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DISCUSSION PAPER SERIES

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Where the Rubber Meets the Road: Examining Efficiency and Equity in Designing Summer Youth Employment Programs

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ABSTRACT

Where the Rubber Meets the Road: Examining Efficiency and Equity in Designing Summer Youth Employment Programs*

Summer Youth Employment Programs are known to have significant impacts on youth outcomes based on lotteries from oversubscribed programs. But most cities cannot use a lottery design due to heterogeneity across youth and jobs. How can programs achieve efficiency and equity under alternative assignment mechanisms? Using hiring platform data, we study youth application and employer selection behavior to explore these design challenges. We find large mismatches between the distribution of youth versus jobs leaving 10% to 25% of positions unfilled. Moreover, employers were nearly twice as likely to select white youth relative to their representation in the applicant pool. This disparity persisted when controlling for other demographics, the number and timing of applications, and job readiness. Our findings reveal that workforce development programs may perpetuate inequities in the absence of simple random assignment. Using a job matching algorithm, we show that placing just 30% of positions by lottery can improve both equity and efficiency.

JEL Classification: D63, D91, I38, J13, M51

Keywords: youth, workforce development, summer jobs, job matching, algorithm

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I. INTRODUCTION

Cities across the United States have developed Summer Youth Employment Programs (SYEPs) that aim to improve a range of academic, economic, and behavioral outcomes for low-income youth. Participants typically work 20-25 hours per week for 6-8 weeks during the summer at a city, nonprofit, or private sector employer and are paid the minimum wage. The stated goals of these programs are two-fold: (1) to increase labor market attachment by providing youth with the tools and experience needed to navigate the job market on their own; and (2) to reduce inequality of opportunity across different racial, ethnic, and socioeconomic groups by increasing access to early employment experiences (City of Boston, 2017).

Over the past decade, an emerging literature has confirmed that SYEPs have significant impacts on youth outcomes such as reducing violent crime, increasing high school graduation, and boosting subsequent employment and wages–both during and beyond the summer (Heller, 2014; Gelber et al., 2016; Leos-Urbel, 2014; Kessler et al., 2022; Modestino, 2019; Modestino and Paulsen, 2022). Moreover, summer job programs appear to have greater benefits for low-income and at-risk youth, such as those having prior involvement with the criminal justice system or disengagement from school (Li et al., 2022). Most of this prior research has been based on lotteries from oversubscribed programs in the handful of cities where participants are picked at random from a pool of applicants, allowing for an experimental design to robustly evaluate outcomes.

Yet most cities do not use random assignment when making SYEP job placements. Even prior to the pandemic, 20 out of 27 SYEP programs across the largest U.S. cities used an allocation mechanism other than random assignment such as first come first serve, merit, or income based (Heller and Kessler, 2017). Since 2020, several additional cities have moved away from using lotteries due to post-pandemic shifts in the population of youth who apply, the number and types of employers who participate, and the nature of the job opportunities that are available.[1] These programs are often faced with a high degree of heterogeneity among both job applicants and job attributes, creating a complex job matching process each summer that needs to balance both youth and employer interests to ensure participation.[2] Moreover, even among programs that use random assignment, many run their lotteries at the employer level among those youth who applied to each job site rather than using simple random assignment across all available jobs.[3] Although some cities intentionally target certain groups of youth,[4] most cities have open access programs where the lack of random assignment may reduce access for less advantaged youth living in marginalized communities, thereby unintentionally failing to meet their intended goals of reducing inequality.

In this paper we show that using an allocation mechanism other than random assignment results in both large inefficiencies in the number of jobs filled as well as sizeable inequities by race and ethnicity that run counter to the stated objectives of many SYEPs. To better understand youth labor market dynamics and document how the job matching process unfolds within a

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[1] Given the disruption caused by the pandemic, 3 of the 7 remaining programs that had exclusively used random assignment in the past (Austin, Baltimore, and New York) now use other assignment mechanisms for either a significant portion or all of their job placements. For example, New York City only uses random assignments for youth sourced through community-based organizations whereas those sourced through select schools, public housing, or programs that provide services to those with employment barriers are assigned using other criteria. https://www.nyc.gov/site/dycd/services/jobs- internships/about-syep.page#syep-comp.

[2] Although greater heterogeneity across employers and applicants presents additional challenges, it also comes with important benefits that suggest a one-size-fits-all program might not yield the same positive impacts for youth. On the employer side, workforce practitioners emphasize the need for differentiated job placements to promote skill development by laddering job opportunities from one summer to the next (Valentine et al., 2017; Miles et al., 2020). On the applicant side, previous research has found that limiting heterogeneity by targeting youth with fewer advantages reduces positive peer effects within job training programs such that the optimal allocation preserves some slots for youth with greater advantages who can provide positive peer interactions to other participants (Baird et al., 2023).

[3] For example, prior to the pandemic, New York City assigned youth to jobs through lotteries among those who applied to each job site rather than using simple random assignment across all available jobs (Leos-Urbel, 2014).

[4] For example, the Chicago SYEP targets youth located in high-violence neighborhoods or who were involved in the criminal justice system (Heller, 2014).

large-scale workforce development program, we explore this intersection between efficiency (e.g., the rubber) and equity (e.g., the road) using a novel administrative dataset collected by the City of Boston during the summer of 2022. These data include daily snapshots from the City's hiring platform, providing a unique glimpse into both youth application and employer selection behavior. We observe detailed demographic and profile information for each youth, the number and types of jobs available for each employer, as well as the youth applications, employer selections, and ultimate hiring outcomes for each position.

Our findings inform three specific design challenges facing large-scale workforce development programs that match participants to employers under the dual mandate of increasing equitable access to employment while maximizing the number of jobs filled. First, programs need to create a "thick" job market among applicants to make matches efficiently and equitably. We find that roughly one-third of youth fail to complete the City of Boston application process, suggesting that there are significant barriers to participating. Among those who do complete an application, about half of all youth apply to only one job and many apply to the same employer, often resulting in a high degree of mismatch (e.g., jobs are either over- or under-subscribed), leaving hundreds of youth without a job and many employers with unfilled positions each summer. When the distribution of applications to positions is imbalanced on such a large scale, even cities that run lotteries within each employer (rather than using simple random assignment) can result in a set of job assignments that are inefficient and inequitable.

Second, programs need an assignment mechanism that can coordinate selections across employers to reduce duplicate offers while also limiting disproportionate selections by race, ethnicity, or socioeconomic status that run counter to the program's equity goals. Given that the Boston program is over-subscribed, only two-thirds of youth who applied by the deadline were selected by an employer. However, employers were nearly twice as likely to select white youth relative to the percentage of whites in the overall pool of applicants, to the detriment of Black and Hispanic applicants. This disparity between the applicant and selected pools was also observed for youth who were native English speakers and students from Boston's prestigious "exam" schools and persisted even when controlling for a rich set of youth demographic characteristics and application behaviors. After the initial round of employer selections were made, we applied a job matching algorithm that was stratified by race and ethnicity to fill any vacant positions at the employer site from among the youth who had applied to the position. This simple algorithm was successful at improving equity in youth selections across the program and was shown to be as efficient at filling job openings compared to other, more sophisticated, algorithms.

Third, even oversubscribed programs continually need to back-fill job openings using multiple waves of hiring to employ as many youth as possible during the summer. This is because some youth are selected for multiple positions, find a job outside the program, or fail to make it through the hiring paperwork to get on the payroll—an issue similar to that of "summer melt" among low-income college applicants (Castleman and Page, 2014). As a result of both matching and hiring inefficiencies, upwards of 300-800 of Boston's summer jobs (10 to 25 percent) are left unfilled each summer, leaving SYEP funding unspent, community-based organizations without the workers they need, and youth unemployed each summer. Moreover, Black and Hispanic youth are over-represented among those who fail to make it through the hiring process as well as the pool of youth who apply to the program late. Thus, multiple rounds of assignment are likely needed to achieve both an efficient and equitable set of placements. However, even with an equitable placement process, programs also need to reduce the required paperwork and to convert more selections into actual hires.

Overall, our results indicate that the complexity of the job matching process may prevent many workforce development programs from making full use of their public funding and/or meeting their stated goals to reduce inequality. Large racial and ethnic disparities can exist, even when employers have signed on to be part of a six-week developmental program, for which the City is paying the youth wages, and the youth applicants have little real-world experience upon which to differentiate themselves. However, our job matching algorithm presents one solution by which cities can be more intentional about matching youth to jobs while maximizing both employer and youth participation. For example, instituting a 70-30 rule with just under one-third of the slots filled by a lottery run by the city and the remaining slots filled by employer selection could be a feasible approach going forward. Overcoming the design challenges that we document below can help cities ensure that marginalized youth have equitable access to SYEPs and the opportunity to experience the program's positive impacts on a range of long-term academic, employment, and behavioral outcomes. More broadly, our findings can provide insights for the implementation of other workforce development programs operating at scale that aim to level the play field for other vulnerable populations such as returning citizens, disabled workers, and the long-term unemployed.

II. LITERATURE REVIEW

Designing an optimal job matching protocol within a universal workforce development program that seeks to place participants into job opportunities at scale faces several important design challenges. These challenges arise from complex interactions across youth application behavior, employer selection behavior, and hiring over multiple waves with implications for both efficiency (e.g., filling all allocated job slots) and equity (e.g., selecting participants that are representative of the applicant pool). For summer jobs programs in cities such as Boston, this can actually be a sizeable problem when receiving upwards of 12,000 applications for roughly 9,000 job openings during the span of 7 weeks leading up to the program's start (Modestino and Cope, 2023).

Although simple random assignment works well when both the job applicants and the job attributes are fairly uniform, this becomes less feasible when there is heterogeneity on both sides of the market. For example, prior to 2017 the City of Boston used a simple lottery design with only one round of assignment to place similarly situated youth (e.g., primarily low-income 14- and 15-year old teens) into primarily one type of job (e.g., summer camp counselor), yielding a reliably high take-up rate each year for its SuccessLink summer jobs program. However, as the program expanded to include older youth with a more varied skillset, as well as other types of jobs across city, nonprofit, and private sector employers with more varied requirements, assigning jobs by lottery was no longer feasible since the quality of the match affected both youth take-up as well as employer participation (MAPC 2019).

As a result, the City abandoned its lottery system in 2017 and allowed employer partners to select youth from among the pool of applicants that had applied to their job, resulting in a matching and hiring process that produced inefficient and inequitable outcomes. For example, there were 300 to 800 SuccessLink jobs (10 to 25 percent) left unfilled between 2017 and 2021 (see Panel A of Table 1). Moreover, these job opportunities were not distributed equitably across racial and ethnic groups relative to their representation in the applicant pool with white youth disproportionately placed into summer jobs compared to Black and Hispanic youth. For example, between 2017 and 2021, the share of white youth who were hired was 2.5 to 5.5 percentage points higher than their representation in the overall applicant pool whereas the opposite was true for non-white youth (see Panel B of Table 1). Although these differences between application and placement rates may seem small, when applied to the total number of youth applicants each year (e.g., upwards of 10,000), this translates into several hundred jobs per summer being disproportionately assigned, contradicting the program's stated goal of reducing inequality across different racial, ethnic, and socioeconomic groups.

Designing an efficient and optimal matching system has been intensively studied in several related settings with some useful insights that can be applied to summer jobs programs. In terms of application behavior, marketplaces such as school choice programs, need "thickness"—attracting a sufficient proportion of potential participants on both sides of the market—to make matches efficiently (Roth, 2008b). Similarly, when youth apply to SYEP opportunities at the individual employer level, versus the aggregate program level, many youth apply to only one job and the distribution of applications to positions can be quite imbalanced with some jobs being over-subscribed while others are under-subscribed. Without a sufficiently "thick" labor market, youth and/or employers may not get their first choice or even any choice—even when slots are randomly assigned among the pool of applicants for each position, potentially resulting in large numbers of youth left without a job and large numbers of jobs that are left unfilled.

