

How To Allocate Slots: the Market Design of Summer Youth Employment Programs

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I. Introduction

Summer Youth Employment Programs (SYEPs), in which local governments provide training and a part-time summer job to (often disadvantaged) high school students or out-of-school young adults, are an enduring part of employment policy in the U.S. In addition to state, local, and philanthropic support, SYEPs have been part of the federal budget for half a century. They received federal funding beginning in 1964, became part of the broader Youth Activities annual budget of almost \$1 billion in 2000 as part of the Workforce Investment Act, were expanded under the American Recovery and Reinvestment Act in 2009, and have recently received renewed attention from federal policymakers (Fernandes-Alcantara 2011, <https://www.whitehouse.gov/the-press-office/2016/05/16/fact-sheet-white-house-and-department-labor-announce-21-million-summer>).¹

As highlighted by Gelber, Isen, and Kessler (2016), the goals of SYEPs are three-fold: (1) to transfer money to low-income youth and their families, (2) to help improve the future labor market prospects of youth (e.g. by giving them work experience and work-related skills), and (3) to keep youth “out of trouble” (i.e., keeping youth out of the criminal justice system and putting them onto a safer path). Likely due to the potential promise of these programs, almost every major U.S. city helps connect youth with jobs — often through a SYEP (Gelber, Isen and Kessler 2016; see also Section II). Interest in the operations and goals of SYEPs is growing across government, non-profit, and for-profit institutions (see reports by Brookings 2014 a,b, 2016; Summer Jobs Connect 2016 a,b,c; JP Morgan Chase 2015, 2016).

Historically, SYEPs have received relatively little rigorous research attention. A small set of studies compares youth who participate in a SYEP program with others who do not. Early studies of programs that include both summer and year-round components suggest their potential to generate schooling improvements, especially for black males (Farkas, Smith, and Stromsdorfer 1983; Lalonde 1986; Somers and Stromsdorfer 1972). More recent studies suggest some promise for reducing delinquent behavior or improving financial capabilities (Loke, Libby, and Choi 2013; Sum, Trubskyy, and McHugh 2013). Yet none of these studies can convincingly attribute the differences between participants and non-participants to the programs themselves due to concerns about selection — it is possible that youth who choose (or are chosen) to participate would differ from those who are not part of the program, even in the absence of participation.

¹ Relatedly, the Federal Work Opportunity Tax Credit (WOTC) — along with similar credits at the state level — helps to stimulate summer employment of youth by providing a tax credit to employers who newly hire 16 or 17 year olds from low-income neighborhoods.

A recent set of studies overcomes this problem by leveraging the fact that program slots were randomly assigned.² When program admission is determined by random lottery, the youth who are offered a program slot are, on average, identical to those who lost the lottery; any difference between the two groups can be attributed to the program itself. These recent studies are quite revealing about the value of SYEP programs: in New York City and Chicago, they have a dramatic effect on crime and violence. NYC's program reduces later incarceration in New York State prison by about 10 percent and mortality (largely from homicide) by about 20 percent (Gelber, Isen and Kessler 2016); Chicago's program reduces violent-crime arrests by 43 percent (Heller 2014). The programs accomplish this dramatic decline in offending and victimization without improving post-program employment. Estimates from New York suggest a small decline (about \$100 annually) in income for the three years after the program (Gelber, Isen and Kessler 2016).³ The New York City program does generate small increases in school attendance and high-stakes test-taking (Leos-Urbel 2014; Schwartz, Leos-Urbel and Wiswall 2015), although this does not appear to lead to higher college attainment (Gelber, Isen and Kessler 2016). In part because of this new evidence, SYEPs across the country are quickly expanding.⁴

The renewed interest in providing youth with summer training and employment raises key questions about the market design issues embedded in program delivery. Many summer youth employment programs face a challenge in identifying a sufficient number of employers to meet the demand for jobs expressed by eligible youth as well as a budget constraint on how many program slots they can offer. Faced with excess demand, the programs must decide how to allocate slots in the program to youth. As with many examples from the matching literature within market design (Roth 2016), the programs must determine allocation without the use of a price mechanism (given the nature of the programs, it would be nonsensical to sell the positions to youth and let the market clear in that way). Instead, the programs choose from a variety of non-price allocation mechanisms, described in Section II. These mechanisms may or may not be optimal from a social perspective, as discussed in Section III.

