The Effects of Youth Employment on Crime: Evidence from New York City Lotteries*

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Recent policy discussions have proposed government-guaranteed jobs, including for youth. One key potential benefit of youth employment is a reduction in criminal justice contact. Prior work on summer youth employment programs has documented little-to-no effect of the program on crime during the program but has found decreases in violent and other serious crimes among "at-risk" youth in the year or two after the program. We add to this picture by studying randomized lotteries for access to the New York City Summer Youth Employment Program (SYEP), the largest such program in the United States. We link SYEP data to New York State criminal records data to investigate outcomes of 163,447 youth who participated in a SYEP lottery between 2005 and 2008. We find evidence that SYEP participation decreases arrests and convictions during the program summer, effects that are driven by the small fraction (3 percent) of SYEP youth who are at-risk, as defined by having been arrested before the start of the program. We conclude that an important benefit of SYEPs is the contemporaneous effect during the program summer and that the effect is concentrated among individuals with prior contact with the criminal justice system. *JEL* Codes: J13, J45, J38, J21.

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I. INTRODUCTION

Recent policy discussions have highlighted proposals for government-provided jobs, including a jobs guarantee.[1] Many programs aiming to provide universal employment have provisions for youth jobs in particular, including proposals for national service.[2]

As policy makers push for programs to employ large numbers of youth across the country, it is helpful to explore the effects of such labor market programs on youth outcomes. A natural place to look for such evidence is from summer youth employment programs (SYEPs). SYEPs are social service programs run in cities across the United States that provide jobs to youth during the summer months.

These programs are widespread, large, and costly. Heller and Kessler (2017) survey the 30 largest cities in the U.S. and find that all but three had evidence of a summer youth employment program during the last few years. In 2019, New York City (NYC) hired 75,000 youth. While NYC is by far the largest program in the country, many other cities have programs that are also quite large: Chicago hires roughly 25,000 youth each year; and Los Angeles, Washington DC, Detroit, Baltimore, and Philadelphia each hire roughly 10,000 youth each year (Heller and Kessler 2017). Costs of SYEPs are approximately $2,000 per youth (SYEP Summary 2019).

[1] During the 2020 U.S. presidential primaries, a number of prominent candidates for the Democratic nomination — including Senators Bernie Sanders, Kristen Gillibrand, and Cory Booker — called for some form of federal jobs guarantee (Stein 2018). A federal jobs guarantee is also a cornerstone of the Green New Deal (Hess 2019).

[2] Pete Buttigieg, a prominent candidate for the Democratic presidential nomination in 2019, proposed a national service plan that would employee one million high school graduates each year (*Pete Buttigieg for President - A New Call to Service*).

One of the key rationales for funding SYEPs is that they may help to keep youth "out of trouble," under the assumption that giving youth access to the formal labor market can reduce a range of delinquent behaviors including criminal activity and subsequent contact with the criminal justice system. Findings from early evaluations of SYEP programs have found support for this rationale. Analyses of SYEPs in Chicago and Boston have found relatively large reductions in the number of times at-risk youth are arrested for violent and other serious crimes in the year or so after the program ends (Heller 2014; Modestino 2019); an analysis of the SYEP in New York City found a decrease in incarceration in New York State prison, an outcome associated with serious crimes or repeated contact with the criminal justice system, in the years after the program (Gelber, Isen, and Kessler 2016). These results suggest that SYEPs have medium-term effects on youth behavior and criminal justice outcomes.

Despite the similarities of the findings in Chicago, Boston, and New York, a number of open questions remain. Does SYEP participation have a significant contemporaneous effect during the program summer or does it only affect outcomes after the summer ends? Does SYEP participation decrease the chance that youth end up in contact with the criminal justice system or does it only reduce the number of times certain youth are arrested? Does SYEP participation have beneficial criminal justice effects for youth who are not at-risk?

In this paper, we aim to address these questions by linking four years of data from the New York City Summer Youth Employment Program, the largest SYEP in the country, to criminal records data maintained by the New York

State Division of Criminal Justice Services. Our dataset includes outcomes on 163,447 youth who applied to participate in the NYC SYEP between 2005 and 2008 and who were 16 years or older at the time of the program summer. The program was over-subscribed in each year that we analyze, and the program used a computerized lottery to offer slots to youth.[3] In addition to being large, the NYC SYEP draws from a broad swath of youth in NYC, allowing us to analyze the effect of the program on youth who are not considered at-risk for criminal justice contact (as well as those who are at-risk). The size of our sample gives us statistical power to generate precise estimates, and the composition of the population being studied gives us confidence about the external validity of our findings to broader populations. Since our program years are from last decade, we are also able to look at outcomes for up to five years beyond the program summer.

We find strong evidence of contemporaneous effects during the months of the program summer.[4] Participation in SYEP decreases the chance that youth are arrested during the program summer by 17 percent and decreases the chance that they are arrested for a felony during the program summer by 23 percent. These effects are even larger for arrests that lead to convictions. SYEP participation decreases the chance youth are convicted of a crime committed during the program summer by 31 percent and decreases the chance youth are convicted of a felony committed during the program summer by 38 percent.

[3]Gelber, Isen, and Kessler (2016) uses the same lotteries to analyze the effects of the NYC SYEP on a number of other outcomes, including labor market and mortality data.

[4]Prior literature on SYEP participation had shown little evidence of a contemporaneous effect during the program summer (Heller 2014) or mixed evidence, e.g., finding it with property crimes but not violent crimes (Modestino 2019). Prior analysis of the NYC SYEP did not have arrest or conviction data and so could not speak to the timing of criminal justice contacts (Gelber, Isen, and Kessler 2016).

Effects on the number of arrests are similar in magnitude; SYEP participation decreases the number of arrests during the program summer by 14 percent and the number of convictions by 27 percent. These contemporaneous effects are consistent with prior work showing a relationship between youth employment and crime (Grogger 1998; Jacob and Lefgren 2003) and work that finds incapacitation effects from longer-term youth employment programs (Cave 1993; Schochet, Burghardt, and McConnell 2008).

Our observed contemporaneous effects are driven primarily by youth who may be at elevated risk of criminal justice contact, because of their past involvement with the system. About three percent of the NYC SYEP applicants have been arrested before the program summer, which we take as evidence of being at-risk for future criminal justice contact.[5] We find statistically significant contemporaneous effects among at-risk youth. This finding is consistent with prior literature on SYEP participation, which has found effects of the summer program on higher-risk youth populations. Nearly 20 percent of youth analyzed by Heller (2014) had been arrested prior to the program, and all of the youth in that study were drawn from high-violence high schools. In the population studied by Modestino (2019), rates of pre-program arraignment are also low (around four percent), and that paper only finds treatment effects for the group that had a pre-program arraignment.

Our large sample allows us to estimate a rather precise zero on the contemporaneous effect arising for the 97 percent of SYEP participants without a prior arrest. For example, our 95 percent confidence interval rules out a reduction

[5] While three percent is a small fraction of the program youth, the large size of our dataset means we have 5,092 at-risk youth to analyze, larger than the entire sample in Modestino (2019) and over three times the size of the entire sample in Heller (2014).

in the number of arrests of more than 0.9 arrests per 1000 youth.[6] This result highlights that the criminal justice benefits of SYEP programs come primarily from the small group of youth with prior criminal justice contact.