Prior research suggests that raising awareness and behavioral nudges can help improve application behavior and create a thicker market. For example, Heckman and Smith (2004) found that despite having higher probability of being eligible for the program, youth with a significantly lower level of schooling had a lower probability of awareness of and application to the Job Partnership Training Act (JTPA) leading to lower acceptance rates within the program. However, sending youth reminders to complete applications has been shown to positively influence application take-up rates among SYEPs. In Philadelphia, reminder emails increased SYEP application completion rates by 1.3 percentage points (8.8 percent) among the treatment group relative to the control group, with larger effects when emphasizing the short-term monetary gains from having a summer job (Bhanot and Heller 2022) . In other work, we similarly implemented an experimental application nudge within the City of Boston's Learn and Earn summer program which doubled application rates among youth from Boston public high schools with low college enrollment rates (Marks and Modestino, 2022).

The second set of insights from the literature focus on selection behavior where markets also need to overcome the congestion that thickness can bring by making it possible to consider enough alternatives to arrive at good matches Roth (2008b). In settings such as the medical residency match, this problem has been resolved by using a deferred acceptance (DA) algorithm where actors make offers and/or applications in order of preference until there are no rejected agents who wish to make any additional proposed matches Roth (2008a). However, these type of DA algorithms do not apply to more real-world programs, such as summer jobs, where youth do not submit a rank ordering of job applications from most to least preferred. Instead, youth submit job applications to each employer separately, similar to the real-world labor market.

Selections must also be of sufficient quality such that both participants and employers will accept the placement rather than taking an outside option—and accept it quickly rather than waiting around for a better offer Roth (2008b). Unlike charter schools and medical residency programs where there is no outside market, summer jobs programs are dependent on both sufficiently high employer engagement and youth participation. On the employer side, differences across basic job requirements in terms of skills, experience, and certifications may reduce their participation in the program if jobs are filled completely at random, ignoring their desired qualifications. This is especially true when the supply of youth outside the program is plentiful, as was the case early on in the pandemic during the summer of 2020.[5] On the applicant side, differences across basic job amenities in terms of employer type, location, and responsibilities may reduce take-up rates among youth if placed completely at random, ignoring their preferences. This is especially true when the supply of job opportunities outside the program are plentiful, as has been the case more recently during the summers of 2021 and 2022.[6]

The third set of insights from the literature focus on the implications of conducting multiple rounds of assignment due to late applicants as well as back-filling positions when youth fail to accept job offers or produce the necessary documentation to make it through the hiring process (Valentine et al., 2017).[7] Given that the timing of late applications and the likelihood of failing to complete the hiring process is often skewed by race, ethnicity, and socioeconomic status, these market frictions have important implications for equity as well as efficiency. As such, programs need to make it sufficiently simple for both applicants and employers to participate in the market without having to engage in costly strategic behavior (Roth, 2008b).

For example, the shift towards using online job search platforms can reduce some types of search frictions yet introduce others that can lead to inequitable outcomes. On the worker side, unequal access to or experience using the internet for job search can limit the opportunity

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5 According to the Bureau of Labor Statistics, the employment to population ratio for youth aged 16 to 19 years was nearly seven percentage points lower in May 2020 (23.1 percent) than May of 2019 (29.9 percent).

6 For example, according to the Bureau of Labor Statistics the employment to population ratio for youth aged 16 to 19 years during May of 2021 (33.0 percent) and 2022 (32.7 percent) was two to three percentage points higher than 2019 (29.9 percent), prompting news stories about a "hot" summer job market for teens https://www.nytimes.com/2022/05/27/your-money/summer-jobs-students.html.

7 For example, upwards of one-third of youth declined or failed to accept job offers from the New York City SYEP so positions needed to be back-filled to be able to use all of the funding and employ as many youth as possible.

set and exacerbate differentials between race, education, or age of workers (Sanchez Cumming et al., 2022). On the employer side, posting jobs online can produce large numbers of applicants incentivizing employers become opportunistic and increase skill requirements (Modestino, 2019) or find other means as a way to screen applications. Indeed, anecdotal evidence from the Boston SYEP suggests that some employers strategically guarantee a position to youth with whom they have a pre-existing relationship to take advantage of City funding, thereby creating "phantom" vacancies that are not truly open to other applicants (vacancies which are already filled but still actively posted). Using a directed search model, Albrecht et al. (2023) show that the existence of such "phantom" vacancies can lead to large search frictions and discouragement from the perspective of job seekers.

Finally, the literature provides examples where job matching algorithms may pave the way to reduce inefficiencies and to clear markets more quickly, overcoming some of the capacity constraints that SYEPs face. Indeed, a report by MDRC evaluating the New York SYEP noted that "while providers try to match young people to jobs based on their interests and preferences, it is impossible to do so for all or even most participants given the limited work-site options available and the speed with which so many young people must be placed" (Valentine et al., 2017). Interventions developed in response to the COVID-19 pandemic, such as matching health care workers to long-term care facilities to improve staff-to-resident ratios (Zarei et al., 2023), demonstrate the potential for more widespread use of job matching algorithms in the labor market. Of course, researchers have documented the inherent bias that can be propagated by the use of algorithms across a variety of settings, including the labor market, which suggests workforce development programs should approach such solutions with a high degree of humility and caution (Raghavan and Barocas, 2019). However, if the goal of the program is to increase opportunity while filling every position, then having a certain share of automated placements may be the only way to ensure that those who ultimately get selected are at least representative of the pool of applicants if not targeted towards marginalized groups.

We add to this literature by exploring three particular design challenges facing workforce development programs and SYEPs in particular. These challenges correspond to the three phases of the job matching process that drive our research questions:

- **Youth application behavior: How can programs create a "think" labor market?** *How many youth fail to submit even one job application? Among those who complete at least one job application, how many jobs do youth typically apply to and when? Are youth applications skewed towards certain jobs and if so, to what degree are some jobs over- versus under-subscribed? How does application behavior differ by age, gender, race, ethnicity, and school type?*
- **Employer selection behavior: How can programs limit disproportionate selections?** *Which youth characteristics (e.g., age, gender, race/ethnicity, English proficiency, school type) appear to drive employer selections? How much is explained by differences in youth application behaviors or qualifications across groups? To what degree can automated placements (e.g., job matching algorithms) reduce these disparities?*
- **Hiring over multiple waves: How can programs back-fill positions equitably and efficiently?** *What are the characteristics of youth who apply to the program "late"? Once selected, how many youth fail to complete the hiring process? Which groups of youth are more likely to fail to complete the hiring process?*

III. PROGRAM OVERVIEW

Compared to other cities, the Boston SYEP operates as a coordinated ecosystem that serves upwards of 10,000 youth each summer, braiding together multiple sources of city, state, and philanthropic support. All Boston city residents aged 14 to 24 years are eligible for the program and can apply to jobs through one of five intermediary organizations, some of which specialize in serving different youth populations based on age, school type, and other risk factors (Modestino, Cope and Blakely, 2023). Using the prior lottery-based assignment system, studies have demonstrated that the Boston SYEP reduces both violent and property crime (Modestino, 2019), increases the likelihood of high school graduation (Modestino and Paulsen, 2022), and boosts employment and wages (City of Boston, 2017) in the one to four years after youth participate in the program.

In this paper, we focus our analysis on the City's SuccessLink program operated by the Office of Youth Employment and Opportunity (OYEO). As the largest provider of summer jobs within the Boston ecosystem, SuccessLink provides open access to all youth, yielding a high degree of heterogeneity across both race and socioeconomic status. The program directly serves upwards of 4,000 youth aged 14-18 years from all 23 of the City's neighborhoods with greater representation among low-income communities of color such as Dorchester, Roxbury, and Mattapan.[8] The SuccessLink program also offers a wide range of job opportunities at upwards of 200 employer partners including city agencies, local nonprofits, community-based organizations, and private-sector employers. Our analysis focuses on the 3,500 job slots allocated to SuccessLink's "direct" employer partners who used the OYEO online application portal to advertise positions, review youth applications, and make youth selections.[9] Youth

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[8] There is also a smaller program for youth leaders aged 19-24 who are often prior participants and are paid slightly above the minimum wage. We exclude those youth from our analysis since they are hired through a different process.

[9] The SuccessLink selection and matching process has undergone several changes since the City moved away from random assignment in 2017. Prior to that, assignments were made according to a 60-40 rule where employers were allowed to select youth for 60 percent of their SuccessLink openings and the remaining 40 percent were filled by OYEO using simple random assignment. Since then, OYEO has allowed employers to select 100 percent of their

work a maximum of 25 hours per week for up to 7 weeks during July and August and are paid the minimum wage.[10] Survey data consistently show that more than half of SuccessLink participants use their earnings to pay some type of household bill, such as groceries, housing, utilities or transportation—making the program an important source of support for low-income households during the summer (Modestino, Cope and Blakely, 2023).

A timeline of the SuccessLink job application, selection, and hiring process during 2022 is depicted in Figure 1. In early March, OYEO began its usual outreach efforts to youth which included advertising on public transportation, reaching out to schools, job fairs, and conducting online information sessions. The application portal opened on March 18th at which time youth were able to search for jobs and were encouraged to apply to as many as 15 positions. However, the City's portal was only searchable by employer name and location making it difficult for youth to identify particular occupations or industries without reading through each job ad, which often varied considerably by employer in terms of quality. Before applying to any job, each youth filled out a profile containing their contact information (e.g., first and last name, address, email, and phone number), detailed demographic information, and basic job qualifications (e.g., prior participation in the program, an optional statement about why they want to work this summer, and a resume if they chose to upload one). Each job required a separate application and like the real-world labor market, there was no information provided to the youth regarding the number of openings per employer nor the number of applicants per position.

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youth with the caveat that 40 percent of those youth should be new participants—somewhat in the spirit of the prior 60-40 rule. During the pandemic, OYEO further expanded employer control over the youth placement process by allowing some employers to participate in the summer jobs program as a "grant" partner that simply receives funding to cover youth wages without being required to use the City's hiring platform.

[10] Youth also receive 20 hours of career readiness training that includes exploring their skills and interests; learning about the job search process; and developing soft skills such as communication, collaboration, and conflict resolution.

Employers could start reviewing applications and interviewing youth in late March, although the bulk of the applications were received during April. Unlike typical job application data, employers receive access to all of the information in the youth profiles, including detailed demographic information (e.g., age, gender, race, and ethnicity, language fluency, and school name). Employers were able to view all of this information and contact youth for interviews in real-time, submitting their youth selections through the portal between April 30th and May 30th.[11]

Typically, any remaining openings were back-filled by OYEO directly placing youth into jobs at their in-person "We Hire" event that takes place just before the start of the program. Placing youth into positions at the event in real-time entails matching youth individual interests while also meeting employer job requirements which takes significant personalized attention and time. Often OYEO staff do not have the capacity to fill every position, particularly when upwards of 300-800 jobs are left vacant in the week prior to the program's start. To address this inefficiency, we implemented a job matching algorithm to place youth into unfilled positions between June 2nd (after the employer selection deadline) and June 20th (before the first OYEO in-person "We Hire" event). The algorithm was used to fill positions for (1) undersubscribed jobs that had more openings than applicants and (2) oversubscribed jobs that had vacancies either as a result of youth declining positions or because youth failed to complete the hiring paperwork. Between June 21st and June 24th, OYEO invited any remaining youth that had applied but were not yet placed in a job to the "We Hire" event as well as drop-in office hours during which they could be assigned to any remaining open position, including those jobs where previously selected applicants had failed to make it through the hiring paperwork

[11] However, this deadline was extended through June 2nd as is often the case each year, with a handful of City departments allowed to select youth even beyond this date (through June 15th).

process.

Once a selection was made through any of these methods (employer, job matching algorithm, “We Hire” event), an automated email notified youth to offer them the job and directed them to complete the hiring process by submitting documentation of eligibility and other information for the payroll system. The application and hiring process included upwards of 10 different steps (see Figure A1 in the appendix), most notably uploading multiple documents to prove age, citizenship, and Boston residency such as a social security card, household utility bill, and/or school report card. As one might suspect, a nontrivial number of youth failed to make it through this complex onboarding process, leaving some jobs unfilled and some youth unemployed–despite having selected a youth for each opening prior to the program’s start.