The programs engage in additional market design when they allocate youth to specific jobs in the program. Job assignment is a complicated matching problem that has multiple objectives. Youth have heterogeneous preferences over the types of jobs they do during the summer (e.g., some

² A few earlier studies also use random assignment, but do not necessarily identify the causal impact of summer jobs programs per se. One early experiment of the Summer Training and Education Program (STEP) offered both treatment and control groups training and employment, so the program impacts reflect the effects of an additional life skills and sex education curriculum, not the summer jobs that are more typically the basis of SYEPs (Grossman and Sipe 1992; Walker and Vilella-Velez 1992). A Philadelphia study in theory used random assignment to allocate program slots (McClanahan, Sipe, and Smith 2004), but appears to report program effects that do not make use of the random assignment (see Appendix 2.1.C in Heller 2014 for more detailed discussion).

³ These negative earnings effects disappear by the fourth year after the program. Evidence suggests that at least part of this effect may be driven by job stickiness: in subsequent years, youth return to jobs similar to the ones they had in the program, and these types of jobs appear to be associated with lower earnings.

⁴ See, e.g., <https://www.cityofchicago.org/city/en/depts/sss/provdrs/youth/news/2016/march/mayor-emmanuel-announces-25-000-summer-youth-job-opportunities-av.html> and http://www.phillytrib.com/news/city-pushes-for-more-summer-jobs-for-youth/article_24e26399-31d9-5ed9-a09b-519bd559cf50.html. Also see Schwartz and Leos-Urbel (2014) for an additional review of the literature on SYEPs.

may want to work inside, others outside; some may want to work with children at a day care or day camp, others may want to experience a retail or office environment). Employers have preferences over the types of youth that fill their positions (e.g., employers may care differentially about the youth's prior work experiences or existing skill set). Program providers care about satisfying both the youth and employer preferences — since unsatisfied youth may drop out or need to be reassigned and unsatisfied employers may not offer jobs in subsequent years. In addition, providers likely also care about whether the match has benefits to the youth beyond the summer — that is, how the matching of youth to jobs influences youth outcomes in the longer term, although they may not have complete information on how a particular youth will respond to program exposure in that time frame.

In the following sections, we describe the allocation mechanisms that SYEPs use (Section II) and consider their implications (Section III). We then describe what we have learned so far from the random assignment of slots to youth about who benefits the most from the programs (Section IV) and how program design influences outcomes (Section V). Finally, we offer concluding thoughts about the value of random assignment and what we have left to learn from it (Section VI).

II. Types of Allocation Mechanisms

There are a number of different mechanisms for allocating youth to slots in SYEPs. Table 1 shows data on the allocation mechanisms and approximate sizes of 27 programs from the 30 largest U.S. cities by population. In only three of the largest cities (San Antonio, Fort Worth, and Oklahoma City) do we find no recent indication of SYEP programs.

Table 1: Allocation Mechanisms for Spots in Summer Youth Employment Programs

Allocation Mechanism	City	Name of Program	Approximate program size	Approximate # applicants
Random	New York, New York	Summer Youth Employment Program	54,000	130,000
Random	Los Angeles, California	HIRE LA's Youth	13,000	15,000
Random	Detroit, Michigan	Detroit Summer Youth Employment Program	8,200	11,000
Random	Baltimore, Maryland	YouthWorks	8,000	13,000
Random	Memphis, Tennessee	MPLOY Summer Work	1,000	4,500
Random	Phoenix, Arizona	Phoenix Youth RISE	110	260
Random (by zipcode)	Austin, Texas	Work Based Learning/Summer Youth Employment Program	750	1200
FCFS	District of Columbia	Mayor Marion S. Barry Summer Youth Employment Program	13,000	23,000
FCFS	Columbus, Ohio	S.O.A.R.hire!	800	6,700
FCFS	San Jose, California	San Jose Works	340	N/A
FCFS	Nashville, Tennessee	Metro Summer Youth Internship Program	150	220

