-treatment period for the all-crime sample (including violent, property, drug, and public order crimes). The difference in the post- and pre-treatment mean is also statistically significant ($p < 0.01$). This decline appears to be driven by inmates who were initially imprisoned for violent and public order crimes. These findings are preserved when we employ a longer window for reimprisonments. More importantly, we do not observe similar trends in non-expansion states.

II.B. Empirical Methodology

To examine the causal impact of the ACA Medicaid expansions on the number of times a released inmate is, on average, reimprisoned, we estimate the following generalized difference-in-differences (DID) model:

$$Reimprisonment_{ist} = \beta_0 + \zeta_s + \eta_t + \beta_1 Expansion_{st} + \mathbf{X}_{ist}\mathbf{\Gamma}_1 + \mathbf{\Omega}_{st}\mathbf{\Gamma}_2 + \epsilon_{ist}, \qquad (1)$$

educational attainment at the state level.

[5]Specifically, we want to prevent our policy variable from interacting with the dependent coverage mandate under the ACA as well as Medicare. Since our age variable is categorical, we employ the most plausible restriction.

[6]Since we do not observe a full prison spell for the last year in our data (e.g., inmates released in June 2019), those observations are not used in the construction of our outcome variable. We also do not take into account the observations if the release type is coded as death.

where $Reimprisonment_{ist}$ measures the number of times inmate i, after being released from their first incarceration in state s and year t, has been reimprisoned. We construct the number of reimprisonments within 1-, 2-, and 3-year windows by the category of crime for which an inmate was initially imprisoned: violent, property, drug, or public order. $Expansion_{st}$ denotes the treatment status of an inmate based on the first release year and conviction state. Our main coefficient of interest is β_1, which measures the causal effect of the ACA Medicaid expansions on the number of times previously incarcerated inmates are reimprisoned. To identify the causal effects, we exploit the staggered adoption of Medicaid expansions and compare the outcomes of expansion states with those in the control group that have not been affected by the treatment. Following standard procedures in the literature, we examine the assumption of parallel trends between treated and never-treated (or last-treated) states by conducting a series of event studies.

A rich set of inmate-level covariates are included in the equation. Specifically, the vector $\mathbf{X}_{ist}$ contains an inmate's age at release, gender, and race/ethnicity. We also control for variables that describe the characteristics of the most recent crime(s) committed by an inmate, including sentence length, time served in prison, types of prison admission (court commitment, parole violation, other) and release (conditional release, unconditional release, other). Moreover, to alleviate concerns about state-level confounders, we control for a number of time-varying variables that gauge macroeconomic conditions for each state over time, including the minimum wage, housing price index, poverty rate, and the unemployment rate.[7] We also control for educational attainment at the state level.[8] We use $\mathbf{\Omega}_{st}$ to denote these state-level control variables. ζ_s and η_t capture the state fixed effects and release-year fixed effects, respectively. ϵ_{ist} is the error term. Robust standard errors are clustered at the state level.

We conduct a battery of robustness tests to examine the validity of our empirical re-

[7]The implicit assumption here is that these covariates are not caused by the treatment itself. Caetano et al. (2022) show that this assumption is implausible in various applications, leading to biased estimates of the average treatment effect on the treated (ATT), even in cases of canonical (two-period) DID models. We later test the validity of our assumption by (i) employing specifications without time-varying control variables and (ii) exploiting "imputation estimators" that address potential bias caused by controlling for time-varying covariates (see, e.g., Borusyak, Jaravel, and Spiess, 2021; Gardner, 2021). This approach is similar to the regression adjustment-type strategies proposed by Caetano et al. (2022).

[8]Excluding educational attainment in the regression analysis does not affect our results.

sults in terms of both estimation and inference. First, in all benchmark models, standard errors are clustered at the state level with 43 clusters. While the number of clusters is not small, we provide p-values obtained from wild cluster bootstrap iterations to check the sensitivity of our baseline inference. Second, we implement a randomization inference procedure where treatment status is randomly assigned to states based on the actual number of expansion and non-expansion states in each year from the working sample. We re-estimate Equation (1) using the newly constructed sample and calculate p-values from 1,000 replications of this process. We report these randomization inference p-values for all benchmark regressions.

In terms of estimation, we present point estimates from the static specification by exploiting two separate estimators other than the OLS estimator. The traditional two-way fixed model produces biased estimates of the average treatment effect on the treated (ATT) when there is treatment heterogeneity (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021). Intuitively, the bias stems from using already-treated units as a control, e.g., later treated units versus earlier treated units, in which the changes in treatment effects get netted out from the DID estimate. This may be less of a concern for Medicaid expansions due to (i) having a relatively large never-treated group and (ii) the timing for most treated units being closer to the middle of our sample period (Goodman-Bacon, 2021). Nonetheless, we check the robustness of our estimates by using two different imputation strategies provided by Borusyak, Jaravel, and Spiess (2021) and Gardner (2021), respectively. These imputation estimators also allow for (i) the time-varying effects of our macroeconomic variables and (ii) the possibility of Medicaid expansions affecting these covariates. For the dynamic specification, we further provide estimates using the Sun and Abraham estimator (Sun and Abraham, 2021) to avoid contamination in leads and lags from other periods. We exclude (time-varying) macroeconomic variables in the dynamic specification to show that our approach does not necessitate *conditional* parallel trends.

II.C. Empirical Results

The validity of our identification strategy hinges on the assumption that the path of treated and untreated potential outcomes evolve in a parallel fashion (i.e., the parallel trends assumption). Although this assumption is not directly testable, in practice, it is critical to examine whether the treatment and control groups have parallel trends in the potential outcomes prior to the treatment. Therefore, we begin our empirical analysis by presenting the estimates from the dynamic specification, which depicts the trends in the number of reimprisonments between expansion and non-expansion states. We report the estimates in Figures 1, A1, and A2 for different time windows of our outcome variable and the type of crime. In each specification, we report OLS estimates as a benchmark. To obtain an appropriate weighted average of treatment effects for each state and each relative time pre- or post-expansion, we also exploit the interaction-weighted estimator developed by Sun and Abraham (2021), and report the corresponding estimates in each figure.

Figure 1 reports the event study results for the number of reimprisonments within a year. We do not find any evidence of statistically significant pre-trends between expansion and non-expansion states across specifications. Moreover, results obtained by using the OLS and the Sun and Abraham estimators are consistent with each other. Figure 1a suggests that Medicaid expansions reduce the number of reimprisonments for the all-crimes sample. Perhaps more interestingly, there seems to be a dynamic effect over time as the ATTs gradually increase after states expand Medicaid coverage. We further decompose the outcome by the type of crime and present the findings in Figures 1b-1e. It is clear that the reduction in the number of reimprisonments is most salient among released inmates who were incarcerated for committing violent crimes. We show similar patterns among inmates imprisoned for public order crimes, albeit with slightly lower statistical significance. While there is no statistically meaningful effect detected right after the treatment for property and drug crimes, there seems to be a weak reduction in reimprisonments at the end of the treatment period in our working sample.

We present the estimates for 2- and 3-year windows of reimprisonment in Figures A1 and A2, respectively. Our findings are quantitatively and qualitatively similar to the analysis using reimprisonments within a year. Summarily, the event studies support the validity of our identification strategy and indicate that Medicaid expansions reduce the number of reimprisonments over time.

We next estimate the static specification in Equation (1) and report the estimates in Table 1. Following our approach above, we report the results for various time windows and by the category of crime. Because ATTs could be biased if the treatment affects time-varying covariates, we separately report results obtained from models with and without time-varying macroeconomic covariates. In all specifications, we include state and release-year fixed effects as well as inmate characteristics.[9]

Panel A of Table 1 presents the results for the number of reimprisonments in a year. In the absence of time-varying macroeconomic covariates, column (1) suggests that the Medicaid expansions have a negative and statistically significant effect on the number of reimprisonments among the overall population of inmates. Specifically, Medicaid expansions reduce the number of reimprisonments by 0.026 ($p < 0.05$). This implies a 13.5% decline in the number of reimprisonments relative to the average number of reimprisonments prior to the treatment. On the other hand, the specification that includes time-varying covariates implies a reduction in the number of reimprisonments of 11.5% (0.022/0.192, $p < 0.05$).

We present the ATTs by the type of crime in columns (3)-(10). We find a substantial reduction in reimprisonment when we restrict our sample to violent and public order crimes. Quite importantly, the results show that the Medicaid expansions reduce the number of reimprisonment by about 14.6% (0.026/0.178, $p < 0.05$) and 18.4% (0.035/0.190, $p < 0.01$) among inmates who were initially imprisoned for violent and public order crimes, respectively. In contrast, we find negative but statistically insignificant effects for property and drug crimes.

Our results suggest that Medicaid expansions lead to similar reductions in the number

[9] Our estimates are not sensitive to the exclusion of inmate characteristics.

of reimprisonments within 2- and 3-year windows, as shown in Panels B and C, respectively. In comparison with the number of reimprisonments in a year, the estimated effects are larger when employing longer windows across different samples. However, the statistical significance of the corresponding estimates is weaker in all samples, mainly due to reduced sample size and increased standard errors. Specifically, the point estimates remain statistically significant in all models except those employing the 3-year window for all crimes, as shown in columns (1) and (2) in Panel C. On the other hand, we continue to find no evidence of a statistically meaningful effect of Medicaid expansions among inmates who were initially imprisoned for property or drug crimes, albeit having a negative coefficient. This result complements the findings of Aslim et al. (2022).