IV. DATA AND METHODS

One of the unique advantages of this paper is the incredibly rich set of observable data that was made available not only to us as researchers but also to the employers as part of the job selection process. In particular, we do not have to infer whether employers knew the race and ethnicity of the job applicants as this information was provided to them as part of each youth’s profile along with a detailed array of other qualifications collected systematically by the City’s hiring platform. As such, our methodology is quite simply to explore disparities in youth application behavior, employer selection behavior, and hiring over multiple waves using this rich dataset of demographic characteristics, job qualifications, and matching within a relatively well-defined labor market where the stated goal is to promote youth workforce development and reduce inequality across racial, ethnic, and socioeconomic groups.

A. Data Collection and Variable Creation

Our analytical data set was created by appending recruiting reports provided daily by OYEO from the City of Boston's online application and hiring portal during the summer of 2022. These reports consisted of each youth's profile, their application for each job they applied to, as well as the status of each application.[12] When a youth creates their profile they are assigned a unique system ID which enables us to track youth throughout the application and hiring process at the youth-job application level.[13] This includes timestamps documenting the timing and status of each job application that was submitted including whether and when the youth completed an application, was selected by an employer, and completed the hiring process (see Figure A1 in the appendix).

The daily recruiting snapshots have a few irregularities which required some cleaning prior to analysis. First, we dropped the handful of observations with exact duplicate information in terms of first name, last name, system ID, job posting title, and status where youth had applied to the same job multiple times. There were also a handful of observations which had identical first name, last name, system ID, and job posting title but varied by status so we kept the record with the higher status (e.g., hired versus onboarding versus applicant). In addition, some youth had a status of "School Year Participant" which mean that they had worked for the employer through OYEO's school year program and were selected to continue working with the same employer through the summer. We kept these observations and treated these youth as having been selected by the employer.

Using data collected from the youth's application profile, we examine the usual

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[12] For example, if a youth does not complete the application or does not qualify for the position (e.g., younger than 14 years of age), they are listed as having a status of either 'Incomplete' or 'Initial DNQ' status respectively. See the appendix for a discussion of each status that was tracked including 'Applied', 'Onboarding (Selected)', and 'Hired.'

[13] There are some instances where a youth created more than one profile using different email addresses, resulting in multiple system ID numbers although this occurrence is rare with approximately 2.67 percent (200 youth) having duplicative portal accounts which we were able to identify and remove from our analysis.

demographic variables of interest such as age, gender, race and ethnicity as well as additional variables that proxy for certain characteristics that might be taken into consideration by employers. For example, we observe whether youth indicated they were fluent in a language other than English as well as if their native language was English and use these variables as a proxy for English language skills and immigrant status respectively. We also observe school name and construct a variable for whether youth attended one of the prestigious exam schools within the Boston Public School (BPS) system or another type of school (e.g., traditional public school, private, or parochial school), and use this variable as a proxy for academic preparation.[14] We also know whether youth had previously participated in either the OYEO summer or school year youth employment programs and use this as a proxy for prior work experience. We also observe whether youth choose to answer the open-ended question "Why do you want to participate in the SuccessLink program this summer?" We construct dummy variables for this item, along with measures of its quality and use this information as an indication of job readiness.[15] Finally, we are able to proxy socioeconomic status using the youth's residential ZIP code which largely corresponds to one of the City's 23 different neighborhoods.

B. Methodology

Using this rich dataset and unique setting, we contribute to the literature in three ways. First, we document youth application behavior, employer selection behavior, and hiring over multiple waves using descriptive techniques to understand the general dynamics and design

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[14] The three exam schools (Boston Latin Academy, Boston Latin School, and the John D. O'Bryant School of Mathematics and Science) have entrance exams and GPA requirements for admission.

[15] For the open-ended response, we measure both length as well as reading level (above, at, or below a high school grade level) using the Flesch Kincaid readability score system. For more information, please see https://readable.com/readability/flesch-reading-ease-flesch-kincaid-grade-level/

challenges of structuring a labor market within a workforce development program. For example, we examine how many youth submit at least one valid application and for those completing an application, explore differences in application behavior in terms of demographic characteristics, job readiness. We explore the differences in these same characteristics between youth who are selected by an employer versus not by doing a simple comparison of means and testing for significance. We use a similar comparison to understand which youth are more likely to apply late to the program and fail to make it through the hiring process. We also document the mismatch between supply and demand by comparing the number of applications per job opening across employers.

Second, we explore the racial and ethnic disparities in youth application behaviors, employer selections, and hiring outcomes using a reduced form model where we control for youth demographic characteristics, job qualifications, and application behaviors (where appropriate) to measure the factors driving these inequities. For example, when measuring racial and ethnic differences in employer selections, we use equation (1) where the dependent variable Y_{it} is a dummy variable indicating whether the youth was ever selected by an employer:

$$Y_{it} = BLACK_i\beta_1 + HISPAN_i\beta_2 + ASIAN_i\beta_3 + OTHER\_RACE_i\beta_4 + X_i\beta_5 + SCHOOL_{i(t-1)}\beta_6 + SUCCESLINK_{i(t-1)}\beta_7 + APP\_BEHAVIOR_{i(t)}\beta_8 + JOB\_READINESS_{i(t-1)}\beta_9 + \mu_{it}, \quad (1)$$

where X_i is a set of pre-existing demographic characteristics (e.g., age, gender, fluent in another language, first language is English), $SCHOOL_{i(t-1)}$ is a set of pre-program school characteristics measuring academic preparation (e.g., currently enrolled in school, attends an exam school), $SUCCESLINK_{i(t-1)}$ is a set of indicators for prior participation in the program (e.g., prior school year, prior summer), $APP\_BEHAVIOR_{i(t)}$ is a set of current application behaviors on the part of the youth (e.g., number of applications, average competitiveness of jobs applied to, and month in which they submitted their earliest application), $JOB\_READINESS_{i(t-1)}$ is set of measures assessing whether youth are prepared to enter the job (e.g., whether they answered the "why work" question as well as the length and readability of their response), and μ_{it} is a stochastic error term. We use both ordinary least squares as well as alternative nonlinear methods to relax the linear functional form assumption (see the appendix for details).

Third, we assess whether using automated allocations produced by a simple job matching algorithm can provide a meaningful improvement in both efficiency and equity to address both the design challenges and disproportionate selections facing similarly situated workforce development programs. We do this by comparing the racial and ethnic composition of youth selected by employers to those selected by the algorithm and then test whether the combined distribution of selections (employer + algorithm is sufficient to eliminate the observed disparities relative to the applicant pool. We then compare the effectiveness of the algorithm to what is achieved through the OYEO in-person "We Hire" event.

V. RESULTS

To answer our research questions, we explore the pathway by which youth move through each phase of the City's SuccessLink application, selection, and hiring processes. In phase 1, we document how youth apply to positions through the online portal to determine what barriers might prevent programs from creating a "thick" labor market. In phase 2, we examine how youth are selected by employers from the applicant pool and whether automated assignments using a job matching algorithm can help fill more jobs in real-time while also limiting disproportionate selections by race and ethnicity. In phase 3, we study which youth fail to complete the hiring process and how programs can back-fill positions over multiple waves of assignment to fill every job while also serving the least advantaged youth that the program is intended to help. As youth move through each of these phases, we find that systematic disparities arise, leading to job placement outcomes that are ultimately inefficient and inequitable without some type of intervention.

A. Youth Application Behavior: Creating a "thick" labor market

In this section we explore several aspects of youth application behavior to understand the degree to which Boston youth face (1) barriers in completing at least one SuccessLink application, (2) frictions in completing a sufficient number of job applications, and (3) mismatch in the distribution of applications across positions. Throughout, we explore differences in application rates by age, gender, race/ethnicity, language spoken, and school type to understand ways that summer jobs programs (and workforce development programs more broadly) can overcome these challenges to create a thicker labor market that produces more efficient and more equitable matches.

1. The Application Process: Which Youth Applied for a Job through SuccessLink?

During the 2022 summer job cycle, we observed 5,488 unique youth in our analytical dataset who had started a profile on or before the application portal closed on June 15th. Of those youth, approximately one-third (1,726) did not complete any job applications or had their profile deemed invalid.[16] Although this suggests that there are significant barriers to participating in the Boston SYEP, starting with the application process, it is difficult to assess which groups of youth are most affected due to the large amount of missing data in youth characteristics (hence the incompleteness).[17] As a result, for the remainder of the analysis, we

[16] Of these, only 281 youth had a status of "Initial DNQ" indicating that their application was invalid, often because they did not answer one or more of the screening questions correctly, such as their birthdate. OYEO staff worked with these youth to either correct their information so that they could move ahead in the application process (N=280) or verify that they were indeed ineligible resulting in a status of "Does Not Qualify" (N=1). The remaining 1,445 youth (83.7 percent) had a valid profile but did not complete any job applications and were assigned a status of "Incomplete" in the City's hiring system.

[17] For youth with valid applications race and gender is observed for all applicants whereas for youth with incomplete

focused exclusively on youth who have submitted at least one valid job application.

Table 2 provides descriptive statistics for the 3,762 youth who successfully completed at least one application. Youth who applied to SuccessLink were on average 17 years old, slightly less likely to be female (49 percent), and the majority were youth of color (67 percent identify as Black/African American or Hispanic/Latino).[18] In addition, about 33 percent were fluent in another language although only 16 percent reported that English is not their first language. Just under one-quarter (23 percent) attended an exam school and just over one-quarter (26 percent) had previously participated in the City's summer youth employment program.

Using the rich data collected by the online application portal, we were also able to observe many aspects of youth application behavior. On average, youth submitted three applications, typically applied to jobs that were competitive (e.g., had 9 applications per opening), and didn't submit their first application until April. About 80 percent chose to respond to the open-ended question "Why do you want to participate in SuccessLink this summer?" Among those who answered the open-ended question, nearly half (46 percent) provided a response that was written below the 8th grade level.[19] As in prior years, the program was over-subscribed with only two-thirds of youth being selected for a job by an employer.

Yet those employer selections were not distributed equitably when we compared the representation of youth selected to those who applied for a given position in terms of race, ethnicity, and school type (e.g., exam or open enrollment). Table 3 shows that employers were

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applications roughly 63 percent are missing self-reported race and gender. In addition, 75 percent of youth with incomplete application are missing date of birth compared to only 1 percent of youth with at least one valid job application. See Appendix Table A1 for more details.

18 This is largely representative of the City's population of youth aged 15-17 which is 65.8% Black/African American or Hispanic/Latino according to the American Community Survey. See https://www.bostonplans.org/getattachment/51f1c894-4e5f-45e4-aca2-0ec3d0be80d6

19 Specifically, we use the Flesch score to categorize responses as below the 8th grade level, at the 8th/9th grade level, or above the 9th grade level. See https://readable.com/readability/fleschreading-ease-flesch-kincaid-grade-level/ for more details

nearly twice as likely to select white youth (18 percent) relative to the percentage of whites in the overall pool of applicants (8 percent) and less likely to select Black and Hispanic applicants. Employers also selected a higher proportion of youth relative to their representation in the applicant pool among those who were native English speakers or attended one of Boston's prestigious "exam" schools. However, it was also the case that youth with prior SuccessLink job experience, those who applied to more jobs, less competitive jobs, and earlier in the process were more likely to be selected for employment. Although youth who were selected were *less* likely to respond to the open-ended "why work" question, those that did so had longer responses on average than youth who were not selected by an employer. We next delve more deeply into whether these other aspects of youth application behavior or characteristics might account for the racial and ethnic disparities we observe in employer selections.

2. *Number of Applications per Youth*

The OYEO web site suggested that youth apply to at least 15 jobs to increase their likelihood of being selected by an employer, but few applicants appeared to follow this advice. Figure 2 shows that despite most positions being fairly competitive, over 50 percent of youth applied to only one position. However, interviews with OYEO staff and employer partners revealed that youth who apply to fewer jobs often had either a prior relationship with the employer (e.g., had worked there during a prior summer) or the employer strategically hand-picked the youth in advance and directed them to the online portal to get funding for that position through the City. Thus, having fewer applications does not necessarily correlate with lower odds of landing a job.