Merit	Houston, Texas	Hire Houston Youth	1,100	4,000
Merit	Portland, Oregon	SummerWorks	1,000	2,000
Merit	Indianapolis	Project Indy	1,000	N/A
Merit	San Diego, California	Connect2Careers	880	N/A
Merit	Louisville, Kentucky	Mayor's Summer Works	750	2,600
Merit	Dallas, Texas	Mayor's Intern Fellows Program	350	1,800
Merit	Las Vegas, Nevada	Summer Business Institute	120	520
Merit	San Francisco, California	Business Pathways and Summer Internship Program	70	300
Restriction (Income)	Jacksonville, Florida	Mayor's Summer Jobs Program	340	1,500
Restriction (Income, "Risk")	El Paso, Texas	Hire El Paso Youth!	210	640
Restriction (Income)	Denver, Colorado	Summer Youth Employment Program	150	150
Varies (Merit, FCFS, & Random)	Chicago, Illinois	One Summer Chicago	25,000	66,000
Varies (Merit, FCFS, & Random)	Philadelphia, Pennsylvania	Work Ready Philadelphia-Summer Employment Models	8,800	16,000
Random & Merit	Boston, Massachusetts	Department of Youth Engagement & Employment	3,500	5000
FCFS & Merit	Seattle, Washington	Mayor's Youth Employment Initiative	750	2,000
Merit & Restriction (School District)	Charlotte, North Carolina	Mayor's Youth Employment Program	320	3,500

Notes: Size of program and applicant pool based on data from 2014, 2015, or 2016 and approximated with two significant digits. Data on program size and allocation mechanism collected by a research assistant from various sources including newspapers, program websites, and personal correspondence (phone and email) with program administrators. Programs vary in the range of eligible ages but ranges all fall within 14 to 24 years old. The allocation mechanism assigned to each program may not reflect the allocation of all slots as larger programs may offer additional slots for select youth (e.g. New York City has a "Ladders for Leaders" program targeting high-achieving youth that is merit based despite the vast majority of its slots being randomly assigned).

In addition to basic age and geographic eligibility criteria, there are four distinct allocation methods that are used by the programs. Random assignment ("Random" in the table) provides slots in the program by lottery, generally giving each eligible youth who applies a chance to be selected for a slot. First-come, first-served assignment ("FCFS" in the table) provides slots to youth who apply earliest after some application open date, filling up jobs as youth apply until no more jobs are available. Merit-based assignment ("Merit" in the table) treats youth differently, giving priority for jobs to youth who perform best on a set of merit-based criteria (e.g., those who have the best applications or perform the best in interviews). These criteria may vary by program or by job. Indeed, some merit-based assignment programs are decentralized such that the employers decide which youth to hire directly. Merit-based programs may also offer scope for networking (or nepotism) in that youth already connected to program providers or employers

may get de facto priority for spots. Other programs target youth with particular demographic characteristics (“Restriction” in the table), providing jobs only to youth in that demographic (e.g., youth whose family income is below a certain threshold). Finally, some programs use multiple allocation methods, either applying different allocation methods to different sets of youth and jobs or applying multiple criteria (e.g., random assignment or first-come, first-served among those who are selected using a merit-based process).

Allocation of job types is almost always through administrative assignment in which youth provide information about their preferences, employers provide information about their needs, and program providers match youth to jobs based on skills and preferences as well as geographic factors and other constraints. The alternative model is to avoid assignment and allow the youth and the employers to match with one another through a decentralized process that might include direct interviews or job fairs. To our knowledge, no program has attempted to randomly assign jobs to youth, despite the central importance to successful program expansion of knowing whether different types of job experiences differentially affect youth outcomes — although programs in some cities (e.g., Boston) have considered experimenting with randomization.

III. Goals of Allocation Mechanisms

What should guide which allocation mechanism(s) programs use to decide whom to serve and where youth should work? According to standard economic theory, the optimal choice of an allocation mechanism is the one that maximizes net social welfare. That is, the efficient mechanism is the one that maximizes the overall benefits of the program to participating youth, employers, and society at large (e.g., through any potential externalities of the program) minus the costs of providing the program.

Social welfare maximization is the ideal for all government policy design, but it may be hard to achieve in practice. Maximizing welfare in the case of SYEPs requires knowing which individuals gain the most from the program and what allocation generates the most social gains through externalities.⁵ If the costs of serving different individuals vary (e.g., if some youth are harder to recruit and retain in the program), identifying the optimal allocation mechanism also requires considering the costs to the program, its providers, and employers. Maximizing social welfare may also mean taking a stand on how society values equity; more efficiently targeting youth with the highest gains may make the program appear less fair by prioritizing particular youth over others (see Berger, Black & Smith, 2001 for a discussion of these issues in relation to allocating unemployment insurance).