To check the sensitivity of our inference, we report the *p*-values obtained from the randomization inference and wild bootstrap iterations for all regressions. One can easily observe that these *p*-values from alternative approaches largely support our baseline findings. In addition, as shown in Table A3, the point estimates obtained from the two other imputation methods are very similar to our baseline estimates reported in Table 1.

Taken together, our results indicate that the Medicaid expansions significantly reduce the number of reimprisonments among inmates in expansion states. This is mainly driven by inmates imprisoned for violent or public order crimes. The estimates are larger but less precise when a longer window is employed for the number of reimprisonments. Moreover, the ATTs obtained using alternative estimators are remarkably consistent with our baseline results, suggesting that the current approach for evaluating the effects of Medicaid expansions is insulated from the bias resulting from treatment heterogeneity.

II.D. Marginal Value of Public Funds

Exploiting the causal estimates in Table 1, we next evaluate the welfare implications of providing Medicaid coverage to released inmates under the ACA. Following Finkelstein, Hendren, and Luttmer (2019) and Hendren and Sprung-Keyser (2020), we use the marginal value of public funds (MVPF) framework to quantify the welfare effects of Medicaid expansions. The MVPF generally measures the ratio between the willingness to pay for a policy and the net cost of the policy to the government. As the MVPF gets larger, it generates more welfare per dollar spent. Since market distortions from raising government revenue are not internalized in the MVPF, this measure is commonly used to compare two policies to inform relative cost effectiveness. We obtain the MVPF for the expansion of Medicaid coverage using the following expression:

$$MVPF = \frac{WTP}{MC + FE}, \tag{2}$$

In Equation (2), WTP measures society's willingness to pay for expanding Medicaid coverage to released inmates. MC is the mechanical costs associated with this policy change, and FE covers fiscal externalities. Put differently, the denominator of the MVPF measures the net cost of the policy to the government. In the following sections, we discuss how we calculate each component of the MVPF. We present all values in 2020 dollars.

1. Willingness to Pay for the Policy

We begin our analysis by calculating WTP, which is society's willingness to pay for the policy. Specifically, the willingness to pay contains four parts in our analysis: (i) the willingness to pay for fewer criminal victimizations; (ii) the willingness to pay for improved labor market prospects; (iii) the willingness to pay for the value of public insurance transfer; and (iv) the willingness to pay for avoiding incarceration.

To obtain a measure of willingness to pay for fewer criminal victimizations, we measure the reduction in social costs through averted victimizations per released inmate in expansion states. We present these averted social costs in Table 2.[10]

Our general approach towards calculating these averted costs is to estimate the reduction in the number of victimizations caused by Medicaid expansions and multiply them by the average victimization costs associated with each crime category (violent, property, drug, public order).

The reduction in the number of victimizations within each category is the product of

[10] In the Appendix, we provide a more detailed derivation of the average social cost averted per crime as well as further explanations of victimization costs.

three components, namely (i) the average reduction in the number of reimprisonments, (ii) the proportion of reimprisonment for each crime category, and (iii) the victimization-to-incarceration ratio for each category. For the first component, we use the reductions in the number of reimprisonments in a year, i.e., the estimate reported in Panel A, column (2) of Table 1, which is -0.022. For the second component, we calculate the share of reimprisonments for each category of crime in our working sample, which are reported in the first column of Table 2. We calculate the third component, when possible,[11] as shown in Table A5 by drawing data from the National Crime Victimization Survey, National Prisoner Statistics, and the Supplementary Homicide Reports.[12]

The average victimization costs for each crime category are calculated by multiplying two components, namely (i) the cost of each type of crime within a category (e.g., murder, rape, robbery, aggravated or simple assault, for violent crimes), and (ii) the within-category weights associated with each crime type. We obtain lower and upper bound estimates for the first component from Cohen and Piquero (2009) and Miller et al. (2021), respectively. We calculate the second component by using data presented in Jácome (2020), as explained in Table A4.

Following this method, we obtain estimates of averted victimization costs for each category of crime. To calculate the total social cost per inmate, we sum the costs averted per inmate over the four crime categories. Using the lower and upper bound victimization costs, we estimate the total social cost per inmate as $14,934 and $21,562, respectively.

The second part of WTP is the willingness to pay for improved labor market prospects. We obtain this measure by estimating foregone income during incarceration. Specifically, we let the income loss during incarceration equal $q \times p^J \times$ the employment rate of low-income adults $\times$ the average annual income of low-income adults $\times$ the average sentence served, where q is our causal estimate of the reduction in the number of reimprisonments, and p^J is the share of reimprisonments for category $J \in \{$Violent, Property, Drug, and Public Order$\}$. Moreover, we draw data from the American Community Survey (2009-

[11] Because data on victimizations are not available for drug and public order crimes, we assume victimization-to-incarceration ratio to be 1 for these categories to obtain conservative estimates of averted costs.

[12] See the notes in Table A5 for an explanation about sources.

2013) to measure the employment rate and the average annual income of low-income adults (below 138% of the federal poverty level, which is the means-tested threshold for Medicaid coverage under the ACA). We separately calculate income loss during incarceration for the specific J categories of crime since sentence length varies by J. Then, the total income loss is simply the summation of lost earnings over these categories. Our upper bound estimate of foregone income is \$307. To be conservative, we define the lower bound of foregone income as \$0, assuming that the inmate is unemployed prior to incarceration.

The third part of WTP is the willingness to pay for the value of public insurance transfer. The value of public insurance transfer consists of two components: (i) the value of Medicaid to the recipient, and (ii) the cost of uncompensated care that would be received by uninsured inmates. For the value of Medicaid to the recipient, we use Finkelstein, Hendren, and Luttmer (2019)'s estimate of 20% to 48% of the cost of Medicaid (denoted G).[13] We obtain the Medicaid average cost per beneficiary from the Centers for Medicare & Medicaid Services (CMS), which is \$5,873. We take 48% $\times$ G as the upper bound for the value of Medicaid per beneficiary. On the other hand, we define the lower bound of our WTP measure for Medicaid as 20% $\times$ G plus the average cost of uncompensated care per uninsured adults during the pre-ACA period (\$1,577).[14]

Finally, we consider the willingness to pay to avoid being incarcerated, which measures the value attached to liberties outside of prison. For the lower bound, we assume that ex-offenders are willing to pay \$0 to avoid incarceration. For the upper bound, we extract the value of willingness to pay to leave pretrial detention from Abrams and Rohlfs (2011), which is \$4,603 per year (measured in 2020 dollars). We then calculate the willingness to pay to leave prison based on our causal estimate q, the share of reimprisonments for category J crimes, p^J, and the average sentence served in prison for these different crime

[13] Finkelstein, Hendren, and Luttmer (2019) further show that Medicaid resource costs are 0.4 $\times G$, and estimate the WTP for Medicaid to range between 0.5 and 1.2 $\times$ Medicaid resource costs, which is equivalent to 0.2 and 0.48 $\times$ G.

[14] We obtain the average cost of uncompensated care from the Kaiser Family Foundation (KFF). See Tables 1 and 2 in the following report: https://bit.ly/3sFEnKb. The main source for the number of uninsured is also KFF. See Figure 1 in the following report: https://bit.ly/3qoqopy. We do not find a substantial difference in the pre-ACA ratio (\$1,577) and the post-ACA ratio (\$1,628).

categories, which results in an upper bound estimate of \$242.[15]

Aggregating all components of WTP together, the total value of willingness to pay for the policy change ranges between \$17,686 to \$24,930.

2. Mechanical Costs & Fiscal Externalities

Now, we turn our focus to the denominator of MVPF which measures the net cost to the government for expanding Medicaid coverage to one more recipient. As shown in Equation (2), the denominator consists of two components. The first component is the mechanical costs of the policy change. Finkelstein, Hendren, and Luttmer (2019) show that 60% of the cost of Medicaid is used for covering the uncompensated care spending for uninsured individuals. Consequently, if government bears the cost of uncompensated care, the total cost of providing Medicaid drops to $0.4 \times G$. If, however, individuals bear the cost of uncompensated care, then the cost of Medicaid is simply G.

Following Jácome (2020), the lower bound estimate includes the total cost of Medicaid, G, assuming that individuals bear the cost of uncompensated care. For the upper bound, our estimated cost of providing Medicaid is equal to the total cost of Medicaid, G, minus the average cost of uncompensated care per uninsured adults. Our calculations show that the cost of providing Medicaid to an incarcerated individual ranges between \$4,296 and \$5,873.

Next, we estimate the second component of the denominator by gauging three types of fiscal externalities to the government resulting from the Medicaid expansions. To start our analysis, we first look at the spending on public assistance programs that are usually provided to low-income individuals, including the Supplemental Nutrition Assistance Program (SNAP) and the Temporary Assistance for Needy Families (TANF). Consistent with our objective of providing conservative MVPF estimates, we note that released inmates may be more likely to rely on public assistance programs (Mueller-Smith, 2015).