To more formally explore how application behavior across different groups of youth might affect equity, Table 4 estimates the relationship between the number of job applications submitted by youth and their basic demographic characteristics (age, race, gender, and our proxies for immigrant status and English proficiency). We sequentially add in proxies for academic preparation, prior job experience, application behavior, and socioeconomic status (residential ZIP code). As suspected, more advantaged demographic groups tended to apply to **fewer** jobs. For example, older youth submitted fewer applications, likely because they had some job experience or more outside options compared to those aged 15 years and younger. Youth who participated in a prior summer also submitted fewer applications, probably because they had a pre-existing relationship with the employer. Yet applying to fewer jobs was not perfectly correlated with advantage. Youth attending an exam school tended to apply to more jobs, until we control for neighborhood (e.g., zip code) which likely reflects the influence of socioeconomic status.[20]

In addition, application behavior by marginalized youth suggests that the lower employer selection rate for Black and Hispanic youth was not because these youth apply to fewer jobs. In general, non-white and female youth submitted more applications than white males (the omitted category). In particular, Black and Hispanic youth submitted roughly one additional application (a 33 percent increase over the mean) despite our earlier descriptive statistics showing that employers were twice as likely to select white youth for a job. Including our other observable indicators of youth qualifications does not reduce the racial gap in the number of applications. Even including youth residential zip code as a proxy for socioeconomic status does not reduce the gap, suggesting that racial disparities in the number of applications submitted was not driven by geographical mismatch with youth living in low-income neighborhoods where fewer jobs are located.

[20] Since the number of applications is a count variable, we also conduct these regressions using a Poisson specification as a robustness check. See Table A7 in the appendix.

3. Distribution of Applications across Employers

How did the distribution of youth applications compare to the distribution of job openings across employers? If too many youth were chasing only a handful of positions, then this can result in severe mismatch during the application process, where some youth fail to get selected into any position and some positions don't get filled. Figure 3 indicates that the distribution of job applications was indeed concentrated among a few employers, even when we account for employers having multiple openings available for the same position. On average, there were 17 openings for each position, but some employers received as many as 35 applications per job opening while others received none. As a result, more than 10 percent of employers (N=19) were "undersubscribed"—meaning that they had fewer applicants than openings—while more than one-third (N=48) were highly oversubscribed with more than 5 applicants per opening, even though many of these jobs were quite similar and located in the same neighborhood.[21] This disparity in the number of applications across employers, combined with at least half of the youth applying to only one job, means that the SuccessLink labor market lacked "thickness"—one of the necessary features for alleviating congestion.

The skewed distribution of applications across employers also suggests that youth may lack information on the wide variety of positions that were available. Indeed, the online portal was only searchable by location and employer name, meaning that youth needed to know where they wanted to apply or face the daunting task of paging through hundreds of positions.[22] Given

[21] This disparity even occurred for job openings that were nearly identical in their job descriptions and even located close by to one another. For example, during summer 2022, the Dorchester YMCA received 355 applications for 33 camp counselor positions (10.76 applications per opening), leaving 322 youth potentially unemployed if they only applied to that one job. In contrast, the BCYF Perkins Center, also in Dorchester and located only one mile away, received only 3 applications for their 20 camp counselor positions (0.15 applications per opening) potentially leaving 17 jobs unfilled without some kind of intervention.

[22] Parents have indicated on open ended survey responses that the lack of searchability on the hiring website was a problem for youth when searching for jobs.

that the modal youth apply to only one position and the distribution of applications across positions is skewed towards a limited number of highly favored positions, for some youth the prospect of being selected for a job was very slim unless they had a pre-existing relationship with the employer. As such, the City's selection process essentially replicated that of the broader labor market where "it's not just what you know, but who you know." The concentration of applications among few employers also varied considerably by race. In particular, Black and Hispanic youth were more likely than White and Asian youth to apply to the same employers, suggesting that Black and Hispanic youth may have lacked information on the wide variety of positions that were available beyond their neighborhood (e.g.,YMCA) or other sites they may have visited before (e.g., New England Aquarium).[23]

B. Employer Selection Behavior: Limiting Disproportionate Selections

In this section, we further explore the relationship between youth characteristics and employer selections to determine which youth attributes and application behaviors drive these matches. This is important for understanding the source of the racial and ethnic disparities that we observed in terms of which youth were offered a position. We then evaluate the impact of our job matching algorithm to assess the degree to which cities might use automated placements to limit disproportionate selections and reduce the magnitude of these disparities across the applicant and hiring pools while filling as many openings as possible.

1. The Youth Selection Process

There were three ways that youth could be selected for a position: either by the employer on or before the selection deadline, by the Northeastern job matching algorithm once the selection deadline had passed, or by direct placement with OYEO staff at one of the "We Hire" events or

[23] See Figure A2 in the Appendix for the distribution of applications across employers by race.

drop-in hours just before the program started. We categorize any youth selected for a job on or before the employer deadline as "selected by employer" based on the timestamp of when the youth's status changed. Additionally, several employer-partners were allowed to select youth beyond the deadline. For these employers if a youth ever received a status of selected for that employer, regardless of the timing, we code these youth as being "Selected by Employer." Among the 3,762 youth who submitted at least one valid job application on or before June 15th when the application portal closed, just over two-thirds (2,495) were selected by an employer. However, some employer partners failed to fill all of their openings by the deadline, either because they had staff capacity constraints or because some youth had declined their offer.

After this initial round of employer selections, the remaining 33 percent of youth with valid applications who had not yet been placed in a job (1,254) were eligible to be selected using the Northeastern University job matching algorithm. Unlike the school choice or residency match contexts, the SuccessLink summer jobs program operates more like a real-world labor market, where youth apply to each employer individually. Thus, we could not maximize youth-job matches using a Deferred Acceptance algorithm because neither the applicant nor the employer submitted any rankings. Instead, we took a simpler approach whereby the algorithm filled any under-subscribed jobs first (i.e. jobs with more openings than applicants), followed by lotteries that were run within employer applicant pools starting with employers that had the most openings. The algorithm was also stratified so that the racial/ethnic distribution of the youth hired through the program would match the racial/ethnic distribution of the applicant pool. Upon receiving the list of suggested job matches, OYEO verified that the youth was not already selected by another employer and that the position was still available. If both were true, the youth was selected and placed into hiring for the position.

However, even after the automated placements, there were still jobs that had not yet been filled. This was due to labor market frictions stemming from mismatch between applicants and jobs (e.g., some jobs were under-subscribed with too few applicants per opening), the administrative burdens related to the hiring process (e.g., some youth failed to submit all the necessary documentation to get onto the payroll), or youth declining the position. Thus, a final wave of selections occurred where OYEO staff directly placed youth into remaining positions through their "We Hire" in-person event (June 21st through June 24th) or as "walk-ins" at the OYEO offices through mid-July.

Although it was possible that the remaining youth who did not receive an offer may have found a job on their own outside of the SuccessLink program, administrative data from the state's wage and employment records suggest that this was unlikely. Of the youth who were not selected, only about one-quarter were employed during the summer, confirming that the program has a meaningful impact on employment for this low-income inner-city population, even during periods when Boston's unemployment rate is low (Li et al., 2022).

2. *Employer Selections: Which Youth Received at Least One Job Offer?*

During the 2022 hiring season, there were notable differences in the characteristics of youth who received job offers from employers. Recall that Table 3 showed employers were twice as likely to hire white youth relative to their representation with the applicant pool, but race was not the only factor. Employers were also more likely to select older youth or those who had previously participated as well as youth who attended an exam school. In addition, youth application behaviors also affected the likelihood of receiving a job offer. Youth that had completed more applications, applied for less competitive positions, or applied earlier (in March or April) were more likely to have been selected by an employer.

Table 5 tests whether the racial and ethnic disparity in employer selections might be driven by other observable youth attributes or applications behaviors. Controlling for just the basic demographic characteristics that employers observe from the youth profile (e.g., age, gender, and immigration status, and English proficiency), we find that non-white applicants were significantly less likely to be selected, particularly Black (-19 percent) and Hispanic (-21 percent) applicants relative. These estimates diminish slightly in magnitude when we add in controls for school type (e.g., exam school versus not), having previously participated in the program (e.g., either during the summer or the school-year), and youth application behavior (e.g., number, competitiveness, and timing of applications)—but remain sizeable and statistically significant.

Perhaps non-white youth are more likely to lack the job readiness skills to be able to navigate the selection process or live in neighborhoods with fewer SuccessLink job opportunities nearby. Column (5) of Table 5 adds in our proxies for job readiness such as whether the youth answered the open-ended question ”Why do you want to participate in the SuccessLink program?”, along with measures for the quality (e.g., length and readability level) of those responses, while column (6) adds in dummy variables for zip codes to control for neighborhood characteristics. Controlling for job readiness and/or neighborhood hardly reduces the magnitude of the coefficients on race and ethnicity. Overall, non-white youth had significantly **lower** rates of being selected by an employer compared to white youth, even when controlling for this rich set of observable demographic characteristics, application behaviors, and job readiness proxies.

We should note that one limitation of our analysis is that it is based solely on the observable characteristics collected by the city’s hiring platform. Although the data offer a rich set of attributes and application behaviors, employers may choose to interview youth applicants which may reveal additional information about soft skills or work habits that are not observable to the research team. However, the magnitude of the disparities by race and ethnicity are sizeable with non-white youth being selected 8 to 19 percent less often than white youth—despite the job applicants being fairly unskilled (e.g., high school students with relatively little work experience), the job requirements being fairly entry-level (e.g., temporary six-week job), and the job wages being fully paid by the city.

3. *Automated Placements: Job Matching Algorithm*

After the first round of selections was completed by employers, OYEO implemented several rounds of automated selections between June 2nd and June 20th using the job matching algorithm designed by the Northeastern University (NU) research team. This approach matched youth who had not yet received a job offer to positions that still had openings due to not enough youth applying to the employer, youth failing to submit their hiring documents once selected, or the youth declining the position. There were two explicit goals for this matching process: (1) to maximize the number of openings left filled by making as many matches as possible, and (2) to maximize equity such that the racial and ethnic distribution of the selected youth more closely represented that of the applicant pool.

To investigate whether the job matching algorithm improved the equity of youth selections, Table 6 compares the demographic characteristics of the youth selected by an employer versus the job matching algorithm relative to the applicant pool. For our analysis, we identify youth who were selected and placed by the job matching algorithm using the lists that the research team provided to OYEO each week. We conditioned our analysis on youth who applied before the application portal closed to ensure that youth were eligible to have been selected by the employer prior to the deadline. In total, the Northeastern research team suggested placements for 420 youth. However, due to the timing of some placements, there were 111 youth who were subsequently selected by one of the handful of employers for whom OYEO had extended the deadline to backfill their placements through June 15^{th}. To bias against overestimating the impacts of the algorithm, we only attribute the 309 youth who were placed solely by the algorithm as part of the automated allocations pool.

Comparing columns (1) and (2) shows that youth selected through the automated allocations were less likely to be white, although this is perhaps not surprising given that the algorithm was stratified by race and ethnicity. The algorithm also selected a greater share of youth that were fluent in another language and enrolled in school compared to the employer selections. Overall, the algorithm was 10 percentage points more likely to select Black youth which was large enough to nudge the racial composition of total selections (column 3, Employer + NU selected) towards a more equitable distribution that was more representative of the applicant pool (column 4). However, the algorithm did little to address the over-representation of exam school youth among those selected.

In terms of application behavior, the youth selected by the algorithm were more likely to have applied during the middle of the hiring cycle (April/May) and to have applied to more competitive jobs, which perhaps had put them at a disadvantage compared to earlier applicants and those who had applied earlier or to under-subscribed jobs. However, the youth selected by the algorithm were also more likely to have applied to more jobs and completed the "Why Work" question– actions that would typically get an applicant noticed by an employer–which again makes the racial disparities among the employer selections difficult to explain.

Finally, although the job matching algorithm also aimed to improve efficiency, it did so in a very simplistic way. To test the degree to which the algorithm was efficient, we retroactively applied the Ford–Fulkerson algorithm and compared our results.[24] We found that our simple job matching pilot actually filled slightly more openings while also producing greater equity across racial groups than the Ford–Fulkerson algorithm (see table A9 in the appendix).