In practice, as described in Section II, many programs use some combination of first-come/first-served rules and a merit-based process (e.g., with applications, interviews, and employer choices) to determine assignment. These processes, which essentially allow eligible youth and providers to perform the allocation themselves, seem unlikely to maximize the social gains from the program for several reasons. First, it may be difficult for program administrators to identify

⁵ Since behaviors like crime and violence have a large social impact outside of an individual, it is possible that the people who individually gain the most from participating (e.g., through improved future employment outcomes) are not the same people who generate the most social gains (e.g., through a decrease in violent crime).

which youth would benefit most from the program.⁶ Those who show up first may simply have better information or lower costs of application. Those who perform well at interviews may be better equipped to succeed even in the absence of the program and so may gain less from the program relative to other applicants. Second, in many cases, local non-profit providers are the ones making merit-based admissions decisions. Even the most altruistic organizations are usually contractually obligated to find, recruit, place, and supervise a certain number of youth, making it necessary to weigh the costs of serving someone more heavily than the future (and uncertain) benefits that serving that person might generate for society. Third, governments may want to incorporate equity considerations into the allocation mechanism, and soliciting youth, provider, and employer preferences alone may not successfully maximize these equity considerations.

Moving towards a system that allocates limited program slots to those youth who generate the largest net benefits requires better understanding who responds to the kind of training and jobs offered by SYEPs, as well as whether the particular job allocations within the program matter. Identifying which youth should end up in which jobs raises similar difficulties as identifying who should be in the program in the first place (although solving the latter problem may be more complicated in practice, since it involves many possible youth-employer matches rather than a yes/no decision).

We propose that moving towards an allocation mechanism that maximizes how much society gains from the program requires the random assignment of slots, at least in the short term, and likely in the longer term as well. Random assignment is crucial to the kind of learning needed to ensure that SYEPs do as much social good as possible, and that their benefits justify their costs. No other allocation mechanism allows researchers and program administrators to separate the impact of the program from pre-existing differences between participants and non-participants or to assess the impact of decisions about job allocations and other program components.

It is true that random assignment may add some costs to providers, who might need to serve youth they would not otherwise choose to serve. If this constraint is binding, random assignment could be implemented within subsets of youth who providers are willing to serve. Concerns about the feasibility of large-scale random assignment seem mitigated by the fact that it is already used by a number of large, prominent SYEPs. And more generally, the benefits of learning about who gains from the program seem likely to outweigh any additional costs to providers. Below, we lay out these benefits by discussing the potential random assignment has to help program administrators learn about who benefits, how youth-job matching matters, how different program structures and eligibility criteria affect both the benefits and the costs of the program, and whether the answers differ across different cities with varying labor markets and youth populations.

Random assignment also has an additional benefit: It helps to ensure equality of opportunity in settings where the demand for the program outpaces the available funding (as Table 1 suggests, almost every large-city SYEP is considerably over-subscribed). With a fair lottery, all eligible

⁶ Because so much of the programs' benefits seem to come from its effects on mortality (which may be hard for providers or youth to predict themselves) and from crime and violence (which generate large externalities that the individuals directly involved in the program may not consider), this task is particularly difficult.

applicants have an equal chance of obtaining a program slot regardless of whom they know or whether they have had the opportunity to learn how to give a good interview. It is true that as administrators learn about who benefits most, they may make eligibility and targeting decisions that exclude some of the youth who do not benefit from (or are even harmed by) the program. But as long as there are more youth who meet the eligibility criteria than there is funding to serve, random allocation remains a fair way to allocate a limited resource among those youth.

IV. Allocation of Slots in SYEPs

Random assignment has already begun to teach us about who benefits most from SYEPs. By randomly assigning positions in the program and keeping information about who won and lost the admissions lotteries, programs are creating ideal treatment and control groups to evaluate the effects of the program. Given this randomization, researchers can identify the effects of the program by comparing the future outcomes of youth offered the program to youth who are otherwise identical. This is exactly the exercise that Gelber, Isen and Kessler (2016) perform on data from the New York City Summer Youth Employment program, comparing youth who were randomly assigned a spot in the NYC SYEP program in years 2005-2008 to youth who were randomly turned away. Because of the scale of the program (over 300,000 applications were made to NYC SYEP during the four years the authors study), the authors measure both the outcome of the program overall and evaluate its effect on subgroups of youth.