Looking up to five years after the program summer, we do not find a statistically significant impact of the program for either the at-risk youth or the low-risk youth. In contrast, Heller (2014) finds a 43 percent reduction in violent crime arrests for treated youth in Chicago in the 13 months after the program summer. Modestino (2019) finds a 35 percent reduction in the number of violent crime arraignments and a 29 percent reduction in property crime arraignments during the 17 months after the program. While we do not find similar statistically significant results in our data, our directional estimates suggest that SYEP decreases the likelihood that at-risk youth are arrested or convicted through our entire sample period. We estimate a reduction in felony arrests and felony convictions for the at-risk group that is on the order of 10 percent of baseline rates through five years after the program. Given our standard errors, we cannot reject a 25 percent reduction at either the one-year or three-year mark after the program.[7]

Taken together, our results suggest that SYEP has important contemporaneous effects and highlights an important new channel for employment

[6]While this effect is clearly small, it is worth noting that base rates are also quite small. The low-risk population in the control group has 3.7 arrests per 1000 youth during the program summer.

[7]This is consistent with evidence from Gelber, Isen, and Kessler (2016) on longer-run effects of SYEP. Analysing the same program and program years, it finds a 10 percent reduction overall — and a 44 percent reduction among participants 19 years and older — in the likelihood that youth end up incarcerated in New York State Prison by 2013 for a crime committed at age 19 or older. However, that paper did not have granular data on the timing of the arrests and convictions that led to incarceration. Consistent with NYC SYEP keeping youth out of trouble, that paper also found a 17 percent reduction in mortality from the program by 2014, primarily driven by external causes such as homicide.

programs, particularly those programs targeted at at-risk youth.

Our paper proceeds as follows. Section II describes the SYEP program during the years of our data and describes both our SYEP program data and our criminal justice data. Section III describes our results on both arrests and convictions. Section IV concludes.

II. SETTING AND DATA

In this section, we describe the policy setting, the New York City (NYC) Summer Youth Employment Program (SYEP) during the 2005–2008 program years (see Section II.A). We then describe our data, which comes from two sources. Our SYEP administrative data (see Section II.B) comes from the NYC Department of Youth and Community Development (DYCD); our arrest and conviction data (see Section II.C) comes from the New York State (NYS) Division of Criminal Justice Services (DCJS). After explaining both sets of data, we describe the process by which we match youth in the SYEP data to criminal justice outcomes in the DCJS data (see Section II.D).

II.A. New York City Summer Youth Employment Program (2005–2008)

During 2005–2008, the NYC SYEP program, run by the NYC DYCD, provided city youth aged 14–21 with 25 hours a week of work for six or seven weeks during the summer. Youth were paid NYS minimum wage — which rose from $6.00 to $7.15 during those years — by the city, but jobs were at a variety of employers. In particular, 75 percent of youth had non-profit, private sector jobs; 11 percent had for-profit, private sector jobs; and 14 percent had government jobs. The most common type of job was working at a day camp or daycare center. The mean program expenditure (including wages and administrative cots) was $1,403 per participant.[8]

All NYC youth could apply to the program, and roughly 8 percent of city youth in the eligible age range applied in each year. The program was able to provide jobs for about half of applicants. In response to this over-subscription, the DYCD ran a lottery to determine which youth were offered jobs each summer.[9] Youth who won the lottery were offered a job, and most youth who were offered jobs accepted them, which makes winning the lottery a powerful instrument for SYEP participation that we leverage in an instrumental variables empirical strategy, described in Section III. More details on the SYEP program and the SYEP lottery during the 2005–2008 years can be found in Gelber, Isen, and Kessler (2016).

II.B. SYEP Administrative Data

Data on SYEP application and SYEP program participation comes from DYCD. We have data on each applicant in each year, including: identifiers (name, date of birth, and social security number); the provider through which they applied to SYEP (see footnote 9); whether they won a SYEP lottery; whether they participated in SYEP in that summer; and a number of demographic variables that we use to test balance and that we use as controls in some

[8]Following the prior literature, the cost per participant are reported in 2013 dollars (Gelber, Isen, and Kessler 2016).

[9]In particular, youth applied to jobs through a SYEP "provider," a non-profit organization that contracts with DYCD to administer the program. The providers placed youth in jobs and ran workshops for youth on job readiness and related topics for 17.5 hours, or roughly 10 percent of the SYEP program time. While the lottery process was centralized at the city level, youth were randomized within a provider, which we account for in the empirical analysis that follows.

regression specifications (gender, race, family size, and citizenship status). We drop all applicants who are younger than 16 years of age on July 1 of a program summer, for reasons described in Section II.C. For youth who apply in more than one summer between 2005 and 2008, we only consider them the first time they appear in our lottery data and are old enough to be included in the analysis.[10] We use the identifiable information on SYEP applicants to merge this data to the arrest and conviction data described next.

II.C. DCJS Arrest and Conviction Data

We link the SYEP administrative data to the criminal records maintained by the New York State Division of Criminal Justice Services (DCJS). The DCJS data contain information on all adult arrests in New York State.[11] At the time the data were collected, the criminal age of majority in New York State was 16 years old. Accordingly, we limit the sample to individuals who are at least 16 years old on July 1 of the program year, so we can measure criminal justice outcomes during program months (i.e., July and August). Along with demographic information (including race, sex, and date of birth), the DCJS data contain arrest date, the top charge from the arrest event, arraignment date and charge, conviction date and charge, and information on the disposition.

[10] Youth are eligible to participate in SYEP before the criminal age of majority in NYS. For individuals who participate in multiple lotteries over the study period, we include the first lottery in which they participate once they are at least 16 years old.

[11] Individual level data on juvenile arrests is not available in New York State. In addition, law enforcement encounters that result in a ticket or a "violation" are not captured in these data. The arrest events captured in the DCJS database are those that carry charges severe enough to require police officers to take the individual into custody and take fingerprints. They may later be downgraded to violations in severity, but they would have initially been recorded as an arrest.

We observe arrests and convictions even if they are sealed.[12]

II.D. Matching Process

We identify adult criminal records for 14.26 percent of the youth in our SYEP data.[13] We search for criminal records using a four-tiered matching protocol that identifies records by exactly matching on pairwise combinations of full name, date of birth, and social security number.[14] SYEP applications that do not match exactly to a criminal record during these first three tiers are then passed through a probabilistic matching procedure.[15]

Since we do not expect to find a criminal record for all of the SYEP applicants, we cannot use the match rate to evaluate the performance of the match. However, the four-tiered matching protocol that we used was validated by DCJS against a known sample and has very low false positive and false negative error rates (1.97 percent false positive error rate and a 2.46 percent false negative error rate). As might be expected, the validation procedure revealed that many of the false positives came from the probabilistic matching tier (the exact matching process had a 0.8 percent false positive error rate and 8.0 percent false negative error rate). Tahamont et al. (2020) shows that

[12] Although we observed sealed information, we would not observe the criminal record in the data if *all* of the arrests and convictions associated with an individual record were sealed.

[13] In New York State, any arrest in which an individual gets their fingerprints taken will generate a criminal record linked to a New York State ID (NYSID). Once an individual has an arrest that results in a conviction, the NYSID (and, therefore, the criminal record) is permanently associated with the individual's fingerprints, whether or not any arrests or convictions are sealed.

[14] Although the DCJS criminal records data contain social security numbers, we cannot use them to match to the SYEP data on their own because the social security numbers contained in the criminal records repository are those provided to the police officer at the time of arrest, and so are quite incomplete.

[15] The vast majority of records in our data are identified using the exact matching tiers, fewer than 10 percent of the matched records come from the probabilistic matching tier.

minimizing the sum of false positive and false negative error rates minimizes the bias introduced by linking errors when linking administrative records to identify the presence of a binary outcome, as we do in this paper. Consequently, including the probabilistic matching tier is preferable to excluding it.