[15]Specifically, the calculation is as follows: The willingness to pay to avoid being incarcerated = $\sum_J (q \times p^J \times$ avg. time of sentence served $\times$ the willingness to pay to leave detention). As mentioned before, q is 0.022; p^J takes the values of 20.93%, 32.95%, 27.34%, and 18.78% for violent, property, drug, and public order, respectively; and the WTP for leaving detention is \$4,603 in 2020 dollars. Moreover, the average years of sentence served is 4.8 years for violent crimes. For property, drug, and public order crimes, the average years of sentence served is 1.75 years (Kaeble, 2021).

Therefore, reduced incarceration can increase the costs of these programs to the government, which need to be added as fiscal externalities in the denominator of Equation (2).[16] To take these possible fiscal externalities into account, we obtain participation and cost data on SNAP and TANF for the periods 2011-2013 from the US Department of Agriculture Food and Nutrition Service and the US Department of Health & Human Services Office of Family Assistance, respectively.[17] Exploiting these data, our larger estimate for the increased spending on public assistance is q × average total spending (on SNAP + TANF) per person, which is \$54. Using the take-up rate of public assistance among felons reported by Sugie (2012) as a weight, we estimate a lower weighted average of spending on SNAP and TANF as \$24.[18]

Another type of fiscal externality to the government is the averted costs due to fewer incarcerations. To calculate the costs related to incarceration, we employ the following equation: $\sum_J (q \times p^J \times$ average time served $\times$ average daily cost per inmate$)$. We replace the average daily cost per inmate with the marginal daily cost per inmate in our alternative set of calculations. Note that the average time served in prison varies by crime category. For the upper bound, we follow Aslim et al. (2022) and use the average daily cost per inmate reported by the Vera Institute of Justice.[19] Specifically, the average daily cost per inmate is \$99.56. For the lower bound, following Jácome (2020), we use the marginal cost of incarcerating an individual for one year reported by Owens (2009), and estimate the marginal daily cost per inmate to be around \$41.2. Overall, the averted costs for the government due to fewer incarcerations range from \$788 to \$1,909.

For the last type of fiscal externality, we estimate foregone tax revenue. To calculate the forgone tax revenue due to inmates' lost employment, we utilize an average tax rate of 20% on personal income (Hendren and Sprung-Keyser, 2020) for the upper bound.

[16]Because we err on the side of providing conservative estimates, we do not account for the benefits receivable by released inmates from TANF and SNAP in calculating the numerator of the MVPF.

[17]Participation and cost data for SNAP can be obtained here: https://bit.ly/3iVtzlo, while similar data for TANF are available here: https://bit.ly/3qTdkcF.

[18]Specifically, we calculate the greater estimate by using the following formula: q × (0.19 × Average Total Spending on TANF (2011-2013)/Total Recipients + 0.55 × Average Total Spending on SNAP (2011-2013)/Total Recipients). Note that these cost estimates are in the denominator of Equation (2), and therefore the larger estimate yields a conservative estimate of MVPF.

[19]Prison spending data can be obtain here: https://bit.ly/3uDdGFm.

Consequently, the foregone tax revenue is equal to 0.2 $\times$ the willingness to pay for improved labor market prospects defined above, leading to an upper bound of \$61. For our more conservative estimate, we consider foregone tax revenue to be \$0.

In Figure A3, we use our dynamic DID design to depict how net costs associated with the provision of Medicaid to exiting inmates varies over time. Consistent with our baseline analysis, we observe a declining trend in mechanical costs net of fiscal externalities.

3. Estimates of MVPF

Our analysis yields an estimate for the net costs to the government for expanding Medicaid coverage per eligible inmate ranging from \$2,350 to \$5,139. Combining these net costs with our previously estimated benefits for the policy change, we find the MVPF to be between 3.44 and 10.61. These numbers are largely consistent with Jácome (2020), who estimates the impact of Medicaid eligibility loss among men at age 19 in South Carolina. However, our slightly narrower estimates pertain to the impact of Medicaid expansions across multiple states and for all adults aged 25-54.

III. Conclusion

A recent and expanding body of work finds that increased access to health insurance generates sizeable indirect benefits due to its crime reducing effect. Here, we add to this scholarship by estimating the marginal value of public funds associated with providing Medicaid to exiting inmates, and find that doing so generates benefits that are at least three times as large as the net-costs of providing Medicaid and are in all likelihood much greater. This places the provision of Medicaid to exiting inmates among the most welfare-enhancing policies whose marginal value of public funds have recently been estimated and reported (Hendren and Sprung-Keyser, 2020). Thus, the indirect benefits associated with expanding health insurance ought to be considered in contemporary health policy debates, and counsel in favor of policies whose effect would be an expansion of access to public health insurance for exiting inmates.

References

Abrams, David S and Chris Rohlfs. 2011. "Optimal bail and the value of freedom: Evidence from the Philadelphia bail experiment." *Economic Inquiry* 49 (3):750–770.

Agan, Amanda Y and Michael D Makowsky. 2018. "The Minimum Wage, EITC, and Criminal Recidivism." NBER Working Paper, No. 25116.

Aslim, Erkmen G, Murat C Mungan, Carlos I Navarro, and Han Yu. 2022. "The effect of public health insurance on criminal recidivism." *Journal of Policy Analysis and Management* 41 (1):45–91.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2021. "Revisiting event study designs: Robust and efficient estimation." ArXiv preprint arXiv:2108.12419.

Bronson, Jennifer and Marcus Berzofsky. 2017. "Indicators of Mental Health Problems Reported by Prisoners and Jail Inmates, 2011-12." U.S Department of Justice, Office of Justice Programs, Bureau of Justice Statistics. Accessed at https://bit.ly/2rVBTcF.

Brown, David W, Amanda E Kowalski, and Ithai Z Lurie. 2020. "Long-term impacts of childhood Medicaid expansions on outcomes in adulthood." *Review of Economic Studies* 87 (2):792–821.

Caetano, Carolina, Brantly Callaway, Stroud Payne, and Hugo Sant'Anna Rodrigues. 2022. "Difference in Differences with Time-Varying Covariates." ArXiv preprint arXiv:2202.02903.

Callaway, Brantly and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics* 225 (2):200–230.

Chamorro, Jaime, Silvia Bernardi, Marc N Potenza, Jon E Grant, Rachel Marsh, Shuai Wang, and Carlos Blanco. 2012. "Impulsivity in the general population: a national study." *Journal of Psychiatric Research* 46 (8):994–1001.

Cohen, Mark A and Alex R Piquero. 2009. "New evidence on the monetary value of saving a high risk youth." *Journal of Quantitative Criminology* 25 (1):25–49.

Couloute, Lucius and Daniel Kopf. 2018. "Out of prison & out of work: Unemployment among formerly incarcerated people." Prison Policy Initiative. Accessed at: https://www.prisonpolicy.org/reports/outofwork.html.

De Chaisemartin, Clément and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110 (9):2964–96.

Finkelstein, Amy and Nathaniel Hendren. 2020. "Welfare analysis meets causal inference." *Journal of Economic Perspectives* 34 (4):146–67.

Finkelstein, Amy, Nathaniel Hendren, and Erzo FP Luttmer. 2019. "The value of medicaid: Interpreting results from the oregon health insurance experiment." *Journal of Political Economy* 127 (6):2836–2874.

Gardner, John. 2021. "Two-stage differences in differences." Working Paper, University of Mississippi.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics* 225 (2):254–277.

He, Qiwei and Scott Barkowski. 2020. "The Effect of Health Insurance on Crime: Evidence from the Affordable Care Act Medicaid Expansion." *Health Economics* :1–17.

Heckman, James J, Seong Hyeok Moon, Rodrigo Pinto, Peter A Savelyev, and Adam Yavitz. 2010. "The rate of return to the HighScope Perry Preschool Program." *Journal of Public Economics* 94 (1-2):114–128.

Hendren, Nathaniel and Ben Sprung-Keyser. 2020. "A unified welfare analysis of government policies." *Quarterly Journal of Economics* 135 (3):1209–1318.

Jácome, Elisa. 2020. "Mental Health and Criminal Involvement: Evidence from Losing Medicaid Eligibility." Working Paper, Princeton University.

Kaeble, Danielle. 2021. “Time Served in State Prison, 2018.” US Department of Justice, Office of Justice Programs, Bureau of Justice.

Meier, Robert Frank and Gilbert Geis. 1997. *Victimless Crime?: Prostitution, drugs, homosexuality, abortion.* Roxbury Publishing.

Miller, Ted R, Mark A Cohen, David I Swedler, Bina Ali, and Delia V Hendrie. 2021. “Incidence and Costs of Personal and Property Crimes in the USA, 2017.” *Journal of Benefit-Cost Analysis* 12 (1):24–54.

Mueller-Smith, Michael. 2015. “The criminal and labor market impacts of incarceration.” Working Paper, University of Michigan.

Mungan, Murat C. 2021. “Rewards versus Imprisonment.” *American Law and Economics Review* 23 (2):432–480.

Owens, Emily G. 2009. “More time, less crime? Estimating the incapacitative effect of sentence enhancements.” *Journal of Law and Economics* 52 (3):551–579.