In particular, they look at which groups have the biggest increase in earnings in the year of the SYEP program (since all youth in the program earn similar amounts of money, this exercise is more about identifying groups of control youth who are unlikely to earn money outside of the program). In addition, since the overall earnings impact of the program is slightly negative in subsequent years, they look at which groups have the smallest earnings decrease in the years after the program.

The relatively young applicants (i.e., those between 14 and the median age of 16.25) and those without work experience in the year prior to the program have the biggest increase in earnings in the year of the program. This result may be unsurprising, since these groups are likely the least equipped to find work outside of the program. Interestingly, however, it is also these youth who experience the smallest subsequent decrease in earnings; indeed, neither the young nor the inexperienced suffer an earnings loss in the years after the program. The authors also find that the groups with the biggest decrease in incarceration in New York State prison and the biggest decrease in mortality due to the program are males, those who are relatively young at the time of program participation, and those without work experience in the year prior to the program.

One benefit of estimating these heterogeneous treatment effects in the context of random assignment is that the results can help program administrators target the subgroups who benefit most — a step towards an optimal allocation mechanism (see, e.g., Manski 2004). Prior research suggests there are considerable social gains from improved targeting in other contexts, including adult job-training and unemployment insurance programs (e.g., Black et al. 2003, Frolich 2008, Lechner & Smith 2007) as well as in interventions such as providing anti-malarial bed net subsidies (Bhattacharya & Dupas 2012). In the SYEP context, the results from Gelber, Isen and

Kessler (2016) might suggest targeting available jobs to the relatively young — for example, giving priority to youth 14 to 16 years old — since they are less likely to experience immediate or subsequent earnings crowd out and more likely to reap the benefits of reduced incarceration and mortality.⁷

Given the existing research on who benefits from SYEPs, one important question is whether programs should shift to serving solely the youth who appear to benefit the most in initial studies, or whether random assignment remains a desirable allocation mechanism. From an equity perspective, continued random assignment might be desirable as a way to ensure the fair distribution of a limited resource. But there are also two additional reasons why ongoing random assignment for at least a well-sized subset of the program may be more beneficial than a complete switch to allocating program slots based solely on youth characteristics.

First, experimental studies estimate the effect of a particular iteration of a program relative to what youth would have done otherwise. Programs can change over time, especially as they grow. As administrators locate additional jobs, hire more program staff, and recruit more applicants, it is easy to imagine that the composition of work opportunities, service providers, and applicants could change as well. Outside options also change as economic conditions, school and family programming, demographic shifts in the labor force, and other relevant factors change.

For example, the results from Gelber, Isen and Kessler (2016) provide insight into who benefits most from the NYC SYEP in the years they study. But 2005-2008 is approximately a decade ago. The opportunities and the dangers facing youth in New York City have likely changed, as have the structure of the SYEP program and the array of jobs it offers. Any of these factors could mean the program works differently now, or works particularly well for different types of youth. Relying solely on past evidence to generate the program allocation mechanism might therefore involve some risk; young, inexperienced applicants may no longer be the group that benefits most from the program. Continued random assignment over time, on the other hand, can help administrators be more confident about whether changing economic and social conditions, programming, or applicant populations mean that targeting goals need to be adjusted.

The second reason that ongoing random assignment could be more useful than a complete shift to a deterministic matching algorithm has to do with the role of peers. In most estimates of program effects, researchers assume that an individual's response to the program is unique to the individual and does not depend on anyone else (the “stable unit treatment value assumption”).

⁷ Consistent with the intuition in Section III, this group of youth that seems to receive the largest benefit from the program is not necessarily the group that would be served with a first-come first-served allocation procedure, which might favor those who have experience with the program (e.g., last year's programs participants who by definition have previous work experience and are slightly older). Similarly, merit and interview-based allocation might favor the kind of youth who are able to get jobs on their own outside of the program and so are less likely to see large gains. However, practitioners who determine eligibility criteria must also be careful to avoid introducing powerful perverse incentives. For example, if a SYEP is determined to be particularly beneficial for youth who have never been employed or who already have a criminal history, basing program admission on that of eligibility criteria might provide an incentive for youth to stay out the labor force or engage in other undesirable behavior in order to gain admission to the program.