For youth that we match to a criminal record, we note whether they had an arrest prior to the start of the program summer (i.e., prior to treatment). We define youth with a prior arrest as being particularly "at risk" for future criminal justice contact in the analysis that follows.

III. RESULTS

In this section, we present evidence to validate our empirical approach and then present our results. In Section III.A, we show summary statistics about SYEP applicants and demonstrate balance on both demographic traits and pre-program criminal justice outcomes. In Section III.B, we describe the two-stage least squares estimation strategy we employ to generate our estimates. In Section III.C, we report on the contemporaneous effects of the SYEP program, investigating the effect of the program on arrests and convictions during July and August, when youth are employed in SYEP. In Section III.D, we investigate the persistence of the SYEP program on arrests and convictions after the program, looking up to five years after program participation.

III.A. Summary Statistics and Balance

As described above, we analyze data from 163,447 youth in our DYCD data. Of these youth, 91,908 won a SYEP lottery and were offered a job in SYEP; 71,539 youth were not selected in a SYEP lottery and so were officially not allowed to participate. Table I presents summary statistics for the two groups. The top panel shows demographic variables and the bottom panel shows criminal justice outcomes, both overall and in the 12 months ending April 30 in the calendar year of the program summer (i.e., before randomization). Column (1) shows data for the "control" group (i.e., lottery losers) and column (2) shows data for the "treatment" group (i.e., lottery winners). Appendix Tables A.VII and A.VIII replicate Table I for the at-risk group and the low-risk youth, respectively, showing that these subgroups are balanced as well.

The average age of the youth is just over 17 years old at the start of the program. The youth are 45 percent male, primarily Black and Latino, and over 90 percent are U.S. citizens. They have generally not had exposure to the criminal justice system at the time they apply to SYEP. Only three percent have a prior arrest, and only two percent had an arrest in the prior year.

TABLE I ABOUT HERE

Column (3) shows the p-value of the difference between treatment and control for the listed variables in a regression that includes dummies for each provider interacted with the year of the program, since the provider-year was the level of randomization (as described in footnote 9). Across a total of 18 tests, only one difference — whether the race/ethnicity of the applicant is captured as "other" — is statistically different from 0 and it is only marginally significant ($p = 0.075$).

III.B. Empirical Strategy

As noted in Section II, our empirical strategy is to use the SYEP lottery as an instrument for SYEP participation. The instrument is quite powerful; F-statistics of the first stage range from around 2,400–3,600.

Following Gelber, Isen, and Kessler (2016), we run a two-stage least squares (2SLS) regression specifications described by (1a) and (1b):

$$P_{ij0} = \alpha_1 W_{ij0} + X_j \alpha + u_{ij0}, \tag{1a}$$

$$E_{ijt} = \beta_1 P_{ij0} + X_j \beta + v_{ijt} \tag{1b}$$

Where E_{ijt} is an outcome (e.g., any arrest, any conviction, number of arrests, etc.) in time period t for individual i who participated in a lottery j. W_{ij0} is a dummy for winning the lottery and P_{ij0} is a dummy for participating in SYEP. The vector X_j always controls for the lottery the individual participated in (i.e., provider interacted with program year) since that is the point of randomization. In some specifications, we also include additional demographic controls in X_j. Finally, u_{ij0} and v_{ijt} are error terms. Following Gelber, Isen, and Kessler (2016), we cluster our standard errors by provider. Note that β_1 is the local average treatment effect among SYEP compliers who were induced into SYEP because they won the lottery.

III.C. Contemporaneous Effects

What is the effect of SYEP participation on criminal justice outcomes during the program summer? Table II reports on 2SLS regressions looking at the effect of program participation on outcomes during the program summer (i.e., in July and August of the year in which the applicant was in a lottery for the program). Each cell is its own regression estimated as in (1a) and (1b) without the additional demographic controls (Appendix Table A.I replicates Table II including controls and gets nearly identical estimates).

Panel A shows results on arrests while Panel B shows results on arrests that lead to convictions. Column (1) shows the results for all 163,477 youth in our sample. Columns (2) and (3) show results separately by at-risk youth (i.e., defined as youth with an arrest prior to the program summer) and lower-risk youth (i.e., youth who do not have a prior arrest).

Starting with results from Panel A and column (1), we see that program participation decreases the rate at which youth are arrested by 0.128 percentage points on a base of 0.766 percentage points in the control group. This estimate suggests that program participation decreases the chance a youth is arrested by 17 percent. Looking down column (1), we see that the effect on any arrest comes from both felony arrests and misdemeanor arrests, although only the former is statistically significant on its own. While youth could theoretically be arrested multiple times during the summer, this is relatively rare, so the sum of the *Any Felony Arrest* and *Any Misdemeanor Arrest* coefficients is roughly equal to the *Any Arrest* coefficient.[16] Similarly, the *Number of Arrests* coefficient is -0.00122 on a base of 0.0087 in the control group (i.e., a base of approximately 9 arrests per 1000 youth), or 15 percent of the control group mean. This effect is nearly identical in magnitude to the 0.128 percentage point decrease in the number of youth who have any arrest, suggesting that

[16]Among the individuals arrested during the program summer, approximately 11 percent were arrested more than once.

the effect of SYEP on arrests during the program summer is coming nearly entirely on the extensive margin of keeping youth from being arrested at all.

Columns (2) and (3) split the sample by whether the youth had a prior arrest. The at-risk youth, shown in column (2), have large effects. The likelihood that they are arrested during the program summer declines by about 2.75 percentage points — a decrease of 23 percent on a control mean of just over 12 percentage points. This effect appears to come from both felony and misdemeanor arrests, although neither is statistically significant on its own. The effect on the number of arrests is also marginally statistically significant — SYEP participation reduces the number of times at-risk youth are arrested by 34 arrests per 1000 youth, a 24 percent reduction on a base of 141 arrests per 1000 youth. Column (3) shows estimates for the low-risk youth. For this group, SYEP participation has a directionally negative, but not statistically significant, effect on whether a youth is arrested and also the number of arrests during the program summer.

TABLE II ABOUT HERE

The effects are even starker when considering arrests that lead to convictions in Panel B of Table II. In column (1) of Panel B, we see negative and significant effects of SYEP participation on the likelihood of a conviction, which decreases by 0.0752 percentage points on a base of 0.241 percentage points, a 31 percent reduction in convictions during the program summer. The effect is driven by both felony and misdemeanor convictions, with the former being marginally significant on its own. The decrease in the number of convictions is also statistically significant. Column (2) of Panel B shows that the effect is again driven primarily by the at-risk youth. The decrease in their likelihood of being convicted of a crime they were arrested for during the program summer is 2.09 percentage points, a 52 percent reduction on a base of 4.06 percentage points. This is primarily driven by a decrease in misdemeanor convictions. The effect also comes through in the number of convictions. SYEP participation leads to 21 fewer convictions per 1,000 at-risk youth, a 47 percent reduction on a base of 44 convictions per 1,000 youth. Column (3) of Panel B shows that the effects on low-risk youth are again directionally negative. While the low-risk youth are marginally statistically significantly less likely to be convicted of a felony — SYEP participation reduces the probability of a felony conviction by 0.02 percentage points, a 49 percent reduction on a base of 0.041 percentage points — participation has a directionally positive effect of the likelihood of a misdemeanor conviction, so there is not a statistically significant effect overall.