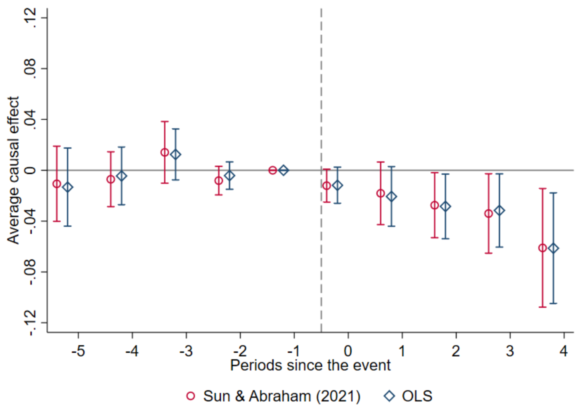
Sugie, Naomi F. 2012. “Punishment and welfare: Paternal incarceration and families’ receipt of public assistance.” *Social Forces* 90 (4):1403–1427.

Sun, Liyang and Sarah Abraham. 2021. “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects.” *Journal of Econometrics* 225 (2):175–199.

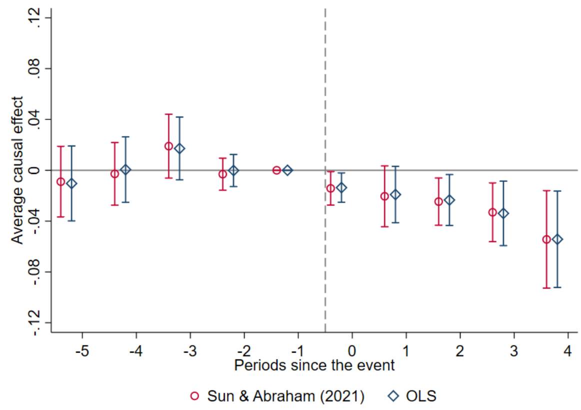
Vogler, Jacob. 2020. “Access to Health Care and Criminal Behavior: Evidence from the ACA Medicaid Expansions.” *Journal of Policy Analysis and Management* 39 (4):1166–1213.

Wen, Hefei, Jason M Hockenberry, and Janet R Cummings. 2017. “The Effect of Medicaid Expansion on Crime Reduction: Evidence from HIFA-Waiver Expansions.” *Journal of Public Economics* 154:67–94.

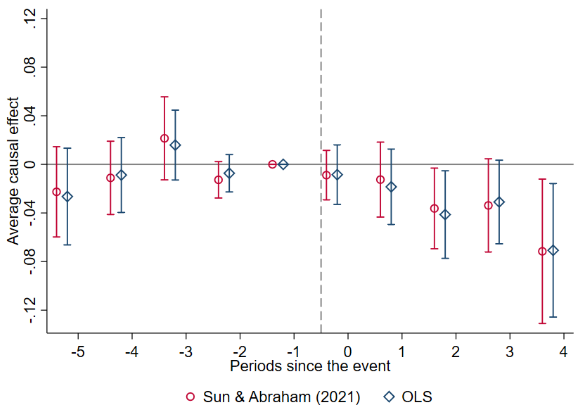
Yu, Han and Naci Mocan. 2019. "The impact of high school curriculum on confidence, academic success, and mental and physical well-being of university students." *Journal of Labor Research* 40 (4):428–462.



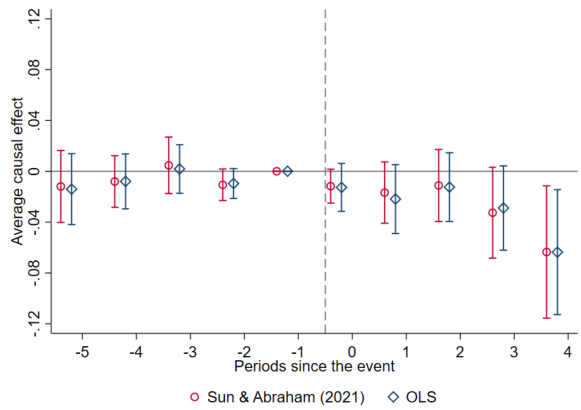
(a) All Crimes



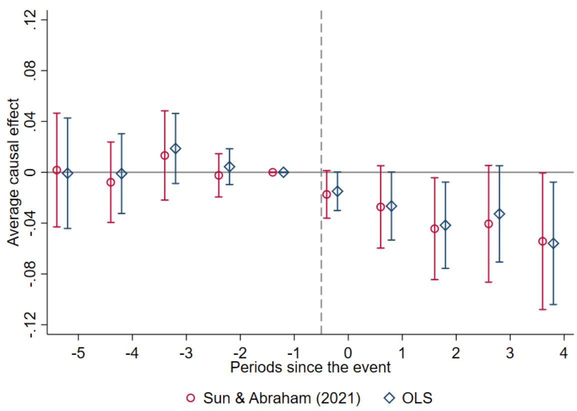
(b) Violent Crimes



(c) Property Crimes



(d) Drug Crimes



(e) Public Order Crimes

Figure 1. Dynamic Difference-in-Differences - Medicaid Expansions and the Number of Reimprisonments (1-Year)

Notes: The figure contains event study results for the effect of the ACA Medicaid expansions on the number of reimprisonments within a 1-year window. The horizontal axis shows relative event years. The vertical axis shows the average treatment effect on the treated (ATT). We report estimates using both the OLS and the interaction-weighted estimator proposed by Sun and Abraham (2021). We report the 95% confidence intervals in the figure.

Table 1. Static Difference-in-Differences - Medicaid Expansions and the Number of Reimprisonments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: 1-Year Window	**All**		**Violent**		**Property**		**Drug**		**Public Order**	
Expansion	-0.026**	-0.022**	-0.029***	-0.026**	-0.022	-0.019	-0.020	-0.015	-0.035**	-0.035***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.011)
Randomization Inference p-value	0.016	0.042	0.001	0.011	0.060	0.095	0.075	0.190	0.009	0.004
Wild Bootstrap p-value	0.033	0.064	0.006	0.013	0.146	0.208	0.164	0.351	0.008	0.002
Mean of Dependent Variable	0.196	0.196	0.177	0.177	0.241	0.241	0.178	0.178	0.191	0.191
N	1,768,232	1,768,232	513,608	513,608	438,782	438,782	502,062	502,062	313,780	313,780
Panel B: 2-Year Window										
Expansion	-0.026*	-0.027*	-0.030**	-0.034**	-0.022	-0.026	-0.016	-0.015	-0.044**	-0.045***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)	(0.017)	(0.015)	(0.016)	(0.018)	(0.016)
Randomization Inference p-value	0.039	0.045	0.015	0.015	0.119	0.094	0.160	0.231	0.010	0.005
Wild Bootstrap p-value	0.069	0.079	0.040	0.020	0.238	0.168	0.339	0.456	0.013	0.008
Mean of Dependent Variable	0.296	0.296	0.272	0.272	0.361	0.361	0.272	0.272	0.285	0.285
N	1,606,648	1,606,648	463,207	463,207	399,959	399,959	457,084	457,084	286,398	286,398
Panel C: 3-Year Window										
Expansion	-0.024	-0.029	-0.034*	-0.042**	-0.018	-0.026	-0.008	-0.013	-0.045*	-0.043**
	(0.018)	(0.017)	(0.017)	(0.017)	(0.023)	(0.023)	(0.019)	(0.020)	(0.024)	(0.019)
Randomization Inference p-value	0.095	0.058	0.025	0.007	0.210	0.135	0.347	0.290	0.031	0.016
Wild Bootstrap p-value	0.193	0.111	0.067	0.017	0.476	0.280	0.724	0.587	0.047	0.027
Mean of Dependent Variable	0.374	0.374	0.345	0.345	0.455	0.455	0.344	0.344	0.358	0.358
N	1,439,707	1,439,707	412,414	412,414	359,132	359,132	410,085	410,085	258,076	258,076
State Fixed Effects	√	√	√	√	√	√	√	√	√	√
Release-Year Fixed Effects	√	√	√	√	√	√	√	√	√	√
State-Specific Time-Varying Controls	×	√	×	√	×	√	×	√	×	√

Notes: This table reports the static difference-in-differences estimates using the OLS estimator. Different panels correspond to various time windows (1-, 2-, and 3-year windows) of the outcome variable. Crime categories refer to the first offense type that end with an imprisonment. State-specific time-varying controls include the minimum wage, housing price index, the unemployment rate, poverty rate, and educational attainment. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Social Costs per Released Inmate

Reoffense Type	Within-Category Weights (w_i^J, %) (1)	Estimated Social Cost Based On: Cohen & Piquero (2009) (2)	Miller et al. (2021) (3)
Violent Crimes (20.93% of all reoffenses)			
Murder	3.33	5,740,800	8,089,301
Rape	4.50	168,480	239,095
Robbery	48.83	14,976	28,592
Aggravated or simple assault	43.34	12,069	28,971
Exp. Cost Averted per Inmate (Violent Crimes)		14,100	20,464
Property Crimes (32.95% of all reoffenses)			
Larceny	17.47	562	2,730
Burglary	72.96	2,496	2,571
Motor vehicle theft	9.57	6,864	8,949
Exp. Cost Averted per Inmate (Property Crimes)		808	1,006
Drug Crimes (27.34% of all reoffenses)	100	0	5,387
Exp. Cost Averted per Inmate (Drug Crimes)		0	32
Public Order Crimes (18.78% of all reoffenses)	100	12,133	14,577
Exp. Cost Averted per Inmate (Public Order Crimes)		26	60
Total Social Cost per Inmate		14,934	21,562

Notes: Within-category weights (w_i^J) are calculated using the share of arrests for each sub-crime category and the average victimization-to-arrest ratios from Jácome (2020). See Table A4 for technical details. The estimated lower bound costs come from Cohen and Piquero (2009) (Table 5, inflated to 2020 dollars). The estimated upper bound costs come from Miller et al. (2021) (Table 5, inflated to 2020 dollars). See the Appendix for a detailed explanation on average victimization (social) costs by crime categories.