For programs that intervene with one individual or household (e.g., encouraging anti-malarial bed nets), this might be a reasonable assumption. But given the group nature of active labor market programs, it might be more problematic (Frolich 2008, Crépon et al. 2012).

For SYEPs in particular, it is plausible that interactions with other youth in the program are one mechanism through which the program works. For example, it may be that young and inexperienced participants learn by watching how their older, more experienced peers interact with employers, or by interacting with older role models who have successfully avoided the criminal justice system. If these types of peer effects are at play, serving solely younger applicants with no work experience could actually diminish the treatment effect experienced by the youth. There may also be other unexpected consequences of changing the composition of the program; when Chicago decided to serve only males as a way to focus on youth at a higher risk of violence involvement, the absence of females created challenges for program retention (anecdotally, at least, as males expressed disappointment about not getting to spend the summer with female peers).

Creative use of ongoing random assignment can test whether these compositional effects matter, and even help estimate the mix of program participants that maximizes overall benefits. For example, suppose prior evidence suggests that a particular subgroup of youth benefited most from a prior version of the program. If a program wanted to only target that group, at a minimum it would be worth testing the benefits of serving only that group by conducting a lottery for slots among applicants with those desired characteristics to estimate whether the effects on that group will remain constant (rather than assuming program effects will remain constant despite the change in program peers). If program effects do remain as large as before, this might suggest that compositional changes do not diminish the effectiveness of the program. On the other hand, we might not be confident that everything else about the program and outside options remained stable over time, so could not rule out that program effects would have been even bigger in the absence of changes in the composition of program youth.

One solution, which would be possible with a large enough program, is to randomly vary the composition of an individual participant's peers within one program year. To see what this would mean in practice, imagine that a SYEP operated many worksites with groups of youth at each site. Suppose that at a random third of the worksites, 20 percent of slots were randomly allocated among all applicants, while 80 percent of slots were randomly allocated among only the target group (e.g., young, inexperienced applicants). At another third of the worksites, 80 percent of slots could be randomly assigned among the entire applicant pool and 20 percent among the target group. And at the final third of the worksites, slots could be randomly assigned as in the past, among the entire applicant pool.

This design, similar in spirit to Crépon et al.'s (2012) work estimating displacement effects, would generate rigorous evidence on how much peer composition matters. The program effects at the final set of worksites provide a baseline for whether the program as a whole was as effective as in the past. In addition, comparing the program effects at the first two sets of worksites tests whether peer composition matters. If interaction with older youth matters, we would expect effects for the younger youth to be smaller at the sites that have fewer older youth by construction. With an estimate of how much smaller treatment effects are with fewer older,

experienced youth, we could calculate whether the gains from serving additional target youth are offset by the reduction in interaction with non-target youth. Repeating a similar process in later program years with different proportions of youth (or different types of targeted subgroups) could eventually isolate the mix of participants that generates the most net social benefits, as well as ensure that implementing that mix generates the expected gains.

In sum, initial tests for heterogeneous treatment effects are a useful starting point for developing hypotheses about optimal targeting. Ongoing random assignment can help test these hypotheses, ensure programs maintain effectiveness in spite of changes in outside options and program populations, and increase perceptions of equity by ensuring equal access to program slots (at least among populations shown to benefit from the program).

V. Allocation Within Programs

As cities implement or expand SYEPs, they must decide not only which youth to serve, but also how youth will spend their time in the programs — what training is needed, which jobs should be included, and which youth should work in which jobs. Since many programs offer a bundled package of interventions, cities must also consider which elements of the program are necessary to generate program benefits. An ongoing random assignment mechanism can help with these questions as well.

As one example, Chicago policymakers wondered whether adding a social-emotional learning curriculum based on cognitive behavioral therapy principles to their SYEP — an intervention that has been shown to decrease violence and improve schooling outcomes on its own (Heller et al., forthcoming) — could improve youth participation and program impacts. Rather than assume it would work, they tested the additional program element by implementing two versions of the program: one where youth worked, supported by a job mentor, for the full work day, and another where they worked fewer hours per day in order to participate in the additional social emotional learning curriculum. Because youth were randomly assigned to the two versions of the program, researchers could test whether the two versions of the program had different effects.