As noted above, and shown in the appendix, results from Table II replicate with the same level of significance when demographic controls are added (see Appendix Table A.I) and are also very similar in the reduced form, estimated with OLS regressions, with or without controls (see Appendix Table A.II).

III.D. Medium-Term Effects

Our arrest and disposition data extends through five years after SYEP participation, and so we are able to see the effects of SYEP participation on future outcomes for all our study youth. Tables III and IV report on the same outcomes as Table II — also using the 2SLS specification without additional demographic controls — but look one year post program, three years post program, and five years post program.[17] The tables report on at-risk youth (Table III) and low-risk youth (Table IV) separately. The pooled sample is shown in Appendix Tables A.V (without controls) and A.VI (with controls).

We see very little evidence of significant effects of SYEP on the likelihood of an arrest or conviction in any of the years after the program summer. Focusing on the at-risk youth in Table III, however, we see a consistently negative directional effect of program participation on future arrests and convictions, through five years after the program. While not generally significant, the effects on the likelihood of felony arrest and conviction are on the order of a 10 percent reduction of the control group mean, mirroring findings from programs in other cities.

TABLE III ABOUT HERE

Despite these consistently negative directional effects for the at-risk group, there is no pattern in the arrests or convictions data for the low-risk group. Instead we find precisely estimated zeros for the arrests and convictions outcomes we consider. For example, results from Column (1) of Panel (A) of Table IV suggests that we can rule out a 10 percent reduction in the likelihood of being arrested in the year after the program. Results from Column (3) of Panel (A) suggest we can rule out a three percent reduction in the likelihood of being arrested in the five years after the program.

TABLE IV ABOUT HERE

[17] The time windows are cumulative: that is, the one-year window is contained within the three-year and five-year windows. However, all windows exclude the program summer months. That is, they look from Sept 1st of the year of the program until August 31st: one year after the program in column (1); three years after the program in column (2); and five years after the program in column (3).

The effects pooling all youth, shown in Appendix Tables A.V (without controls) and A.VI (with controls), tell a story similar to the results from the low-risk youth, which make up 97 percent of the sample. We see no statistically significant effects of the program (except for the effect on felony arrests at the three-year horizon, which is marginally significant in both tables).

IV. DISCUSSION

We find contemporaneous effects of SYEP participation on arrest and conviction outcomes that are largely concentrated among youth who have had prior contact with the criminal justice system. Our findings contribute to the growing body of evidence suggesting that summer youth employment programs affect criminal justice contact among those who are, to some extent, already system involved (Modestino 2019) or otherwise at-risk for criminal justice involvement (Heller 2014).

In this paper, we consider youth who have been arrested prior to the SYEP lottery as being at-risk for criminal justice contact. Given that these individuals have signed up for the SYEP lottery, however, they might be particularly susceptible to intervention. That is, while they have been arrested in the past, these youth signed up to participate in a summer jobs program, potentially signaling a preference for a different trajectory. This is consistent with the arguments in Heller (2014) about summer jobs being an effective intervention for crime and violence *prevention* as opposed to remediation. The efficacy of SYEP at improving the criminal justice outcomes of the at-risk group of SYEP participants suggests benefits from evaluating whether similar programs may also be effective if targeted to similar groups. For example, a jobs program may end up being a relatively cost-effective intervention if added as a *voluntary* supplement to diversion programs or to community supervision.

We use estimates of the cost of crime by type from Cohen and Piquero (2009) and back-of-the-envelope calculations to quantify, in dollar terms, the social crime prevention benefits of SYEP during the program summer, where the bulk of our statistically significant effects arise. Since the cost of a given crime varies dramatically by crime type, we generate weighted average costs using the arrest distribution in the control group during the program summer. Using this approach, the average arrest in the months of the program has a social cost of approximately $19,000 using the bottom-up approach and $37,000 using the willingness-to-pay approach, both from Cohen and Piquero (2009).[18]

Among at-risk youth, where the criminal justice effects of SYEP are concentrated, SYEP prevents 34 arrests per thousand youth in the program summer, generating savings estimates of $652,000 and $1.25 million savings per thousand youth, or around $652 and $1,250 per participant. These estimates suggest that the benefits of averted arrests during the program summer comprise a substantive portion of the costs of the program (between 46.5 percent and 89.4 percent) for these youth.[19] By contrast, the estimated benefits for the

[18]It is worth noting that the cost of crime estimates for murder and rape are substantially higher than for other crimes, and a handful of arrests for these charges pull up the averages significantly. The cost of crime estimates for murder are in the multi-million dollar range, which is several orders of magnitude higher than other crimes. For rape, the estimates are in the hundreds of thousands of dollars. For other crimes, the estimates range from several hundred to tens of thousands of dollars.

[19]Any crime reduction benefits would likely be considered a bonus with respect to the cost-effectiveness of the program, since Gelber, Isen, and Kessler (2016) find that the mortality benefits of SYEP (i.e., that participants are less likely to die in the years after the program) appear to cover the cost of the program on their own. That said, the crime benefits are still meaningful to consider, since the costs of crimes are born by different parties than the mortality costs.

low risk group are dramatically lower, in the range of $2 or $3 per participant. Together, these results suggest that the criminal justice social cost savings of the program, while meaningful, are isolated among the at-risk population. We return to this issue when we discuss program targeting.

Why SYEPs have such profound effects on criminal justice involvement, particularly among the at-risk population, is the remaining puzzle. A number of candidate mechanisms have already been discussed in prior work: incapacitation, disruption of routine activities (Modestino 2019), and learning soft skills from mentors (Heller 2014). Our in-program effects are consistent with incapacitation and perhaps a disruption in routine activities (in the sense that the program reduces opportunities for what Osgood et al. (1996) calls "unstructured socializing" and thus reduces opportunities to engage in deviant behaviors).

While our estimate of the effect on arrests gets relatively less precise over time, the coefficient estimate on the likelihood of a felony arrest is negative in the program and continues to decrease over time, as shown in Figure I. Consistent with prior examinations of summer jobs programs, it appears that the mechanism underlying the effects of SYEP is something that generates a longer-term change in behavior, exposure, or both. This means that while the results may be suggestive of incapacitation effects, they also are suggestive of a mechanism that affects behavior over time.

FIGURE I ABOUT HERE

One potential explanation that has received little, if any, attention in the prior literature is that participation in the program triggers differential exposure to the criminal justice system or differential system response. One possibility is that participation in the program creates differential exposure to police. For example, it is possible that while SYEP participants are at work they are spending less time in more-heavily policed neighborhoods, or that participation in SYEP keeps youth "off the street" and, therefore, less exposed to patrol officers and the associated possibility of being arrested.[20]

It may also be the case that the downstream responses of system actors, like prosecutors, are somewhat more favorable to youth who participate in SYEP. Participation in SYEP could mitigate a plea agreement for an individual who is arrested during the program summer, leading to a lower likelihood of conviction or to a conviction for a violation rather than a misdemeanor. With respect to persistent effects, it is important to consider that the disruption in criminal justice contact induced by SYEP may accumulate over time, since contact with the criminal justice system is often associated with increased system surveillance and cumulative disadvantage (Kurlychek and Johnson 2019). This is consistent with the evidence from Gelber, Isen, and Kessler (2016), which finds — analyzing the same youth and the same program years — that SYEP participants are 10 percent less likely to serve time in New York State prison.