Table 3. Marginal Value of Public Funds (MVPF)

	Estimated Cost	
	(1)	(2)
Willingness to Pay:		
Fewer crime victimizations	\$14,934	\$21,562
Improved labor market prospects	\$0	\$307
Value of insurance transfer	\$2,752	\$2,819
Avoiding incarceration	\$0	\$242
Aggregate willingness to pay:	\$17,686	\$24,930
Costs to the Government:		
Cost of providing Medicaid	\$5,873	\$4,296
Public assistance	\$54	\$24
Fewer incarcerations	-\$788	-\$1,909
Foregone tax revenue	-\$0	-\$61
Net Cost:	\$5,139	\$2,350
Marginal Value of Public Funds:	3.44	10.61

Notes: This table shows the welfare implications of providing Medicaid to a released inmate under the Affordable Care Act. Columns (1) and (2) report the lower and upper bound estimates for the marginal value of public funds (MVPF), respectively. The lower bound provides a conservative estimate for the MVPF ratio. We adjust the estimated values to 2020 dollars.

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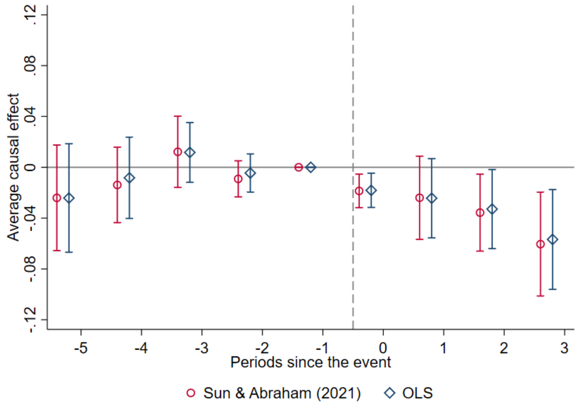
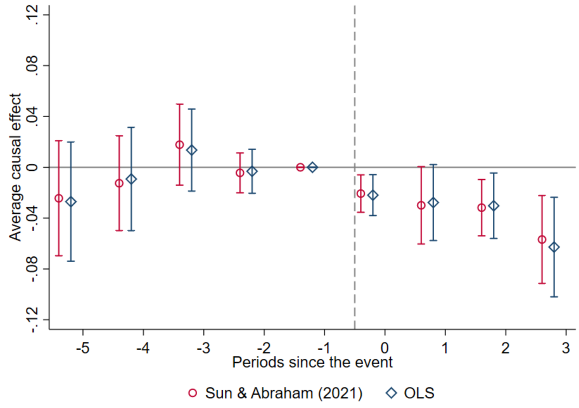
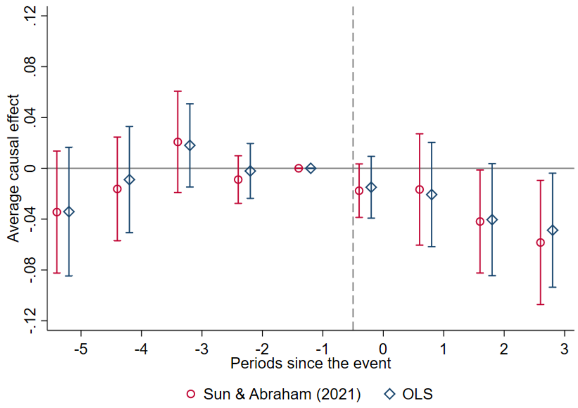


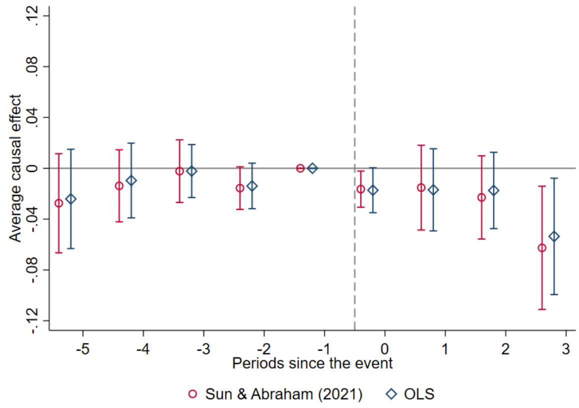
(a) **All Crimes**



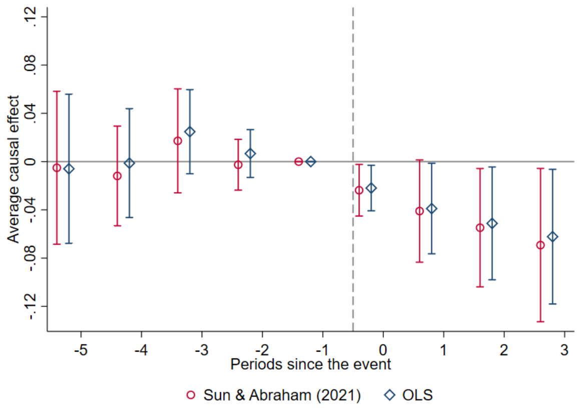
(b) **Violent Crimes**



(c) **Property Crimes**



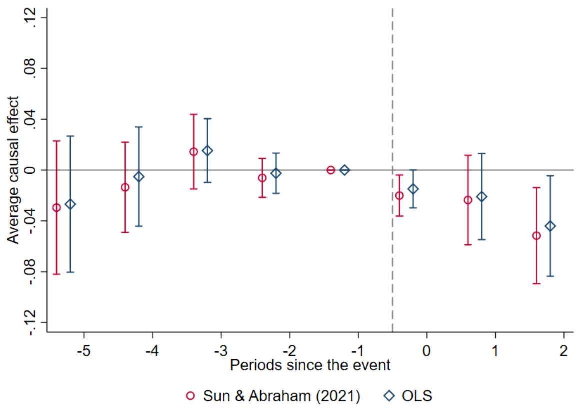
(d) **Drug Crimes**



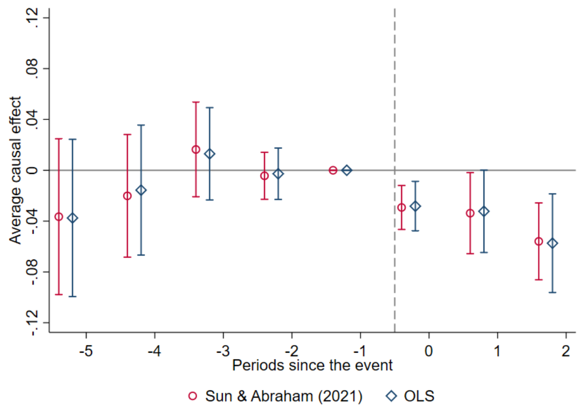
(e) **Public Order Crimes**

Figure A1. Dynamic Difference-in-Differences - Medicaid Expansions and the Number of Reimprisonments (2-Year)

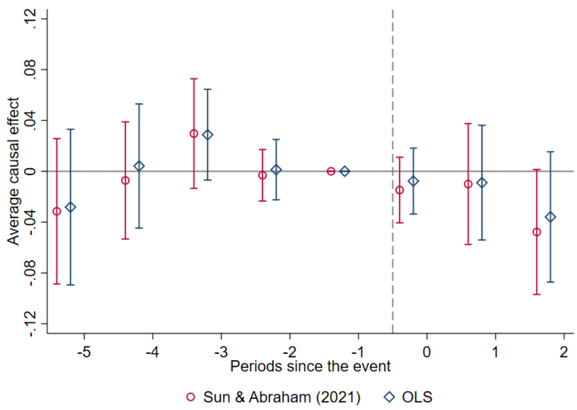
Notes: The figure contains event study results for the effect of the ACA Medicaid expansions on the number of reimprisonments within a 2-year window. The horizontal axis shows relative event years. The vertical axis shows the average treatment effect on the treated (ATT). We report estimates using both the OLS and the interaction-weighted estimator proposed by Sun and Abraham (2021). We report the 95% confidence intervals in the figure.