C. Hiring over Multiple Waves: Back-Filling Positions

In this section, we examine the effectiveness of OYEO's process to back-fill any remaining open positions with late applicants with regard to further improving the efficiency and equity of youth selections. Across many SYEPs, including the Boston summer jobs ecosystem, most intermediaries conduct hiring over multiple waves for several reasons. First, the combination of labor market frictions and paperwork barriers discussed earlier prevent some youth from ever completing the hiring process, which is unknown until just before the program starts.[25] This can result in a sizeable number of unexpected vacancies for employers with upwards of 26 percent of youth selected for a position never making it onto the payroll. Second, many youth do not start applying for summer jobs until the end of the school year, with only 28 percent of youth submitting an application in March. Finally, many youth need to reconcile having a summer job with going to summer school or participating in extracurricular activities, schedules which are often not released until the last few weeks of school, resulting in a surge of late applicants as shown in Figure 4. Thus, having only one wave of hiring would mean either an earlier application closing deadline which would exclude many youth or a later application deadline which would leave less time for employers to select youth and get them through the hiring

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[24] The Ford–Fulkerson algorithm finds the maximum number of "matches" between youths and job slots (or flow network). See the appendix for details.

[25] This sometimes happens when youth are selected for multiple positions and fail to decline one or more offers, essentially "ghosting" the employer. More commonly, the burdensome hiring paperwork creates substantial barriers such that youth start but never finish the onboarding process.

paperwork.

1. Characteristics of Late Applicants

We explore the characteristics of these late applicants to understand whether imposing stricter deadlines could improve efficiency without harming equity. If youth who apply late to the program have characteristics that put them at a disadvantage, then the timing of the hiring decisions will matter for achieving the City's goal of improving equity by providing access to these early employment experiences. This is especially important if these marginal applicants have more to gain from participating in the program compared to youth who apply earlier, as suggested by prior research (Davis and Heller, 2020; Kessler et. al, 2022).

Although the online portal advertised a deadline of May 29th for youth applications, in practice, youth had the ability to submit new applications through mid-July in two ways. First, any youth who had previously applied but had not yet been selected for a summer job were invited via email to attend the in-person "We Hire" event between June 21st to June 24th, at which time they could apply to any remaining positions and be matched in real-time. Second, OYEO also conducted additional outreach through the Boston Public Schools and community based organizations to provide access to youth who had **not** previously applied for a job as walk-ins to the OYEO office on a rolling basis through July 22nd.

As a result, the timing of youth applications varied considerably over the recruiting season as shown in Figure 4 which plots the number of youth by the date of their first application. The number of first-time applicants is quite high when the SuccessLink portal first opens in March but then drifts down over time until May 29th when we see a spike as youth respond to the application deadline. We can see also spike in applicants during the "We Hire" event between June 21st and June 24th when OYEO placed any remaining youth applicants into any remaining job openings in real-time.

Although this late wave of applicants might seem inefficient, there are important equity implications associated with allowing hiring to occur over multiple waves, including late applicants. This is because youth who submit applications later in the recruitment process differ in terms of key demographic traits.[26] To explore how efficiency and equity change with hiring over multiple waves, we categorize youth according to the date of their first application. We consider youth an "early" applicant if they submitted their first application before most employers had made their selections (between March 18th and April 30th), a "late" applicant if they submitted their first job application after the employer selection process was well underway but before the application portal was closed (between May 1st and June 15th), or a "very late" applicant if they submitted their first application after all employers had finished selections (after June 15th).

Table 7 reveals that compared to "early" applicants, "late" applicants are significantly more likely to be older, Black, and female. They are also less likely to speak English as their first language, to be enrolled in school at all or attend a prestigious exam school, or to have previously participated in the SuccessLink program. In terms of application behavior, "late" applicants submit fewer applications, apply to more competitive positions, and are less likely to have completed the "Why Work" question on the application. Compared to "late" applicants "very late" applicants are even more likely to Black but also younger and much less likely to have previously participated or complete the "Why Work" question on the application.

Thus, providing an opportunity for youth to apply later appears to be quite important for ensuring equity and open access among less advantaged youth who are seeking employment. Of

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[26] See Appendix tables A2-A6 for descriptive statistics of youth applicants by each month of their earliest application (e.g., March through July).

the total number of applicants, there are 737 youth who submitted their first application after the employer selection deadline. In the absence of a mechanism such as the ”We Hire” event to help match these youth to jobs, these marginal applicants would miss out on the well-documented benefits of summer employment programs for improving a range of academic, employment, and criminal justice outcomes (Modestino 2019, Kessler et al. 2016, Heller 2014, Modestino and Paulsen, 2023).

2. *Direct Placements: We Hire Event*

We explore both the efficiency and equity implications of conducting multiple waves of hiring leading up to and through the start of the program by assessing the effectiveness of OYEO's ”We Hire” event and other outreach efforts to late applicants.[27] To do this, we identified youth who participated in the "We Hire" event as those with an application status of 'Recruiter Submitted' that occurred after June 20th in any daily snapshot from the hiring platform. Note that it is possible that a youth may have already been selected by an employer, declined the position, and was then subsequently placed for a second time during the "We Hire" event into a different position. To bias against overestimating the impacts of these direct OYEO placements, we only attribute these observations as being selected by an employer and not by the "We Hire" event to provide a more conservative assessment of the benefits of back-filling positions.

Table 8 compares the descriptive statistics of youth who were selected by an employer, and those who were selected by attending the "We Hire" event. In terms of efficiency, these direct OYEO placements yielded an additional 572 youth selected to fill any remaining openings left vacant due to having too few applicants, youth who declined the job offer, or selected youth

[27] Note that for this section of the analysis, we no longer impose the June 15th submission deadline for our observations of interest.

who failed to make it through the hiring process. Thus, the direct OYEO placements from this final wave produced an even larger impact on efficiency than the algorithm, largely due to redirecting youth not selected in prior waves to apply to the remaining job openings. In terms of equity, youth selected during the event were 19 percentage points more likely to be Black compared to the youth selected by employers, again producing an even larger impact on equity than the algorithm, largely due to the characteristics of the “very late” applicant pool. The “We Hire” event also favored younger youth, youth whose first language is not English, youth who did not attend one of the prestigious exam schools, and youth who had not previously participated in the program. Similar to those selected by the job matching algorithm, youth selected through the “We Hire” event had submitted more applications, applied to jobs that were more competitive, and were more likely to complete the “Why Work” question.

D. Assessing Overall Improvements in Efficiency and Equity

Finally, we assessed whether OYEO achieved greater overall efficiency through the combination of both the automated (job matching algorithm) and direct placements (OYEO “We Hire” event plus walk-ins). In total, OYEO had 2,652 job openings available through their online job portal. As of June 15th, employers had roughly 500 slots that remained open with no youth selected. At the end of the OYEO placement period, 93% of all job slots were accounted for with a youth placement. This overall level of efficiency was at least on par with the prior performance level achieved pre-pandemic in 2017 (9 percent left unfilled) and a vast improvement over more recent years during which upwards of 18 percent of jobs were left unfilled.[28]

[28] In 2023, OYEO expanded the use of the job matching algorithm to include not just back-filling empty slots but also filling an additional 30 allotment given to employers which ultimately resulted in zero jobs left unfilled that year (Modestino and Cope, 2023).

To assess the overall impact of both the automated and direct placement mechanisms on equity, we compare the demographic characteristics of the two mechanisms combined relative to the selections of employers versus the overall distribution of youth applicants. Figure 5 shows that youth selected using either of the two OYEO alternative placement mechanisms were more racially diverse than those selected by an employer. Moreover, when used in combination, these two methods served to largely offset the racial disparities between the applicant and the selected pool (see also Table A10 in the appendix).

1. Remaining Barriers to the Hiring Process

However, just because OYEO was able to achieve more efficient and equitable youth **selections** through automated and direct placements, it could still be the case that the number or distribution of youth hires fell short of these goals. This is because of the remaining barriers to the hiring process that exist regardless of how youth are selected by either an employer, the job matching algorithm, or through the We Hire Event. Once a youth is notified of their job offer, they need to complete 10 different steps to before they are officially hired, including the submission of official documents including a work permit authorizing them to work, a school report card or utility bill to show proof of residency and a social security card to allow for payroll deductions. Parent surveys and youth focus groups confirm that navigating this process and obtaining and submitting all of the required documentation is burdensome at best and at worst, presents a significant barrier for some youth.

To explore the equity implications of these remaining barriers, we document the number and characteristics of youth who fail to make it through the hiring process. Our analysis focuses on those who were selected for a position and then proceeded to the hiring stage, but ultimately did not get hired. Specifically, we code youth as entering the hiring stage if they ever reached a status of "Onboarding" after having completed an application and then check if they ever reached a status of "Hired" after being selected.[29] On average, youth took 25 days to complete onboarding with most taking upwards of 5-6 weeks, potentially delaying their start date until after the program had already started (see Figure A3).

Those who reached onboarding but did not get hired were more likely to have characteristics similar to those who were less likely to be selected by an employer. They were more likely to be Black, Hispanic, and female but less likely to have their first language be English, attend an exam school, or have participated in the SuccessLink program before. Table 9 shows that controlling for these other demographics as well as the number and timing of applications, and the method of selection does not eliminate these initial racial and gender disparities in whether youth make it through the hiring process. Our findings suggests that programs need to consider how to reduce paperwork and administrative barriers to convert more youth selections into hires if ensuring equity among who is able to participate, not just who gets selected to participate, is a primary goal of the program.

V. CONCLUSION

Matching participants to jobs within a workforce development program when there is heterogeneity on both sides of the market involves a complex balancing act to maintain participation while ensuring all jobs are filled and are filled equitably. This matching problem has become increasingly complex over time for summer jobs programs where intermediaries need to balance both the increasingly diverse career interests of youth as well as the growing demands for skill among employers across many types of positions, making random assignment infeasible in many cases.

[29] This includes youth who were hired and later self-withdrew from the position.

However, the hiring platforms used by many programs were not designed to process high volumes of applications over multiple employer-partners, cross-check matches for duplicate placements in real-time and provide a user-friendly experience for youth to successfully complete the hiring process in a timely manner. As a result, the application and selection process can become inefficient, serving to slow down or even derail the likelihood of landing a job for a meaningful number of youth. Moreover, when the employer selection process is left unchecked, workforce development programs run the risk of replicating many of the inequities that are observed in the real-world labor market.

Given that one of the intended goals of the Boston SYEP is to level the playing field for low-income and inner-city youth of color, City leaders sought to increase both the efficiency and equity of how jobs assignments are made. During the summer of 2022, Northeastern partnered with OYEO to perform an efficiency and equity audit of the SuccessLink application and hiring system. Overall, it appears that youth applicant behaviors do not maximize the probability of being selected by an employer. Roughly one-third of youth fail to complete the application process, suggesting that there are significant barriers to participating. Although youth are encouraged to apply for multiple jobs, more than half (53 percent) of all youth apply to only one job, indicating that the application process is cumbersome. Some employers are oversubscribed, receiving dozens of applications per opening, while other employers are undersubscribed, receiving less than one application per opening. The combination of youth submitting too few applications and many applying to the same employers signals a lack of information and creates a severe mismatch that can leave youth unemployed and jobs unfilled.

Employer selections show disparities by race and ethnicity with employers being twice as likely to select white youth relative to percentage of whites in the overall pool of applicants.

Employers also select a larger proportion of English speakers and exam school students relative to their representation in the overall pool of applicants. This was true even when controlling for previous program participation, the timing and number of applications, and having completed the job readiness “Why Work” application question. Fortunately, the combination of our pilot job matching algorithm along with the OYEO “We Hire” event was able to greatly reduce these disparities by race and ethnicity. However, more than one-quarter of youth who are matched to a job still do not complete the hiring process due to a combination of not being aware of the offer, not accepting the offer, or not completing the hiring paperwork. In particular, Black, Hispanic and female youth who are selected by an employer were less likely than white or male youth to transition from being selected for a job to getting onto the payroll and starting work.