It turned out that even youth in the standard SYEP program who did not participate in the extra curriculum showed a significant decline in violence, suggesting that the two activities were somewhat interchangeable (it may be that the mentors and employers taught many of the same lessons as the curriculum informally) (Heller 2014). But, importantly, policymakers learned that the additional curriculum was not the sole reason for the program’s effects, allowing future iterations to unbundle the two intervention types and reduce program costs.

This example demonstrates how random assignment within the program can help to identify program mechanisms and test how to maximize benefits while reducing costs. SYEP administrators may find it useful to test particularly expensive elements of their program, or to test solutions to weaknesses uncovered by initial evaluations. Chicago is now experimenting with how much the separate adult mentor matters, as well as whether different types of providers generate different effects. New York is experimenting with strategies to leverage the program experience into improved labor market outcomes. As in the previous section, since different aspects of the program may interact in unexpected ways, it seems worth testing different

combinations of program elements rather than assuming that the impact of each one in isolation will be the same as combinations of services.

As cities work to find additional employment slots for expanding programs, the question of job type and quality will be central to how successful these programs are in achieving similarly sized treatment effects as they expand. For example, if expanding programs requires identifying lower-quality jobs, program benefits may become smaller. Notice, however, that introducing some form of randomization in the way that youth are assigned to jobs would help uncover whether the type of job, or the quality of the youth-job match, affects the efficacy of the program. And, in a world where many cities are randomly assigning youth to versions of their programs that vary only slightly, cities could start answering a range of programmatic and mechanism questions including how wages, program hours or duration, various training or learning opportunities, and different job tasks affect different behavioral outcomes across different local contexts. Using random assignment to allocate youth across program variants is another way that allocation mechanisms can help policymakers learn how to maximize the social benefits of SYEPs and ensure that scarce resources are well spent.

VI. Conclusion

Incorporating random assignment into the process of assigning SYEP slots, jobs, and other program elements has the potential to help move programs towards more socially beneficial allocations. Random assignment would allow researchers to explore treatment heterogeneity across youth and/or job or program types. Newly developed machine learning methods (see, e.g., Athey and Imbens 2016) may help this process, at first by using the existing data to identify which combination of characteristics best predicts how a youth will respond to a slot in a SYEP, or a specific job as part of the program, and perhaps later helping policymakers allocate the program among new cohorts of youth.⁸

It is important to realize, however, that using random assignment should be the beginning, not the end, of the process of improving program allocation. We likely also need to collect information on the costs of serving different types of youth. And, if policymakers care about more than the net benefits of behavioral responses alone — for example, if they care about how much the individual youth value the opportunity — then the ideal allocation mechanism will incorporate more than just observed treatment heterogeneity.⁹

Similarly, these evaluations cannot speak to general equilibrium effects of SYEP. For example, expanding the program to include all youth predicted to respond well in an entire city might create other detrimental effects (e.g., if employers can only offer so many job opportunities over

⁸ Note that using machine learning to determine allocation raises other issues that may enter the social welfare function, such as how transparent an allocation mechanisms is and the relative social values of equality of opportunity and maximization of social efficiency.

⁹ Those youth that value the program the most may not be the youth that generate the most private benefit from the program, and it would be unlikely if the youth that value the program the most are the ones that generate the largest social benefits from the program, so these factors may be at odds in determining allocation rules.

the summer, significant program expansions might push non-program youth who would otherwise have had jobs, out of the labor market).

Fortunately, the effects of new targeting criteria, matching approaches, or program elements are empirically testable. As knowledge about who benefits from what kind of programming grows, we should update program allocation mechanisms accordingly and continue to test the effects of the new targeting mechanisms. The process should be iterative: generate a hypothesis about program eligibility or structural improvements from one set of studies, then test those changes in a new set of studies. In addition, developing a formal theory for why and how programs work to improve outcomes could be a valuable complement to the tests we propose here (Deaton 2009; Deaton and Cartwright 2016). Theory can help guide programs in what they should test, and experimentation can in turn help to refine theory. Eventually, identifying the fundamental mechanisms at work can explain program success across cities and help generalize results. There are enough cities operating enough program variants in the U.S. that if they all started testing who benefits from what type of opportunities, we could make huge strides towards maximizing net benefits in a relatively short period of time.

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