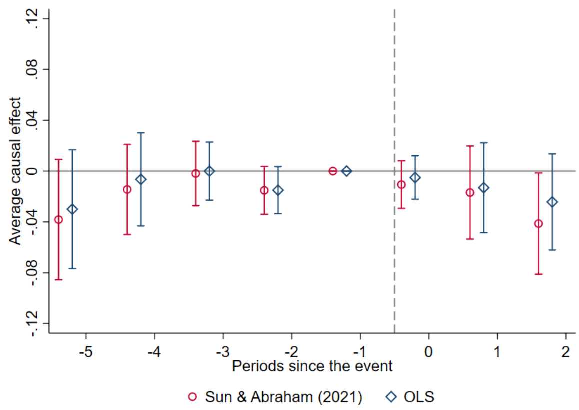
(a) All Crimes



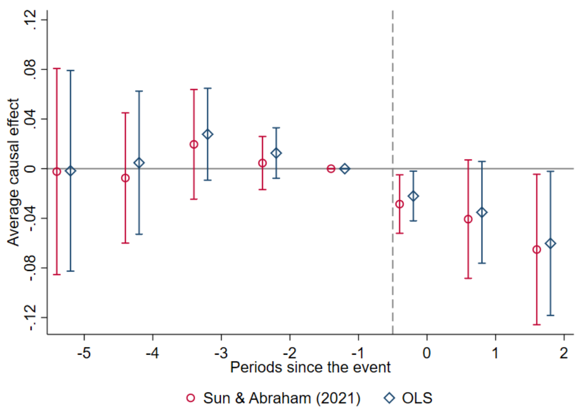
(b) Violent Crimes



(c) Property Crimes



(d) Drug Crimes



(e) Public Order Crimes

Figure A2. Dynamic Difference-in-Differences - Medicaid Expansions and the Number of Reimprisonments (3-Year)

Notes: The figure contains event study results for the effect of the ACA Medicaid expansions on the number of reimprisonments within a 3-year window. The horizontal axis shows relative event years. The vertical axis shows the average treatment effect on the treated (ATT). We report estimates using both the OLS and the interaction-weighted estimator proposed by Sun and Abraham (2021). We report the 95% confidence intervals in the figure.

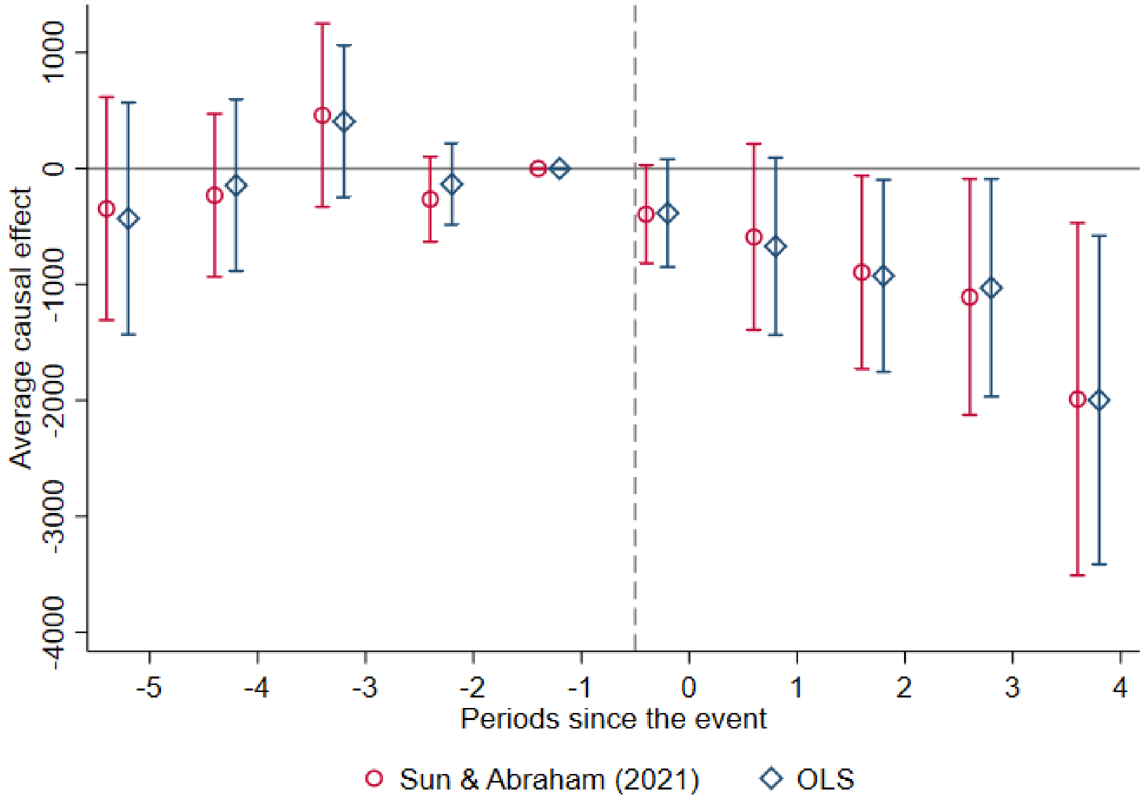


Figure A3. Dynamic Difference-in-Differences (DID) - Mechanical Costs Net of Fiscal Externalities (1-Year) - All Crimes

Notes: The figure contains dynamic DID estimates showing the effect of Medicaid expansions on net costs (mechanical costs net of fiscal externalities) associated with the reduction in the number of future reimprisonments within a 1-year window among all inmates. The vertical axis show the average treatment effect on the treated (ATT). We report estimates using both the OLS and the interaction-weighted estimator proposed by Sun and Abraham (2021). We also report the 95% confidence intervals in the figure.

Table A1. Summary Statistics - Reimprisonments

Dependent Variables	All States		Expansion States					Non-Expansion States				
	Pre-treatment Mean	Post-treatment Mean	Mean	Std. Dev.	Pre-Treatment Mean	Post-Treatment Mean	Diff. p-values	Mean	Std. Dev.	Pre-Treatment Mean	Post-Treatment Mean	Diff. p-values
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1-Year Reimprisonments by Crime Type:												
All	0.192	0.200	0.230	0.504	0.232	0.228	0.001	0.161	0.407	0.151	0.173	0.001
Violent	0.178	0.175	0.214	0.483	0.222	0.204	0.000	0.140	0.383	0.134	0.146	0.000
Property	0.237	0.246	0.285	0.553	0.284	0.287	0.180	0.200	0.448	0.193	0.209	0.000
Drug	0.167	0.192	0.203	0.468	0.197	0.210	0.000	0.155	0.399	0.139	0.175	0.000
Public Order	0.190	0.194	0.226	0.516	0.232	0.218	0.000	0.146	0.388	0.133	0.164	0.000
2-Year Reimprisonments by Crime Type:												
All	0.192	0.202	0.340	0.637	0.341	0.338	0.032	0.253	0.526	0.244	0.268	0.000
Violent	0.178	0.178	0.321	0.613	0.327	0.310	0.000	0.223	0.498	0.218	0.230	0.000
Property	0.237	0.247	0.414	0.691	0.413	0.417	0.220	0.313	0.575	0.307	0.322	0.000
Drug	0.167	0.193	0.301	0.592	0.294	0.312	0.000	0.245	0.517	0.230	0.269	0.000
Public Order	0.190	0.194	0.331	0.657	0.339	0.317	0.000	0.227	0.500	0.213	0.249	0.000
3-Year Reimprisonments by Crime Type:												
All	0.192	0.200	0.422	0.741	0.424	0.417	0.000	0.328	0.619	0.320	0.343	0.000
Violent	0.178	0.178	0.402	0.713	0.407	0.390	0.000	0.291	0.585	0.286	0.299	0.000
Property	0.237	0.245	0.510	0.801	0.511	0.508	0.379	0.406	0.682	0.402	0.413	0.001
Drug	0.167	0.190	0.374	0.686	0.369	0.387	0.000	0.316	0.607	0.304	0.341	0.000
Public Order	0.190	0.191	0.411	0.770	0.421	0.388	0.000	0.290	0.581	0.279	0.312	0.000

Notes: This table reports the summary statistics for the number of reimprisonments within 1-, 2-, and 3-year windows by crime type. The working samples correspond to those in Table 1. Crime categories refer to the first offense type that end with an imprisonment. For non-expansion states, we consider years before 2014 as pre-treatment years for the purpose of constructing the means for the dependent variable. Differences in p-values reported in columns (7) and (12) measure the statistical significance of the differences between post- and pre-treatment means of the outcome variables in expansion and non-expansion states, respectively.

Table A2. Summary Statistics - All Crime Sample

Variables	1-Year Window Mean	1-Year Window Std. Dev.	2-Year Window Mean	2-Year Window Std. Dev.	3-Year Window Mean	3-Year Window Std. Dev.
Age When Released						
25-34 years	0.510	0.500	0.509	0.500	0.508	0.500
35-44 years	0.298	0.458	0.297	0.457	0.296	0.457
45-54 years	0.186	0.389	0.188	0.391	0.190	0.392
Gender						
Female	0.170	0.376	0.168	0.374	0.166	0.372
Race/Ethnicity						
White	0.453	0.498	0.452	0.498	0.451	0.498
Black	0.269	0.443	0.272	0.445	0.275	0.446
Hispanic	0.148	0.355	0.150	0.357	0.151	0.358
Other Races	0.019	0.135	0.018	0.134	0.018	0.134
Time Served						
<1 year	0.457	0.498	0.457	0.498	0.458	0.498
1-1.9 years	0.206	0.404	0.206	0.405	0.206	0.404
2-4.9 years	0.198	0.399	0.199	0.399	0.200	0.400
5-9.9 years	0.089	0.284	0.088	0.284	0.088	0.283
>=10 years	0.050	0.218	0.050	0.217	0.049	0.216
Sentence Length						
<1 year	0.183	0.387	0.186	0.389	0.190	0.392
1-1.9 years	0.079	0.269	0.078	0.268	0.077	0.267
2-4.9 years	0.329	0.470	0.327	0.469	0.327	0.469
5-9.9 years	0.219	0.413	0.218	0.413	0.217	0.412
10-24.9 years	0.153	0.360	0.152	0.359	0.151	0.358
>=25 years	0.027	0.163	0.028	0.164	0.028	0.164
Life, LWOP	0.007	0.082	0.007	0.081	0.007	0.081
Admission Type						
Court Commitment	0.904	0.295	0.904	0.295	0.905	0.293
Return from Parole / Revocation	0.072	0.259	0.073	0.260	0.073	0.260
Other	0.004	0.061	0.004	0.062	0.004	0.062
Release Type						
Conditional Release	0.659	0.474	0.651	0.477	0.642	0.479
Unconditional Release	0.283	0.451	0.288	0.453	0.293	0.455
Other Types of Release	0.008	0.088	0.008	0.090	0.008	0.092
Minimum Wage	7.463	0.884	7.398	0.778	7.337	0.696
Housing Price Index	258.921	73.183	254.238	71.207	250.201	70.184
Unemployment Rate	6.849	2.304	7.143	2.207	7.462	2.102
Poverty Rate	14.738	3.055	14.957	2.990	15.187	2.902
High School Diploma or Higher	0.862	0.030	0.860	0.030	0.858	0.030
Obs.	1,768,232		1,606,648		1,439,707	

Notes: This table reports the summary statistics for both individual- and state-level characteristics used in the analysis. The working samples correspond to those reported in columns (1)-(2) in Table 1 for *all crimes*. Missing values are not reported in the table. However, we include an indicator variable for missing values in our analysis.