Overall, our results indicate that despite having honorable goals of reducing inequality, youth workforce development programs that face heterogeneity on both sides of the job matching process are likely to result in job placements that perpetuate the inequities found in the labor market when random selection is not feasible. These disparities are eye-opening given that SYEP employer partners have signed a contract as part of a six-week developmental program where the City is paying the youth wages and youth applicants have little real-world experience upon which to differentiate themselves. However, our findings suggest that by using a combination of automated and direct program placements, cities can be more intentional about matching youth to jobs while maximizing both employer and youth participation. Instituting some kind of 70-30 rule with just under one-third of the program slots filled by a lottery run by the city and the remaining filled by the employer selection could be a feasible solution going forward.

However, while running lotteries within employers can help alleviate some of the disparity due to employer selection bias, because youth choose to apply to jobs based on location and/or a pre-existing relationship with the employer, there is still room for youth self-selection to perpetuate systemic inequality. Greater outreach and marketing of opportunities could help reduce the disparity in applicants across employers, creating a thicker market and improving the matching process in terms of both efficiency and equity. Additional research could help programs find actionable ways to nudge youth to apply better, guide employers to select youth more equitably, and reduce paperwork to better meet their intended goals of expanding opportunities for young people that level the playing field across racial, ethnic, and socioeconomic groups.

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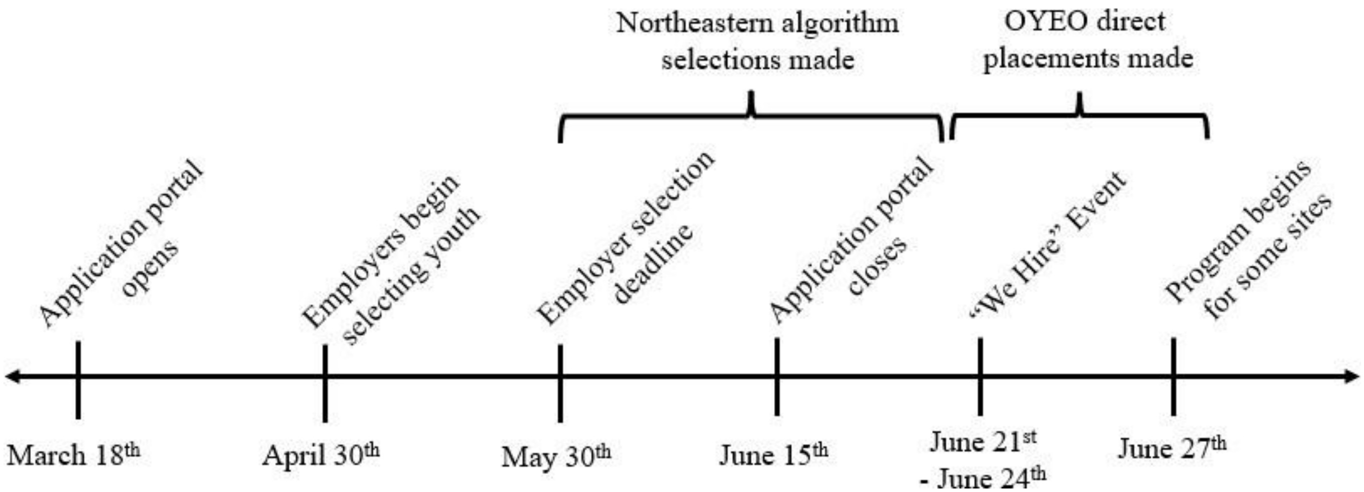
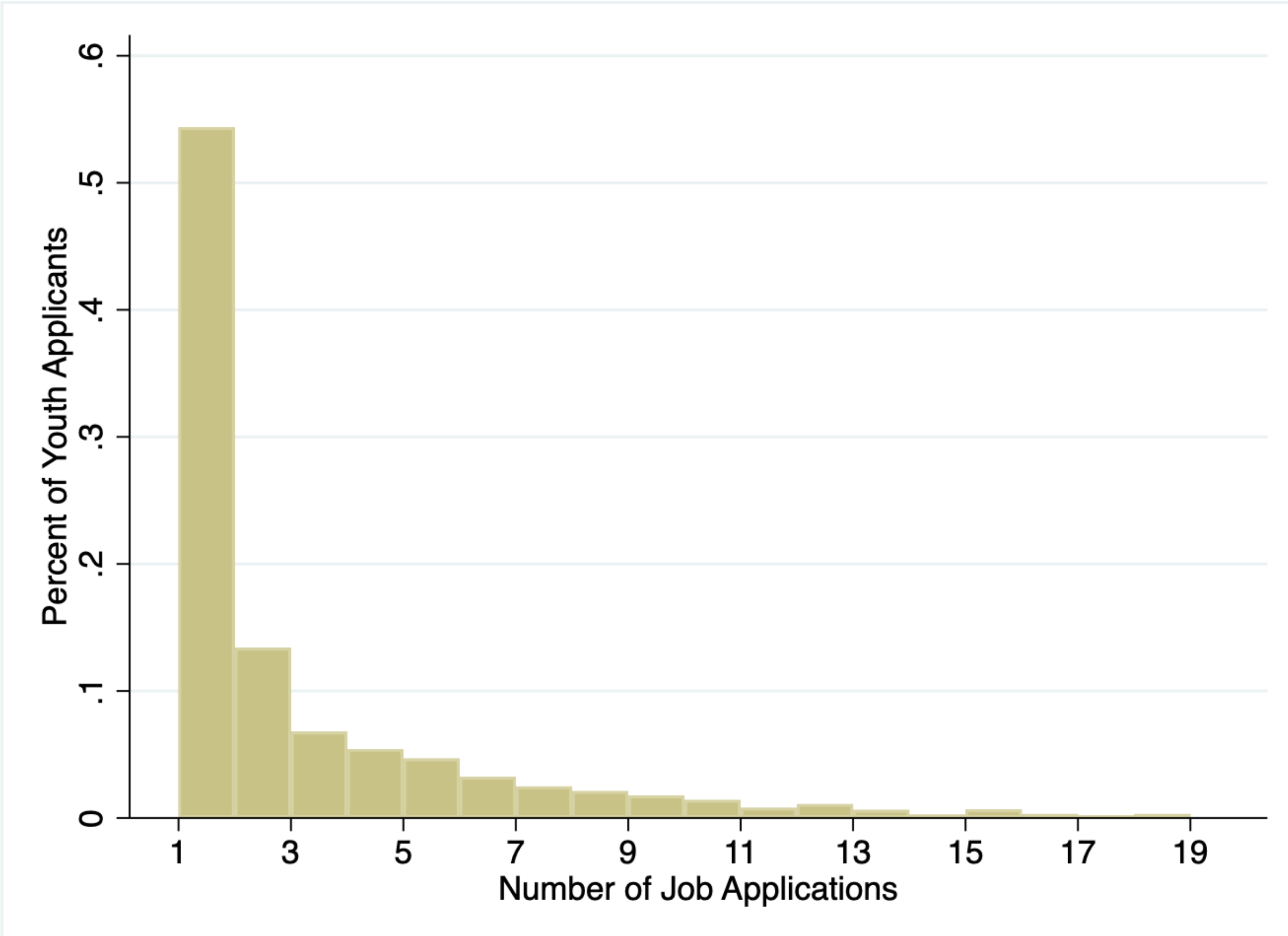
Figure 1: OYEO Job Application Timeline, Summer 2022



Source: Authors' illustration based on information regarding the application, screening, and hiring process for "direct" employer partners from the City of Boston's Office of Youth Employment and Opportunity.

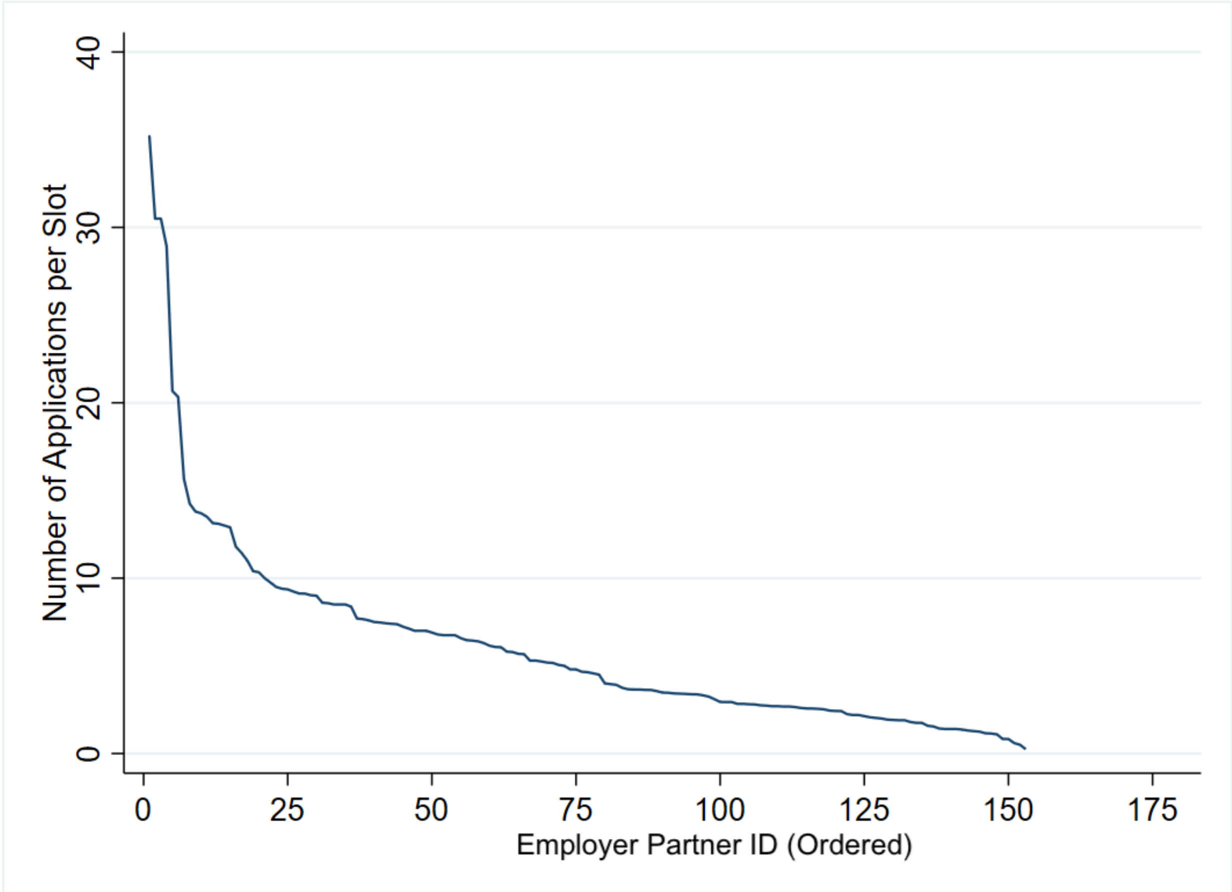
Note: Some employers made selections after May 30th deadline. These included STRIVE Madison, STRIVE Wentworth Training Program, BCYF - SOAR Boston, Hawthorne Youth and Community Center, WriteBoston, STRIVE: Document Imaging Service Center, and Boston Parks and Recreation. For these employers if a youth ever received a status of selected for that employer, regardless of the timing, we code these youth as being "Selected by Employer."