Our findings also speak to how one might target summer jobs programs in the future. On this point, prior literature has also explored whether summer jobs have heterogeneous effects on different segments of the youth population (Davis and Heller 2017). Davis and Heller (2017) specifically recruited "discon-

[20] However, we do not observe what control youth do when not employed by SYEP (Felson 1994). To the extent that these youth stay inside their homes, it is possible that the summer job generates relatively *more* exposure to police.

nected" youth (who were even more at-risk than the youth in Heller (2014)) and found that the program was effective even among this population, which is traditionally less responsive to less-intensive interventions. In a similar spirit, we find that the effects of NYC SYEP are concentrated among those we identify as at-risk for criminal justice contact, and that the social cost savings are meaningful among this subgroup. In addition, the size of the lower-risk population in our sample allows us to estimate relatively precise zero effects of the program on arrests and convictions for that group. Taken together, the evidence suggests that the criminal justice benefits of summer jobs programs arise only — or at least primarily — among relatively disconnected youth with prior criminal justice contact.

A natural response to these findings is to suggest that the benefits of this program would be maximized if the program were optimally targeted to this more responsive segment of the population. However, there are several reasons to exercise caution here. First, we do not yet know the extent to which the composition of a program's population affects its criminal justice treatment effects (Heller and Kessler 2017). Participation in SYEP could change the composition of a youth's peer group in a way that mitigates criminal justice contact, and the program might therefore have a different effect if it were offered exclusively or primarily to at-risk youth. Future work aimed at understanding the optimal peer group for SYEP will be a necessary precursor to any effort to effectively target such programs. Second, summer jobs programs have a multi-dimensional set of objectives, among which keeping youth "out of trouble" is only one. So, while targeting the program towards at-risk youth may maximize program impact on criminal justice outcomes, it is unclear how such targeting would influence the effects of the program on other dimensions.

More broadly, our findings add to a growing literature on the efficacy of summer jobs to mitigate youth violence and criminal justice involvement. This work may be particularly relevant in light of recent policy debates. For example, recent calls to "defund the police" identify expanding job opportunities as a way to reduce crime and violence (Ray 2020). SYEPs have a growing track record of doing just that. SYEPs also make an agency focused on youth and community development an institutional touch point for at-risk youth, which could have advantages relative to having a department of corrections or some other criminal justice agency in that role (Brayne 2014). Future research should further explore summer jobs programs and how they might be optimally designed to achieve policy goals.

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TABLE I

SUMMARY STATISTICS

	Control	Treatment	Difference p-value
Age at SYEP Start Date	17.153 (1.265)	17.164 (1.267)	0.938
Race/Ethnicity			
White	0.073	0.195	0.602
Black	0.518	0.434	0.423
Latino	0.266	0.251	0.498
Other	0.143	0.120	0.075*
Male	0.451	0.447	0.913
US Citizenship	0.914	0.923	0.212
Family Members	4.129 (1.872)	4.491 (2.324)	0.853
Prior Arrest	0.034	0.029	0.545
Prior Conviction	0.018	0.016	0.471
Arrests (May 1 to April 30)			
Any Arrest	0.020	0.018	0.957
Any Felony Arrest	0.010	0.008	0.360
Any Misdemeanor Arrest	0.014	0.013	0.620
Arrest Count	0.032 (0.266)	0.027 (0.239)	0.639
Convictions (May 1 to April 30)			
Any Conviction	0.007	0.006	0.834
Any Felony Conviction	0.003	0.003	0.848
Any Misdemeanor Conviction	0.005	0.003	0.690
Conviction Count	0.008 (0.109)	0.007 (0.098)	0.814
Number of Observations	71,539	91,908	163,447

Notes. This table shows the summary statistics for the treatment and control group across a host of demographic variables and crime outcomes. The means are shown with the standard deviations in parentheses. “Prior Arrest” and “Prior Conviction” are defined through program start date (July 1st). The “Arrests” and “Convictions” outcomes are for the year before randomization, May 1st through April 30th. The difference p-value column is the p-value of the difference between the treatment group and the control group.
*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE II

2SLS ARRESTS AND CONVICTIONS OUTCOMES IN MONTHS OF PROGRAM (WITHOUT CONTROLS)

	(1)	(2)	(3)
Panel A: Arrests	All Youth	At-Risk Youth	Low-Risk Youth
Any Arrest	-0.128**	-2.754*	-0.0357
	(0.0544)	(1.489)	(0.0318)
	[0.766]	[12.047]	[0.340]
Any Felony Arrest	-0.072**	-1.124	-0.0348
	(0.0341)	(1.034)	(0.0235)
	[0.310]	[4.856]	[0.138]
Any Misdemeanor Arrest	-0.0487	-1.100	-0.0075
	(0.0425)	(1.246)	(0.0268)
	[0.492]	[7.898]	[0.212]
Number of Arrests	-0.00122*	-0.0335*	-0.000089
	(0.000690)	(0.0202)	(0.000415)
	[0.0087] (0.1084)	[0.141] (0.418)	[0.0037] (0.0701)
Panel B: Convictions			
Any Conviction	-0.0752**	-2.092***	-0.0104
	(0.0336)	(0.793)	(0.0223)
	[0.241]	[4.057]	[0.0964]
Any Felony Conviction	-0.0360*	-0.507	-0.0200*
	(0.0216)	(0.550)	(0.0119)
	[0.095]	[1.537]	[0.0406]
Any Misdemeanor Conviction	-0.0338	-1.560**	0.0146
	(0.0268)	(0.621)	(0.0192)
	[0.151]	[2.612]	[0.0581]
Number of Convictions	-0.000712**	-0.0207**	-0.0000636
	(0.000360)	(0.00892)	(0.000234)
	[0.0026] (0.0542)	[0.0439] (0.225)	[0.0010] (0.0327)
First Stage Estimate	0.6898 (0.0114)	0.6151 (0.0144)	0.6922 (0.0116)
Number of Observations	163,447	5,092	158,355

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) in the program months without controls. At-Risk Youth are defined as having an arrest in the data prior to the program summer, and Low-Risk Youth are defined as not having an arrest prior to the program summer. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE III

2SLS ARRESTS AND CONVICTIONS OUTCOMES OVER TIME FOR AT-RISK YOUTH (WITHOUT CONTROLS)

Panel A: Arrests	(1) 1 Year Post Program	(2) 3 Year Post Program	(3) 5 Year Post Program
Any Arrest	-0.650	-2.374	-2.045
	(2.414)	(2.866)	(2.527)
	[41.43]	[61.49]	[67.64]
Any Felony Arrest	-2.600	-4.510*	-2.809
	(2.142)	(2.552)	(2.315)
	[19.76]	[36.57]	[44.53]
Any Misdemeanor Arrest	1.699	0.474	-1.882
	(2.217)	(2.830)	(2.634)
	[31.96]	[53.53]	[61.96]
Number of Arrests	-0.00451	0.0335	0.0557
	(0.0660)	(0.144)	(0.190)
	[0.803] (1.262)	[2.122] (2.630)	[3.216] (3.850)
Panel B: Convictions			
Any Conviction	-1.361	-2.790	-1.259
	(1.613)	(2.074)	(2.357)
	[14.843]	[29.164]	[35.126]
Any Felony Conviction	-0.795	-0.991	-1.670
	(1.116)	(1.510)	(1.747)
	[7.160]	[14.382]	[18.132]
Any Misdemeanor Conviction	-1.541	-2.644	-0.747
	(1.088)	(1.862)	(2.212)
	[9.158]	[19.760]	[25.230]
Number of Convictions	-0.0420	-0.00884	0.0273
	(0.0258)	(0.0575)	(0.0742)
	[0.216] (0.605)	[0.570] (1.239)	[0.867] (1.850)
Number of Observations	5,092	5,092	5,092