Table A3. Static Difference-in-Differences - Alternative Estimators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All		Violent		Property		Drug		Public Order	
Panel A: 1-Year Window										
Expansion	-0.026**	-0.026**	-0.029**	-0.031***	-0.023	-0.021*	-0.019	-0.019	-0.038***	-0.038***
	(0.013)	(0.010)	(0.012)	(0.010)	(0.015)	(0.013)	(0.014)	(0.013)	(0.015)	(0.012)
Mean of Dependent Variable	0.196	0.196	0.177	0.177	0.241	0.241	0.178	0.178	0.191	0.191
N	1,768,232	1,743,512	513,608	504,197	438,782	432,593	502,062	496,751	313,780	309,971
Panel B: 2-Year Window										
Expansion	-0.024	-0.025**	-0.027*	-0.031**	-0.020	-0.019	-0.011	-0.013	-0.045**	-0.045***
	(0.015)	(0.013)	(0.015)	(0.014)	(0.019)	(0.015)	(0.017)	(0.014)	(0.019)	(0.017)
Mean of Dependent Variable	0.296	0.296	0.272	0.272	0.361	0.361	0.272	0.272	0.285	0.285
N	1,606,648	1,590,320	463,207	457,039	399,959	396,084	457,084	453,396	286,398	283,801
Panel C: 3-Year Window										
Expansion	-0.019	-0.023	-0.027	-0.033*	-0.012	-0.015	-0.000	-0.004	-0.044*	-0.046**
	(0.018)	(0.016)	(0.018)	(0.017)	(0.024)	(0.019)	(0.020)	(0.017)	(0.024)	(0.021)
Mean of Dependent Variable	0.374	0.374	0.345	0.345	0.455	0.455	0.344	0.344	0.358	0.358
N	1,439,707	1,433,053	412,414	409,915	359,132	357,832	410,085	408,323	258,076	256,983
Two-stage estimator à la Gardner (2021)	√	×	√	×	√	×	√	×	√	×
Imputation estimator à la Borusyak et al. (2021)	×	√	×	√	×	√	×	√	×	√

Notes: This table reports the static difference-in-differences estimates using the imputation estimators proposed by Gardner (2021) and Borusyak, Jaravel, and Spiess (2021), respectively. Different panels correspond to various time windows (1-, 2-, and 3-year windows) of the outcome variable. Crime categories refer to the first offense type that end with an imprisonment. All regressions include state fixed effects, release-year fixed effects, and inmate characteristics. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Victimization related costs and benefits

Here, we provide a brief explanation of how we calculate expected criminal justice cost reductions associated with the receipt of Medicaid by a released inmate. We separate benefits from victimization cost reductions into four categories based on the expected reduction in the four categories of crimes we analyze. Specifically, b^J denotes the expected benefit generated by reductions in the number of victimizations of category $J \in$ {Violent, Property, Drug, Public Order} crimes. Thus, $b = \sum_J b^J$ denotes the total expected benefits from reduced victimization.

As indicated in Table 2, when possible, we break down each crime category in to subcategories, which we henceforth call 'types'. By letting i denote the type of crime within category J, e.g., for violent $i \in$ {Murder, Sex Offenses, Robbery, Assault }, we use the following notation:

M: number of released inmates receiving Medicaid[20];

q: reduction in the average number of reimprisonment per inmate (i.e., the coefficient reported in Table 1, Panel A, Column 2);

p^J: share of reimprisonment for category J crimes (i.e., the percentages reported in the first column of Table 2 for each reoffense type);

r^J: victimization-to-incarceration ratio for category J crimes[21];

$\bar{C}^J$: average victimization cost of a category J crime (i.e., the numbers reported in the lowest row of each crime category in Table 2, Columns 3 and 4);

C_i^J: victimization cost of a type i crime in category J (i.e., the numbers reported in Table 2, Columns 3 and 4); and

w_i^J: share of victimization reduction of type i crime within category J (i.e., the percentages reported in the second column of Table 2).[22]

[20]As will become clear from the derivations below, the specific value of M is irrelevant to the derivation of b^J and other values of interest, because it appears only in intermediate steps that are helpful in deriving expressions for these values.

[21] The numbers reported in Table A5 for $J \in$ {Violent, Property}. Because data on these ratios are not available for drug and public order crimes, we assume r^J=1 for these categories to obtain conservative estimates of b^J.

[22]The derivation of these weights are explained in Table A4 and the notes accompanying it.

It then follows that $qp^J M$ is an estimate of the number of category J *imprisonments* averted by the policy change. Multiplying this number by r^J converts it to an estimate of the number category J *victimizations* reduced, which equals $qp^J r^J M$. Therefore, the total benefit from reduced category J victimizations is

$$B^J = qp^J r^J M \bar{C}^J \tag{3}$$

where

$$\bar{C}^J \equiv \sum_i w_i^J C_i^J \tag{4}$$

is the average victimization cost associated with a category J crime.

Therefore, the expected benefit from category J crimes obtained from receipt of Medicaid per released inmate is

$$b^J = B^J / M = qp^J r^J \bar{C}^J \tag{5}$$

which can be used to calculate the total expected victimization cost reductions associated with providing a released inmate Medicaid as

$$b = \sum_J b^J \tag{6}$$

Average victimization costs by crime categories

In this section, we discuss how we obtain average victimization costs reported in Table 2. For consistency, we borrow some of the notation introduced in the previous section.

We use two sources for the costs associated with different types of crime within categories $J \in$ {Violent, Property, Drug, Public Order} crimes. Specifically, we extract victimization costs from Table 5 in Cohen and Piquero (2009) (henceforth 'C&P') and Table 5 in Miller et al. (2021) (henceforth 'MCSAH') for the lower and upper bound estimates, respectively. All victimization costs in Table 2 are reported in 2020 dollars. Because the estimated costs in C&P do not include costs associated with public services, e.g., the use of police and fire services, we also exclude these categories from MCSAH.

Our discussion below follows the order of the category J crimes in Table 2.

Violent Crimes

There are four main types of violent crimes: murder, rape, robbery, and assault. We obtain the average victimization cost for murder directly from C&P and MCSAH. The lower and upper bound estimates, adjusted for inflation, are \$5,740,800 and \$8,089,301, respectively. Similarly, we extract victimization costs for rape and robbery from C&P and MCSAH and inflate the costs to 2020 dollars accordingly, which are \$168,480 and \$174,579, respectively. The lower bound for robbery is \$14,976 while the upper bound is \$28,592.

The average victimization cost for assault in MCSAH is \$28,971. C&P, however, report the cost estimates for aggravated and simple assaults separately. For consistency, we calculate a weighted average using the estimated costs for aggravated and simple assaults reported in C&P and the number of aggravated and simple assaults reported in MCSAH. Specifically, the weighted average for aggravated and simple assaults is $\frac{N_{aa}}{N_{aa}+N_{sa}} \times C_{aa} + \frac{N_{sa}}{N_{aa}+N_{sa}} \times C_{sa} = \frac{1{,}417{,}526}{1{,}417{,}526+7{,}492{,}068} \times \$37,000 + \frac{7{,}492{,}068}{1{,}417{,}526+7{,}492{,}068} \times \$4,500 = \$9,670.78$ (in 2007 dollars), where N_{aa} and N_{sa} are the number of aggravated and simple assaults extracted from Table 4 in MCSAH, and C_{aa} and C_{sa} denote victimization costs associated with aggravated and simple assaults, respectively. Adjusting to 2020 dollars, the estimated cost for assault is \$12,069.[23]

Using Equation (5), we estimate the expected benefit from averting violent crimes, which yields a lower bound estimate of $0.022 \times 20.93\% \times 14.51 \times (3.33\% \times \$5,740,800 + 4.5\% \times \$168,480 + 48.83\% \times \$14,976 + 43.34\% \times \$12,069) = \$14,100$. Employing the same approach, the upper bound estimate is $0.022 \times 20.93\% \times 14.51 \times (3.33\% \times \$8,089,301 + 4.5\% \times \$239,095 + 48.83\% \times \$28,592 + 43.34\% \times \$28,971) = \$20,464$.