Figure 2: Histogram of Number of Applications per Youth, Summer 2022



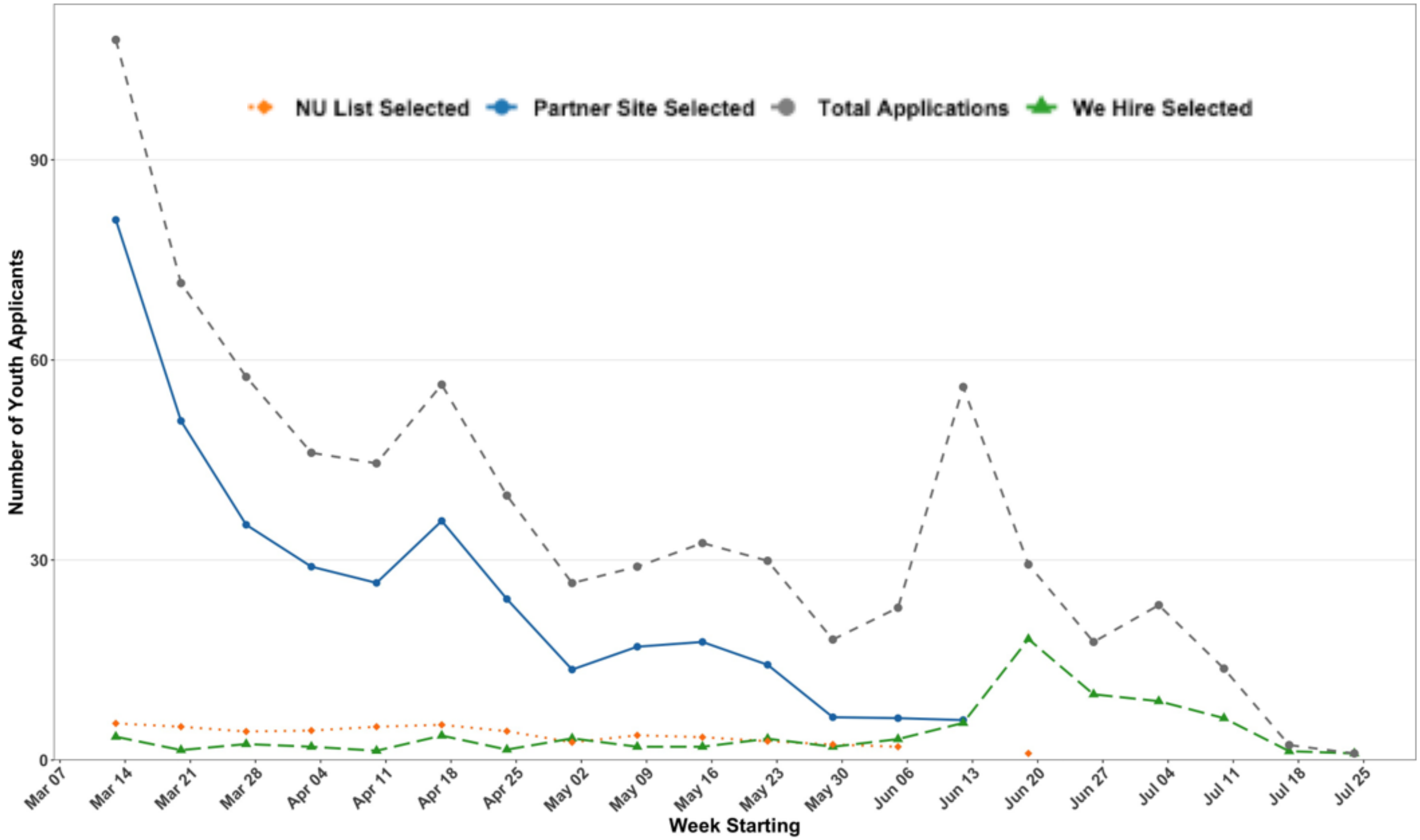
Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Figure 3: Distribution of Number of Youth Applications per Job Opening



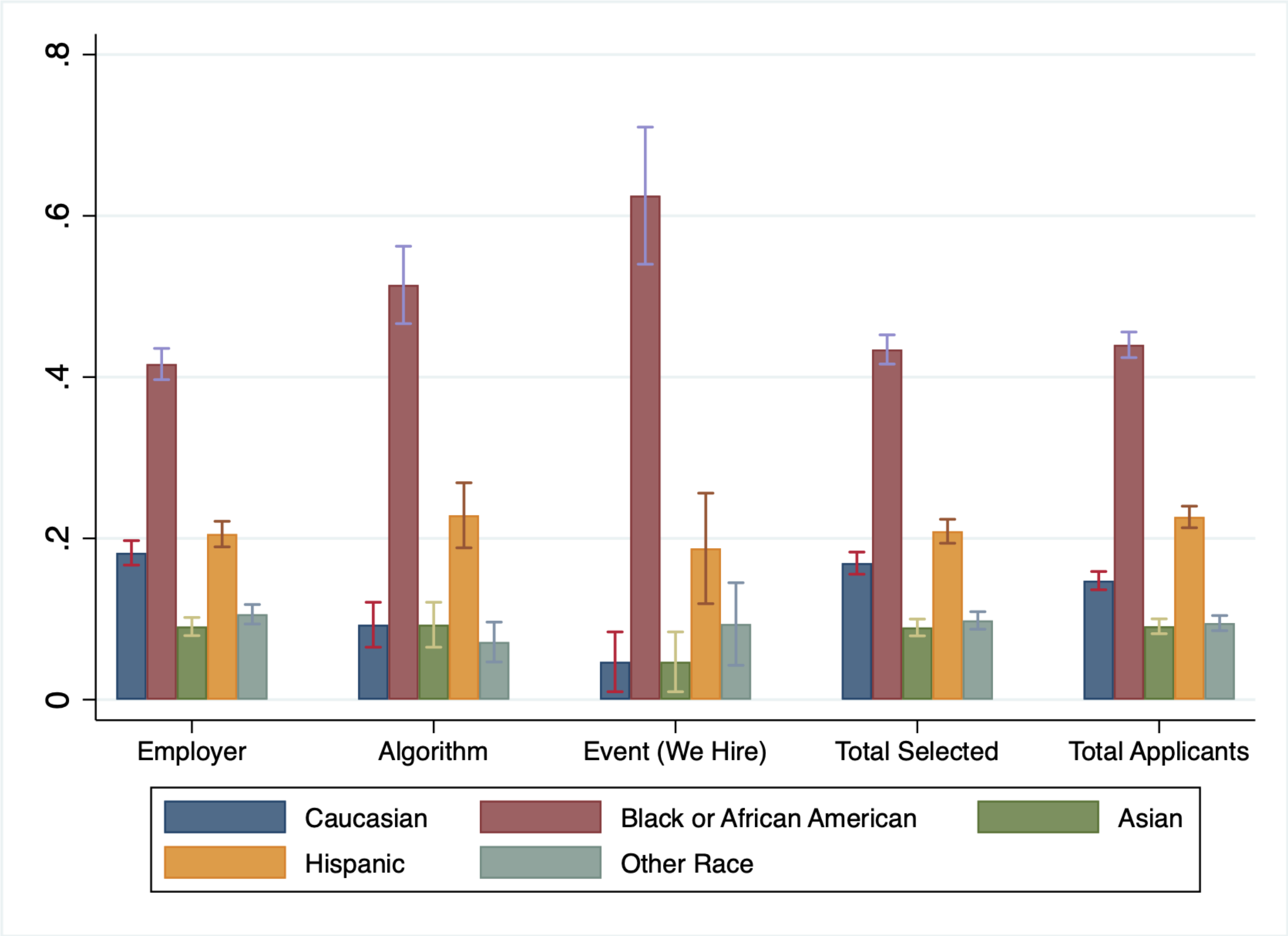
Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Figure 4: Number of Youth Applying to the Program by Date of First Application



Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: The dashed blue line represents youth selected by an employer-partner, the green solid line represents those selected by the research team's job matching algorithm, and the red solid line represents those selected at the City's "We Hire" event.

Figure 5: Racial Distribution of Selected Youth by Method versus Total Applicants



Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table 1: Program Efficiency and Equity over Time

Panel A. Efficiency	Number of Jobs Filled				
	2017	2018	2019	2020	2021
Number of applicants	7,156	6,508	6,190	10,839	7,018
Number of openings	3,133	3,189	3,025	4,057	3,297
Number of youth hired	2,848	2,587	2,637	3,477	2,467
Number of openings unfilled	285	602	388	580	830
Percent of openings unfilled	9.1%	18.9%	12.8%	14.3%	25.2%
Panel B. Equity	**Share of Hiring Pool minus Share of Applicant Pool**				
	2017	2018	2019	2020	2021
White (Not Hispanic or Latino)	5.47	4.01	3.75	2.56	5.51
Asian (Not Hispanic or Latino)	-1.51	-1.77	-0.61	1.99	0.20
Black or African American (Not Hispanic or Latino)	0.15	1.40	-0.85	-1.77	-2.01
Hispanic or Latino	-3.53	-3.26	-1.71	-2.46	-4.56
Two or More Races (Not Hispanic or Latino)	0.13	-0.06	-0.27	0.00	0.04

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table 2: Descriptive Statistics for Youth who have Completed at Least One Valid Job Application

	Mean	Std. Dev.	Count
Age	16.7	1.37	3,727
Black or African American	0.44	0.50	3,761
White	0.15	0.35	3,761
Hispanic or Latino	0.23	0.42	3,761
Asian	0.09	0.29	3,761
Other Race	0.10	0.29	3,761
Female	0.49	0.50	3,761
Fluent in Another Language	0.33	0.47	3,652
First Language English	0.84	0.36	3,652
Attends Exam School	0.23	0.42	3,418
Enrolled in School	0.99	0.08	3,652
School Year Participant	0.10	0.30	3,762
Prior Summer Participant	0.26	0.44	3,762
Number of Applications	3.04	3.74	3,762
Avg. # of Applications per Slot	8.92	12.3	3,762
Earliest App Submitted in March	0.28	0.45	3,762
Earliest App Submitted in April	0.36	0.48	3,762
Earliest App Submitted in May	0.23	0.42	3,762
Earliest App Submitted in June	0.14	0.35	3,762
Completed Work Question	0.83	0.37	3,762
Avg. Work Question Length (in 100s)	3.08	2.80	3,143
Avg. Work Question Flesch Score - Below grade level	0.49	0.50	3,134
Avg. Work Question Flesch Score - At grade level	0.27	0.45	3,134
Avg. Work Question Flesch Score - Above grade level	0.24	0.43	3,134
Employer Selected	0.66	0.22	3,762
Total Number of Observations			3,762

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: This sample includes youth who submitted at least one valid application by June 15th. Counts vary across variables reported as some variables are missing for youth. The 'Other Race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race.

Table 3: Descriptive Statistics for Youth Selected versus Not Selected by an Employer

	Not Selected Mean/Std. Dev.	Selected Mean/Std. Dev.	Diff in Means/ Std.Err. in Diff
Age	16.45	16.84	−0.39***
	(1.27)	(1.39)	(0.05)
Black or African American	0.49	0.42	0.07***
	(0.50)	(0.49)	(0.02)
White	0.08	0.18	−0.10***
	(0.27)	(0.39)	(0.01)
Hispanic or Latino	0.27	0.21	0.06***
	(0.44)	(0.40)	(0.01)
Asian	0.09	0.09	0.00
	(0.29)	(0.29)	(0.01)
Other Race	0.07	0.11	−0.03***
	(0.26)	(0.31)	(0.01)
Female	0.49	0.48	0.01
	(0.50)	(0.50)	(0.02)
Fluent in Another Language	0.36	0.31	0.05***
	(0.48)	(0.46)	(0.02)
First Language English	0.83	0.85	-0.02
	(0.37)	(0.36)	(0.01)
Attends Exam School	0.17	0.26	−0.09***
	(0.38)	(0.44)	(0.02)
Enrolled in School	0.99	1.00	−0.01***
	(0.11)	(0.06)	(0.00)
School Year Participants	0.00	0.15	−0.15***
	(0.00)	(0.35)	(0.01)
Prior Summer Participant	0.18	0.31	−0.13***
	(0.38)	(0.46)	(0.02)
Number of Applications	2.46	3.33	−0.87***
	(2.57)	(4.19)	(0.13)
Avg. # of Applications per Slot	13.39	6.65	6.75***
	(17.88)	(7.16)	(0.41)
Earliest App Submitted in March	0.21	0.31	−0.09***
	(0.41)	(0.46)	(0.02)
Earliest App Submitted in April	0.35	0.36	-0.00
	(0.48)	(0.48)	(0.02)
Earliest App Submitted in May	0.30	0.19	0.10***
	(0.46)	(0.40)	(0.01)
Earliest App Submitted in June	0.13	0.14	-0.01
	(0.34)	(0.35)	(0.01)
Completed Work Question	0.88	0.81	0.07***
	(0.33)	(0.39)	(0.01)
Avg. Work Question Length (in 100s)	2.62	3.34	−0.71***
	(2.58)	(2.89)	(0.10)
Avg. Work Question Flesch Score - Below grade level	0.48	0.49	-0.01
	(0.50)	(0.50)	(0.02)
Avg. Work Question Flesch Score - At grade level	0.29	0.27	0.02
	(0.45)	(0.44)	(0.02)
Avg. Work Question Flesch Score - Above grade level	0.23	0.25	-0.02
	(0.42)	(0.43)	(0.02)
Observations	1,267	2,495	3762