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrest (Panel A) and convictions (Panel B) over time among the sample of At-Risk Youth (i.e., individuals who had an arrest prior to the program summer) without controls. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. The first stage estimate is 0.6151 (0.0144). This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE IV

2SLS ARRESTS AND CONVICTIONS OUTCOMES OVER TIME FOR LOW-RISK YOUTH (WITHOUT CONTROLS)

Panel A: Arrests	(1) 1 Year Post Program	(2) 3 Year Post Program	(3) 5 Year Post Program
Any Arrest	0.0124	-0.0301	0.175
	(0.112)	(0.172)	(0.220)
	[2.259]	[6.087]	[8.939]
Any Felony Arrest	-0.0699	-0.105	-0.0421
	(0.0663)	(0.107)	(0.133)
	[0.928]	[2.571]	[3.807]
Any Misdemeanor Arrest	0.0735	-0.0802	0.0686
	(0.100)	(0.170)	(0.223)
	[1.661]	[4.886]	[7.289]
Number of Arrests	-0.000554	-0.000309	0.000507
	(0.00215)	(0.00623)	(0.00100)
	0.0349 (0.279)	0.131 (0.716)	0.223 (1.100)
Panel B: Convictions			
Any Conviction	-0.0258	-0.0127	0.0575
	(0.0637)	(0.108)	(0.127)
	[0.700]	[1.924]	[2.770]
Any Felony Conviction	-0.0356	-0.00942	-0.0264
	(0.0447)	(0.0654)	(0.0758)
	[0.359]	[0.878]	[1.246]
Any Misdemeanor Conviction	0.0105	-0.0449	0.0542
	(0.0494)	(0.102)	(0.110)
	[0.373]	[1.225]	[1.847]
Number of Convictions	-0.000272	-0.000426	-0.000106
	(0.000803)	(0.00219)	(0.00341)
	[0.0082] (0.109)	[0.0272] (0.242)	[0.0453] (0.374)
Number of Observations	158,355	158,355	158,355

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) over time among the sample of Low-Risk Youth (i.e., individuals who did not have an arrest prior to the program summer) without controls. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. The first stage estimate is 0.6923 (0.0116). This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

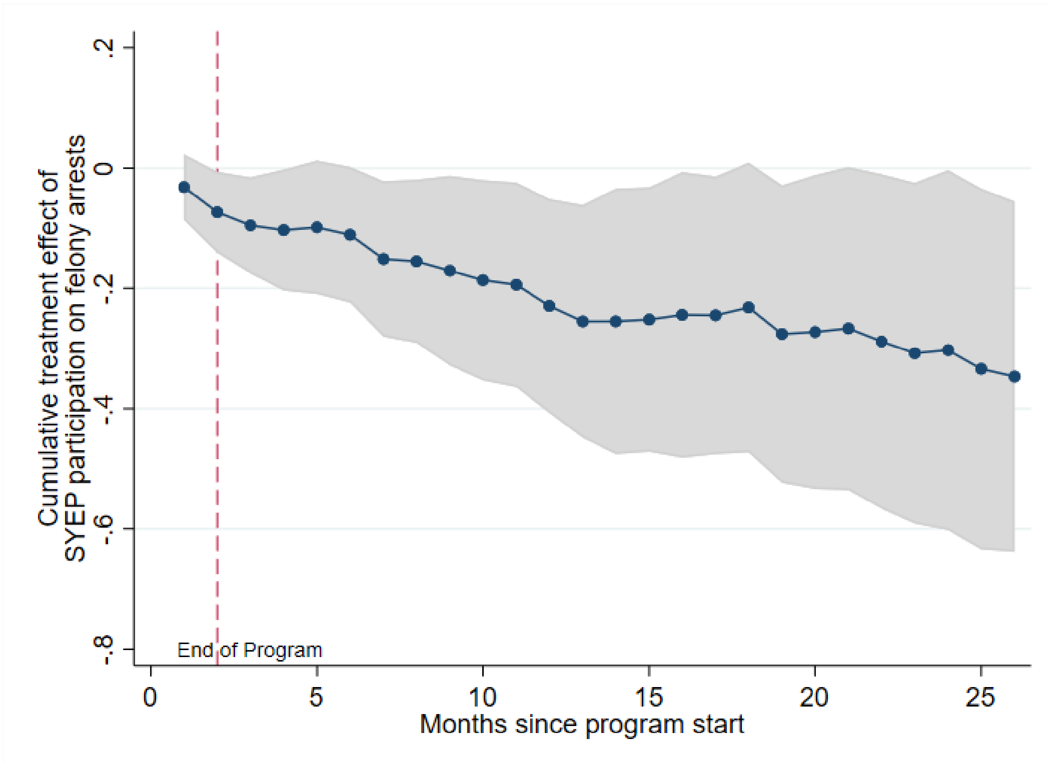

FIGURE I
Cumulative treatment effect of SYEP participation on having a felony arrest over time (all youth)

Notes. This figure shows the cumulative treatment effect of the percentage of youth with felony arrests for all youth over time (by month). Month 0 indicates the beginning of the program, and the program ended at month 2. The confidence intervals are calculated using robust standard errors.

ONLINE APPENDIX

The Effects of Youth Employment on Crime: Evidence from New York City Lotteries

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TABLE A.I

2SLS Arrests and Convictions Outcomes in Months of Program (with controls)

Panel A: Arrests	(1) All Youth	(2) At-Risk Youth	(3) Low-Risk Youth
Any Arrest	-0.132**	-2.659*	-0.0381
	(0.0558)	(1.506)	(0.0320)
	[0.766]	[12.047]	[0.340]
Any Felony Arrest	-0.0734**	-1.075	-0.0359
	(0.0345)	(1.039)	(0.0236)
	[0.310]	[4.856]	[0.138]
Any Misdemeanor Arrest	-0.0506	-1.042	-0.00886
	(0.0429)	(1.245)	(0.0268)
	[0.492]	[7.898]	[0.212]
Number of Arrests	-0.00126*	-0.0322	-0.000116
	(0.000700)	(0.0205)	(0.000416)
	[0.0087] (0.108)	[0.141] (0.418)	[0.0037] (0.0701)
Panel B: Convictions			
Any Conviction	-0.0761**	-2.045**	-0.0110
	(0.0339)	(0.798)	(0.0224)
	[0.241]	[4.057]	[0.0964]
Any Felony Conviction	-0.0365*	-0.477	-0.0203*
	(0.0217)	(0.547)	(0.0119)
	[0.095]	[1.537]	[0.0406]
Any Misdemeanor Conviction	-0.0342	-1.542**	0.0142
	(0.0268)	(0.622)	(0.0192)
	[0.151]	[2.612]	[0.0581]
Number of Convictions	-0.000722**	-0.0201**	-0.0000703
	(0.000362)	(0.00893)	(0.000234)
	[0.0026] (0.0542)	[0.0439] (0.225)	[0.0010] (0.0327)
First Stage Estimate	0.6906 (0.0113)	0.6151 (0.0143)	0.6931 (0.0115)
Number of Observations	163,447	5,092	158,355

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) in the program months among All Youth, At-Risk Youth (i.e., individuals who had an arrest prior to the program summer), and Low-Risk Youth (i.e., individuals who did not have a prior arrest), controlling for male (1 missing), white (733 missing), black (733 missing), latino (733 missing), citizen (1 missing), family members (2 missing), and age at SYEP start (0 missing). The number of missing observations are denoted in the parentheses. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE A.II