[23]Information on the number of crimes is not available in C&P. For consistency, we employ the same number of crimes reported in MCSAH to calculate the weighted average for assault when using the estimated costs from C&P.

Property Crimes

For property crimes, we obtain the lower bound cost estimates for larceny, burglary, and motor vehicle theft from C&P. After adjusting to 2020 dollars, the average victimization costs are \$562, \$2,496, and \$6,864, respectively. The upper bound cost estimates for the same type of crimes come from MCSAH. The average victimization costs for larceny, burglary, and motor vehicle theft are \$2,730, \$2,571, and \$8,949, respectively. Following the same approach discussed above using Equation (5), we estimate the expected benefit from averting property crimes, which yields a lower bound estimate of $0.022 \times 32.95\% \times 43.25 \times (17.47\% \times \$562 + 72.96\% \times \$2,496 + 9.57\% \times \$6,864) = \$808$. The upper bound estimate, on the other hand, is $0.022 \times 32.95\% \times 43.25 \times (17.47\% \times \$2,730 + 72.96\% \times \$2,571 + 9.57\% \times \$8,949) = \$1,006$.

Drug-related Crimes

Victimization costs for drug-related crimes are not reported in C&P. To be conservative, we consider the lower bound as \$0. Therefore, the expected benefit from averting drug-related crimes is also \$0. The intuition is that drug-related crimes such as drug trafficking and possessing are considered by some as "victimless" crimes (Meier and Geis, 1997).[24] For the upper bound, we directly obtain the estimated costs for drug possession/sales from MCSAH. The upper bound for drug-related victimization costs is equal to \$5,387 in 2020 dollars. Because there is only one type of crime under the category of drug-related crimes, the upper bound for the expected benefit is $0.022 \times 27.34\% \times 1 \times 100\% \times \$5,387 = \$32$.[25]

Public Order Crimes

The final category of crimes is public order. C&P report the victimization cost for DUI but not other type of public order crimes. However, C&P report the willingness-to-pay (WTP) for averting "other offenses", which include specific types of crimes under

[24]In Jácome (2020), drug crimes include driving under intoxication (DUI) as well as drug trafficking and possessing. In the NCRP data, however, DUI is included under the category of public order crimes.

[25]As mentioned in footnote 21, we assume $r^J = 1$ for drug-related crimes to obtain a conservative estimate for the expected benefit.

the category of public order crimes, which is $1,000. There are ten different types of crimes that fall under this category (Table A6).[26] To obtain a lower bound, we use the WTP measure as a proxy for victimization costs for the types of crimes that fall under public order crimes. For our upper bound estimate, we directly obtain victimization costs for public order crimes from MCSAH. Using the number of crimes, and thus, the share of each type of crime (DUI, prostitution, gambling, loitering, etc.) reported in Table A6, we estimate a weighted average of victimization costs for public order crimes.[27] We find that the lower and upper bound estimates are $4,992 and $13,804, respectively. After converting these estimates to 2020 dollars, the average victimization costs range from $6,230 to $14,577. Employing Equation (5), we obtain the expected benefit from averting public order crimes. The lower bound for the expected benefit is $26, and the upper bound is $60.

Total expected victimization cost reductions

As our last step, we calculate the total expected victimization cost reductions using Equation (6). Specifically, the lower bound is $14,100 + $808 + $0 + $26 = $14,934, and the upper bound is $20,464 + $1,006 + $32 + $60 = $21,562.

[26]The type of public order crimes include DUI, other impaired driving, carrying weapons, prostitution/pandering, gambling, liquor laws, drunkenness, disorderly conduct, vagrancy, curfew/loitering violations. We also obtain the number of crimes for each type of crime from Table 4 in MCSAH.

[27]For each crime type, the *share* is simply equal to the number of the specific type of crime divided by the total number of public order crimes. We report the number of crimes and shares for each type of crime in Table A6.

Obtaining the Within-Category Weights

Table A4. Within-Category Weights (w_i^J)

Reoffense Type	Percent	Ratio	Weight	Within-Category Weights (w_i^J, %)
Violent Crimes				
Murder	9.91	1.52	15.06	3.33
Rape	4.48	4.55	20.38	4.50
Robbery	37.24	5.94	221.21	48.83
Aggravated or simple assault	48.36	4.06	196.34	43.34
All Violent			452.99	100
Property Crimes				
Larceny	14.43	17.28	249.35	17.47
Burglary	65.33	15.94	1041.36	72.96
Motor vehicle theft	20.24	6.75	136.62	9.57
All Property			1426.33	100
Drug Crimes	-	100	-	100
Public Order Crimes	-	100	-	100

Notes: Within-category weights are calculated using the share of arrests for each sub-crime and the average victimization-to-arrest ratios from Jácome (2020). Percent denotes the share of arrests for each sub-crime category that end with a custody. Ratio denotes the victimization-to-arrest ratio. Weight = Percent × Ratio. Within-Category Weights (w_i^J) = Weight/ $\sum_i$Weight, where i refers to the type of crime (e.g., murder, rape, larceny, etc.) within crime category $J \in$ {Violent, Property, Drug, Public Order}.

Calculating the Victimization-to-Incarceration Ratios

Table A5. Victimization-to-Incarceration Ratios (r^J)

	1996		1997		1998	
Reoffense Type	Total	Inc.	Total	Inc.	Total	Inc.
Violent Crimes						
Murder	19.645	16	18.208	14.724	16.974	14.22
Rape/sexual assault	98	32	115	34	110	35
Robbery	757	59	607	61	610	60
Aggravated or simple assault	1,910	45	1,883	49	1,674	52
All Violent	2,784.65	152.03	2,623.21	157.56	2,410.97	160.27
Property Crimes						
Larceny	4,216	38	3,955	41	3,693	44
Burglary	4,056	71	3,893	73	3,380	75
Motor vehicle theft	938	18	1,007	18	822	18
All Property	9,967	187.09	9,462	192.84	8,505	196.56
	1999		2000		2001	
	Total	Inc.	Total	Inc.	Total	Inc.
Violent Crimes						
Murder	15.522	12.673	15.586	12.907	16.037	13.264
Rape	141	34	92.4	35	83.6	34
Robbery	530	56	520.1	55	426.7	53
Aggravated or simple assault	1,503	53	1,292.50	57	1,222.20	57
All Violent	2,189.52	155.67	1,920.59	160.91	1,748.54	156.13
Property Crimes						
Larceny	3,394	46	3,177	50	3,176	49
Burglary	3,064	73	2,909	74	2,687	71
Motor vehicle theft	808	17	641.9	18	724.1	18
All Property	7,796	191.87	7,248	197.69	7,013.80	189.92
Average Violent Ratio (r^J)			14.51			
Average Property Ratio (r^J)			43.25			

Notes: Total denotes the total number of victimizations (in thousands) reported the National Crime Victimization Survey (NCVS), excluding murder. These victimization numbers are also consistent with those reported in Heckman et al. (2010). We obtain the total number of victimizations for murder from the Supplemental Homicidal Report (SHR). The number of victimizations in SHR can be easily obtained from the Office of Juvenile Justice and Delinquency Prevention: https://www.ojjdp.gov/ojstatbb/ezashr/. Inc. denotes the number of sentenced prisoners (in thousands). We calculate the number of sentenced prisoners based on the distribution of sub-crimes in the NCRP and the state prison totals obtained from the National Prisoners Statistics. Average victimization-to-incarcerations ratios (r^J) for each crime category is calculated using the following formula: $\sum_t$ (All Category J Crime Total $)_t$/(All Category J Incarceration$)_t$, where $J \in$ {Violent, Property} and t = 1996, . . . , 2001. Since data on these ratios are not available for Drug and Public Order Crimes, we assume r^J =1 for these categories to obtain conservative estimates of the expected benefit from category J crimes.

Obtaining the victimization cost for public order crimes

Table A6. Victimization Costs for Public Order Crimes

Type of Crime	Number of Crimes (1)	Share of Crimes (2)	Cohen & Piquero (2009) (2007 dollars) (3)	Miller et al. (2021) (2017 dollars) (4)
DUI	321,681	14.78%	$28,000	$83,665
Other impaired driving	668,997	30.75%	$1,000	$1,195
Weapons carrying	164,984	7.58%	$1,000	$3,646
Prostitution/pandering	36,247	1.67%	$1,000	$365
Gambling	3,237	0.15%	$1,000	$365
Liquor laws	207,332	9.53%	$1,000	$1,740
Drunkenness	366,824	16.86%	$1,000	$1,740
Disorderly conduct	353,151	16.23	$1,000	$1,740
Vagrancy	23,321	1.07%	$1,000	$1,740
Curfew/loitering violations	30,131	1.38%	$1,000	$1,740
Total	2,175,905	100%		
Weighted average			$4,992	$13,804

Notes: The number of crimes are obtained from Miller et al. (2021). The victimization cost for DUI is from Table 5 in Cohen and Piquero (2009). All other costs in column (3) are willingness-to-pay estimates for averting these crimes, which are obtained from Table 5 in Cohen and Piquero (2009). The victimization costs in column (4) are obtained from Table 5 in Miller et al. (2021). In the analysis, we adjust victimization costs to 2020 dollars.