OLS ARRESTS AND CONVICTIONS OUTCOMES IN MONTHS OF PROGRAM

	(1) All Youth		(2) At-Risk Youth		(3) Low-Risk Youth	
Panel A: Arrests	No Controls	Controls	No Controls	Controls	No Controls	Controls
Any Arrest	-0.0827**	-0.0838**	-1.887*	-1.796*	-0.0210	-0.0219
	(0.0373)	(0.0382)	(0.960)	(0.968)	(0.0224)	(0.0227)
	[0.766]	[0.766]	[12.047]	[12.047]	[0.340]	[0.340]
Any Felony Arrest	-0.0465*	-0.0471*	-0.614	-0.571	-0.0230	-0.0234
	(0.0235)	(0.0238)	(0.671)	(0.676)	(0.0164)	(0.0165)
	[0.310]	[0.310]	[4.856]	[4.856]	[0.138]	[0.138]
Any Misdemeanor Arrest	-0.0293	-0.0299	-0.895	-0.837	-0.00219	-0.00267
	(0.0291)	(0.0293)	(0.819)	(0.816)	(0.0816)	(0.0817)
	[0.492]	[0.492]	[7.898]	[7.898]	[0.212]	[0.212]
Number of Arrests	-0.000758	-0.000772	-0.0222	-0.0209	-0.0000118	-0.0000213
	(0.000479)	(0.000485)	(0.0136)	(0.0137)	(0.000300)	(0.000301)
	[0.0087] (0.108)	[0.0087] (0.108)	[0.141] (0.418)	[0.141] (0.418)	[0.0037] (0.0701)	[0.0037] (0.0701)
Panel B: Convictions						
Any Conviction	-0.0498**	-0.0503**	-1.180**	-1.135**	-0.00614	-0.00638
	(0.0235)	(0.0236)	(0.530)	(0.535)	(0.0158)	(0.0158)
	[0.241]	[0.241]	[4.057]	[4.057]	[0.0964]	[0.0964]
Any Felony Conviction	-0.0235	-0.0237	-0.360	-0.335	-0.0135	-0.0136
	(0.0150)	(0.0151)	(0.357)	(0.356)	(0.00845)	(0.00844)
	[0.095]	[0.095]	[1.537]	[1.537]	[0.0406]	[0.0406]
Any Misdemeanor Conviction	-0.0222	-0.0225	-0.789*	-0.767*	0.0108	0.0107
	(0.0190)	(0.0190)	(0.407)	(0.408)	(0.0136)	(0.0136)
	[0.151]	[0.151]	[2.612]	[2.612]	[0.0581]	[0.0581]
Number of Convictions	-0.000463*	-0.000469*	-0.0116*	-0.0110*	-0.0000318	-0.0000346
	(0.000254)	(0.000255)	(0.00583)	(0.00587)	(0.000165)	(0.000165)
	[0.0026] (0.0542)	[0.0026] (0.0542)	[0.0439] (0.225)	[0.0439] (0.225)	[0.00010] (0.0327)	[0.00010] (0.0327)
Number of Observations	163,447	163,447	5,902	5,902	158,355	158,355

Notes. This table shows the results of OLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) in the program months among All youth, At-Risk Youth (i.e., individuals who had an arrest prior to the program summer), and Low-Risk Youth (i.e., individuals who did not have a prior arrest), controlling for male (1 missing), white (733 missing), black (733 missing), latino (733 missing), citizen (1 missing), family members (2 missing), and age at SYEP start (0 missing). The number of missing observations are denoted in the parentheses. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE A.III

2SLS ARRESTS AND CONVICTIONS OUTCOMES OVER TIME FOR AT-RISK YOUTH (WITH CONTROLS)

Panel A: Arrests	(1) 1 Year Post Program	(2) 3 Year Post Program	(3) 5 Year Post Program
Any Arrest	-0.332	-1.945	-1.609
	(2.361)	(2.867)	(2.531)
	[41.426]	[61.494]	[67.640]
Any Felony Arrest	-2.452	-4.225*	-2.455
	(2.098)	(2.521)	(2.281)
	[19.760]	[36.570]	[44.530]
Any Misdemeanor Arrest	1.967	0.856	-1.473
	(2.231)	(2.812)	(2.607)
	[31.961]	[53.534]	[61.955]
Number of Arrests	0.00188	0.0491	0.0811
	(0.0656)	(0.143)	(0.182)
	[0.803] (1.262)	[2.122] (2.630)	[3.216] (3.850)
Panel B: Convictions			
Any Conviction	-1.255	-2.582	-0.953
	(1.598)	(2.066)	(2.333)
	[14.843]	[29.164]	[35.126]
Any Felony Conviction	-0.731	-0.876	-1.487
	(1.117)	(1.484)	(1.657)
	[7.160]	[14.382]	[18.132]
Any Misdemeanor Conviction	-1.468	-2.500	-0.534
	(1.076)	(1.861)	(2.206)
	[9.158]	[19.760]	[25.230]
Number of Convictions	-0.0405	-0.00633	0.0327
	(0.0284)	(0.0574)	(0.0731)
	[0.216] (0.605)	[0.570] (1.239)	[0.867] (1.850)
Number of Observations	5,092	5,092	5,092

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) over time among the sample of At-Risk Youth (i.e., individuals who had an arrest prior to the program summer), controlling for male (0 missing), white (26 missing), black (26 missing), latino (26 missing), citizen (0 missing), family members (0 missing), and age at SYEP start (0 missing). The number of missing observations are denoted in the parentheses. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. The first stage estimate is 0.6151 (0.0144). This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE A.IV

2SLS ARRESTS AND CONVICTIONS OUTCOMES OVER TIME FOR LOW-RISK YOUTH (WITH CONTROLS)

	(1) 1 Year Post Program	(2) 3 Year Post Program	(3) 5 Year Post Program
Panel A: Arrests			
Any Arrest	-0.00383	-0.0693	0.119
	(0.111)	(0.166)	(0.209)
	[2.259]	[6.087]	[8.939]
Any Felony Arrest	-0.0773	-0.123	-0.0677
	(0.0663)	(0.107)	(0.133)
	[0.928]	[2.571]	[3.807]
Any Misdemeanor Arrest	0.0620	-0.111	0.0229
	(0.0996)	(0.163)	(0.212)
	[1.661]	[4.886]	[7.289]
Number of Arrests	-0.000820	-0.00404	-0.00113
	(0.00212)	(0.00608)	(0.00974)
	[0.0349] (0.279)	[0.131] (0.716)	[0.223] (1.100)
Panel B: Convictions			
Any Conviction	-0.0305	-0.0259	0.0395
	(0.0629)	(0.107)	(0.127)
	[0.700]	[1.924]	[2.770]
Any Felony Conviction	-0.0385	-0.0154	-0.0347
	(0.0442)	(0.0650)	(0.0747)
	[0.359]	[0.878]	[1.246]
Any Misdemeanor Conviction	0.00807	-0.0534	0.0418
	(0.0495)	(0.101)	(0.110)
	[0.373]	[1.225]	[1.847]
Number of Convictions	-0.000330	-0.000613	-0.000413
	(0.000795)	(0.00216)	(0.00335)
	[0.0082] (0.109)	[0.0272] (0.242)	[0.0453] (0.374)
Number of Observations	158,355	158,355	158,355

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) over time among the sample of Low-Risk Youth (i.e., individuals who did not have an arrest prior to the program summer), controlling for male (1 missing), white (707 missing), black (707 missing), latino (707 missing), citizen (1 missing), family members (2 missing), and age at SYEP start (0 missing). The number of missing observations are denoted in the parentheses. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. The first stage estimate is 0.6923 (0.0116). This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE A.V

2SLS ARRESTS AND CONVICTIONS OUTCOMES OVER TIME FOR ALL YOUTH (WITHOUT CONTROLS)

	(1) 1 Year Post Program	(2) 3 Year Post Program	(3) 5 Year Post Program
Panel A: Arrests			
Any Arrest	-0.0576	-0.169	0.0350
	(0.155)	(0.202)	(0.222)
	[3.685]	[8.104]	[11.076]
Any Felony Arrest	-0.167	-0.275*	-0.175
	(0.113)	(0.166)	(0.174)
	[1.613]	[3.808]	[5.289]
Any Misdemeanor Arrest	0.0799	-0.128	-0.0585
	(0.128)	(0.183)	(0.211)
	[2.764]	[6.657]	[9.279]
Number of Arrests	-0.00168	-0.00468	-0.00190
	(0.00351)	(0.00901)	(0.0133)
	[0.062] (0.391)	[0.203] (0.941)	[0.332] (1.421)
Panel B: Convictions			
Any Conviction	-0.0820	-0.127	-0.0218
	(0.0891)	(0.127)	(0.152)
	[1.216]	[2.917]	[3.950]
Any Felony Conviction	-0.0661	-0.0554	-0.0960
	(0.0599)	(0.0864)	(0.102)
	[0.607]	[1.371]	[1.862]
Any Misdemeanor Conviction	-0.0451	-0.143	0.00131
	(0.0669)	(0.110)	(0.122)
	[0.694]	[1.901]	[2.700]
Number of Convictions	-0.00174	-0.00138	-0.000411
	(0.00130)	(0.00313)	(0.00472)
	[0.016] (0.162)	[0.047] (0.350)	[0.0753] (0.532)
Number of Observations	163,447	163,447	163,447

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) over time among the sample of All Youth without controls. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. The first stage estimate is 0.6899 (0.0114). This table shows marginal effects and robust standard errors on the SYEP participation dummy.

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE A.VI

2SLS ARRESTS AND CONVICTIONS OUTCOMES OVER TIME FOR ALL YOUTH (WITH CONTROLS)

Panel A: Arrests	(1) 1 Year Post Program	(2) 3 Year Post Program	(3) 5 Year Post Program
Any Arrest	-0.0743	-0.205	-0.0148
	(0.152)	(0.193)	(0.209)
	[3.685]	[8.104]	[11.076]
Any Felony Arrest	-0.174	-0.293*	-0.198
	(0.111)	(0.162)	(0.171)
	[1.613]	[3.808]	[5.289]
Any Misdemeanor Arrest	0.0674	-0.157	-0.0996
	(0.127)	(0.173)	(0.196)
	[2.764]	[6.657]	[9.279]
Number of Arrests	-0.00198	-0.00564	-0.00352
	(0.00346)	(0.00874)	(0.0128)
	[0.062] (0.391)	[0.203] (0.941)	[0.332] (1.421)
Panel B: Convictions			
Any Conviction	-0.0870	-0.139	-0.0382
	(0.0874)	(0.124)	(0.150)
	[1.216]	[2.917]	[3.950]
Any Felony Conviction	-0.0685	-0.0604	-0.103
	(0.0589)	(0.0847)	(0.0993)
	[0.607]	[1.371]	[1.862]
Any Misdemeanor Conviction	-0.0480	-0.151	-0.0106
	(0.0667)	(0.108)	(0.121)
	[0.694]	[1.901]	[2.700]
Number of Convictions	-0.00180	-0.00157	-0.000717
	(0.00127)	(0.00307)	(0.00462)
	[0.016] (0.162)	[0.047] (0.350)	[0.0753] (0.532)
Number of Observations	163,447	163,447	163,447

Notes. This table shows the results of 2SLS regressions of SYEP participation and arrests (Panel A) and convictions (Panel B) over time among the sample of All Youth, controlling for male (1 missing), white (707 missing), black (707 missing), latino (707 missing), citizen (1 missing), family members (2 missing), and age at SYEP start (0 missing). The number of missing observations are denoted in the parentheses. Control means are included in brackets below the standard errors. The binary outcomes in this table are presented in percentage points. The first stage estimate is 0.6899 (0.0114). This table shows marginal effects and robust standard errors on the SYEP participation dummy.
*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE A.VII

SUMMARY STATISTICS FOR AT-RISK YOUTH

	Control	Treatment	Difference p-value
Age at SYEP Start Date	17.931 (1.460)	17.849 (1.414)	0.714
Race/Ethnicity			
White	0.012	0.022	0.291
Black	0.677	0.657	0.553
Latino	0.261	0.442	0.959
Other	0.049	0.229	0.401
Male	0.780	0.779	0.357
US Citizenship	0.964	0.965	0.304
Family Members	3.925 (1.820)	3.792 (1.922)	0.604
Prior Arrest	1	1	-
Prior Conviction	0.539	0.539	0.915
Arrests (May 1 to April 30)			
Any Arrest	0.607	0.610	0.595
Any Felony Arrest	0.290	0.272	0.394
Any Misdemeanor Arrest	0.423	0.438	0.313
Arrest Count	0.961 (1.101)	0.935 (1.056)	0.757
Conviction (May 1 to April 30)			
Any Conviction	0.204	0.207	0.87
Any Felony Conviction	0.097	0.095	0.925
Any Misdemeanor Conviction	0.113	0.119	0.793
Conviction Count	0.239 (0.543)	0.237 (0.524)	0.885
Number of Observations	2,414	2,678	5,092

Notes. This table shows the summary statistics for the treatment and control group within individuals who were arrested prior to the program start across a host of demographic variables and crime outcomes. "Prior Arrest" and "Prior Conviction" are defined through program start date (July 1st). The "Arrests" and "Convictions" outcomes are for the year before randomization, May 1st through April 30th. The difference p-value column is the p-value of the difference between the treatment group and the control group..

*** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

TABLE A.VIII
SUMMARY STATISTICS FOR LOW-RISK YOUTH

	Control	Treatment	Difference p-value
Age at SYEP Start Date	17.126 (1.250)	17.144 (1.257)	0.798
Race/Ethnicity			
White	0.075	0.201	0.482
Black	0.512	0.427	0.286
Latino	0.266	0.251	0.469
Other	0.147	0.122	0.055*
Male	0.439	0.437	0.930
US Citizenship	0.912	0.922	0.167
Family Members	4.137 (1.873)	4.512 (2.332)	0.807
Prior Arrest	0	0	-
Prior Conviction	0	0	-
Arrests (May 1 to April 30)			
Any Arrest	0	0	-
Any Felony Arrest	0	0	-
Any Misdemeanor Arrest	0	0	-
Arrest Count	0 (0)	0 (0)	-
Conviction (May 1 to April 30)			
Any Conviction	0	0	-
Any Felony Conviction	0	0	-
Any Misdemeanor Conviction	0	0	-
Conviction Count	0 (0)	0 (0)	-
Number of Observations	69,125	89,230	158,355

Notes. This table shows the summary statistics for the treatment and control group within individuals who were not arrested prior to the program start across a host of demographic variables and crime outcomes. The means are shown with the standard deviations in parentheses. The difference p-value column is the p-value of the difference between the treatment group and the control group. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.