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: Column 1 reports the averages for youth who were not selected for employment by at least one employer. Column 2 reports the average for youth who were selected by an employer. Column 3 reports the differences in the reported averages. Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Relationship between Youth Characteristics and Number of Applications Submitted

	(1)	(2)	(3)	(4)	(5)
Age	-0.34***	-0.34***	-0.27***	-0.28***	-0.29***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Black or African American	1.01***	1.12***	1.10***	1.10***	1.15***
	(0.18)	(0.19)	(0.19)	(0.19)	(0.22)
Hispanic or Latino	0.79***	0.90***	0.86***	0.85***	0.91***
	(0.22)	(0.22)	(0.22)	(0.22)	(0.24)
Asian	0.68**	0.60**	0.59**	0.58**	0.71**
	(0.27)	(0.27)	(0.27)	(0.27)	(0.29)
Other Race	1.13***	1.20***	1.35***	1.32***	1.39***
	(0.25)	(0.25)	(0.26)	(0.26)	(0.27)
Female	0.32***	0.30**	0.34***	0.33***	0.32**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Fluent in Another Language	0.05	0.03	0.05	0.04	0.06
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
First Language English	0.54***	0.51***	0.51***	0.48***	0.47**
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Attends Exam School		0.34**	0.35**	0.28*	0.25
		(0.17)	(0.17)	(0.17)	(0.17)
Enrolled in School		0.87	1.03	0.88	0.86
		(0.74)	(0.74)	(0.74)	(0.76)
School Year Participants			-0.93***	-0.80***	-0.81***
			(0.22)	(0.23)	(0.23)
Prior Summer Participant			-0.11	-0.13	-0.12
			(0.15)	(0.15)	(0.15)
Completed Work Question				0.36*	0.36*
				(0.21)	(0.21)
Avg. Work Question Length (in 100s)				0.05**	0.04
				(0.03)	(0.03)
Avg. Work Question Flesh Score - At grade level				0.02	-0.00
				(0.16)	(0.16)
Avg. Work Question Flesh Score - Above grade level				0.24	0.23
				(0.17)	(0.17)
Observations	3762	3762	3762	3762	3762
Postal Code Controls	No	No	No	No	Yes

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: White, male, and work question Flesch Score - below grade level are omitted categorical variables. The 'Other Race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race. Although not reported here, we also include controls a set of dummy variables for missing data on the application for each of the demographic characteristics (columns 1-5), school enrollment status and school name (columns 2-5), and previous SYEP participation (columns 3-5). Column (5) also includes a set of dummy variables for youth ZIP code. Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Relationship between Youth Characteristics and Likelihood of being Selected by an Employer

	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.02***	0.02***	0.01*	0.01***	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black or African American	-0.19***	-0.17***	-0.15***	-0.13***	-0.13***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Hispanic or Latino	-0.21***	-0.20***	-0.17***	-0.14***	-0.14***	-0.13***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Asian	-0.16***	-0.18***	-0.17***	-0.15***	-0.16***	-0.19***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Other Race	-0.08**	-0.06*	-0.11***	-0.11***	-0.11***	-0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Female	-0.00	-0.00	-0.02	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Fluent in Another Language	-0.03*	-0.01	-0.01	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
First Language English	-0.06***	-0.02	-0.02	-0.03	-0.03	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Attends Exam School		0.09***	0.08***	0.07***	0.07***	0.08***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Enrolled in School		0.23**	0.19**	0.07	0.06	0.05
		(0.09)	(0.09)	(0.08)	(0.08)	(0.09)
School Year Participants			0.31***	0.42***	0.41***	0.40***
			(0.03)	(0.03)	(0.03)	(0.03)
Prior Summer Participant			0.10***	0.09***	0.08***	0.08***
			(0.02)	(0.02)	(0.02)	(0.02)
Number of Applications				0.02***	0.02***	0.02***
				(0.00)	(0.00)	(0.00)
Avg. # of Applications per Slot				-0.01***	-0.01***	-0.01***
				(0.00)	(0.00)	(0.00)
Earliest App Submitted in March				0.09***	0.09***	0.24***
				(0.02)	(0.02)	(0.03)
Earliest App Submitted in April				0.06***	0.05***	0.21***
				(0.02)	(0.02)	(0.03)
Earliest App Submitted in May				-0.15***	-0.15***	0.16***
				(0.03)	(0.03)	(0.03)
Completed Work Question					-0.02	-0.02
					(0.02)	(0.02)
Avg. Work Question Length (in 100s)					0.01***	0.01***
					(0.00)	(0.00)
Avg. Work Question Flesh Score - At grade level					-0.03*	-0.03*
					(0.02)	(0.02)
Avg. Work Question Flesh Score - Above grade level					0.01	0.01
					(0.02)	(0.02)
Observations	3762	3762	3762	3762	3762	3762
Zip Code Controls	No	No	No	No	No	Yes

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: The sample includes youth who submitted at least one complete and valid job application prior to the application deadline. The dependent variable is equal to one if the youth was selected for employment by at least one employer and is equal to zero otherwise. Omitted categorical variables are white, male, earliest application submitted in June, and below grade level work question Flesch Score. The 'Other race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race. Although not reported here, we also include controls a set of dummy variables for missing data on the application for each of the demographic characteristics (columns 1-6), school enrollment status and school name (columns 2-6), and previous SYEP participation (columns 3-6). Column (6) also includes a set of dummy variables for youth ZIP code. Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Characteristics of Youth Selected for a Job versus Youth Applicants: Employer versus Algorithm

	(1) Employer Selected	(2) NU Algorithm Selected	(3) Employer or NU Algorithm Selected	(4) Youth Applicants	(5) Difference: (2)–(1)	(6) Difference: (3) – (4)
Age	16.73	16.66	16.71	16.56	−0.07	0.16**
	(1.96)	(1.84)	(1.97)	(2.10)	(0.10)	(0.05)
Black or African American	0.42	0.51	0.43	0.44	0.10***	−0.01***
	(0.49)	(0.50)	(0.50)	(0.50)	(0.03)	(0.01)
White	0.18	0.09	0.17	0.15	−0.09***	0.03***
	(0.39)	(0.29)	(0.38)	(0.36)	(0.02)	(0.01)
Hispanic or Latino	0.21	0.23	0.21	0.23	0.02	−0.02
	(0.40)	(0.42)	(0.41)	(0.42)	(0.02)	(0.01)
Asian	0.09	0.09	0.09	0.09	0.00	0.00
	(0.29)	(0.29)	(0.29)	(0.29)	(0.02)	(0.01)
Other Race	0.11	0.07	0.10	0.09	−0.04**	0.01
	(0.31)	(0.26)	(0.29)	(0.29)	(0.02)	(0.01)
Female	0.48	0.49	0.48	0.49	0.01	−0.01
	(0.50)	(0.50)	(0.50)	(0.50)	(0.03)	(0.01)
Fluent in Another Language	0.30	0.34	0.30	0.32	0.04*	-0.02
	(0.46)	(0.47)	(0.46)	(0.47)	(0.02)	(0.01)
First Language English	0.81	0.85	0.82	0.82	0.04	0.00
	(0.39)	(0.36)	(0.39)	(0.39)	(0.02)	(0.01)
Attends Exam School	0.23	0.21	0.23	0.21	−0.02	0.022**
	(0.42)	(0.41)	(0.42)	(0.41)	(0.02)	(0.01)
Enrolled in School	0.95	0.99	0.96	0.96	0.04***	−0.01
	(0.21)	(0.05)	(0.20)	(0.18)	(0.01)	(0.01)
Number of Applications	3.33	4.33	3.37	3.04	0.99***	0.33***
	(4.19)	(3.60)	(4.08)	(3.74)	(0.22)	(0.10)
Avg. # of Applications per Slot	6.65	9.54	6.99	8.92	2.88***	−1.92***
	(7.17)	(8.99)	(7.54)	(12.32)	(0.39)	(0.26)
Earliest App Submitted in March	0.31	0.28	0.30	0.28	−0.03	0.02**
	(0.46)	(0.45)	(0.46)	(0.45)	(0.02)	(0.01)
Earliest App Submitted in April	0.36	0.41	0.37	0.36	0.05**	0.01
	(0.48)	(0.49)	(0.48)	(0.48)	(0.03)	(0.01)
Earliest App Submitted in May	0.19	0.26	0.20	0.23	0.07**	−0.03*
	(0.40)	(0.44)	(0.40)	(0.42)	(0.02)	(0.01)
Earliest App Submitted in June	0.14	0.05	0.13	0.14	0.09***	−0.01
	(0.35)	(0.21)	(0.34)	(0.35)	(0.02)	(0.01)
Completed Work Question	0.81	0.86	0.82	0.83	0.05**	−0.02*
	(0.39)	(0.35)	(0.39)	(0.37)	(0.02)	(0.01)
Avg. Work Question Length (in 100s)	2.70	2.82	2.70	2.57	0.12	0.13**
	(2.92)	(3.12)	(2.94)	(2.81)	(0.16)	(0.97)
Avg. Work Question Flesch Score - Below grade level	0.40	0.39	0.40	0.41	−0.01	0.01
	(0.49)	(0.49)	(0.49)	(0.49)	(0.03)	(0.01)
Avg. Work Question Flesch Score - At grade level	0.22	0.25	0.22	0.23	0.03	0.01**
	(0.41)	(0.43)	(0.41)	(0.42)	(0.02)	(0.01)
Avg. Work Question Flesch Score - Above grade level	0.20	0.22	0.20	0.20	0.02	0.00
	(0.40)	(0.42)	(0.40)	(0.40)	(0.02)	(0.01)
Observations	2495	309	2804	3762		

Source: Authors' calculations based on data from the Boston Office of Youth Employment and Opportunity.
Note: This sample includes youth who applied before the deadline of June 15th. Column 1 reports the averages for youth who were selected for employment by at least one employer. Column 2 reports the averages for youth who were selected by the NU job matching algorithm and were not selected by an employer partner. Column 3 reports the averages of youth selected either by an employer partner or by the NU job matching algorithm. Column 4 contains the averages of all youth who applied before the deadline of June 15th. Column 5 reports the differences in averages between employer selected youth and the NU job matching algorithm selected youth. Column 6 contains the differences in averages between column 3 (employer partner and NU job matching algorithm selected youth) and column 4 (all applicants). Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: * p<0.1, ** p<0.05, *** p<0.001.

Table 7: Characteristics of Youth by Timing of Job Application

	(1) Early Applicants	(2) Late Applicants	(3) Very Late Applicants	(4) Difference: (1)-(2)	(5) Difference: (2)-(3)
Age	16.51	16.62	15.7	-0.11	0.88***
	(1.75)	(2.59)	(3.07)	(0.07)	(0.13)
Black or African American	0.43	0.47	0.57	-0.04*	-0.11***
	(0.49)	(0.50)	(0.50)	(0.01)	(0.02)
White	0.17	0.11	0.09	0.07***	0.02
	(0.38)	(0.31)	(0.28)	(0.01)	(0.01)
Hispanic or Latino	0.22	0.24	0.22	-0.03	0.03
	(0.41)	(0.43)	(0.41)	(0.01)	(0.02)
Asian	0.10	0.08	0.036	0.020*	0.04***
	(0.30)	(0.27)	(0.19)	(0.01)	(0.01)
Other Race	0.09	0.11	0.09	-0.02*	0.02
	(0.28)	(0.31)	(0.29)	(0.01)	(0.01)
Female	0.47	0.52	0.45	-0.05**	0.07***
	(0.50)	(0.50)	(0.50)	(0.02)	(0.02)
Fluent in Another Language	0.32	0.32	0.29	-0.001	0.03
	(0.47)	(0.47)	(0.45)	(0.02)	(0.02)
First Language English	0.85	0.76	0.82	0.09***	-0.06**
	(0.36)	(0.43)	(0.38)	(0.01)	(0.02)
Attends Exam School	0.25	0.19	0.15	0.06***	0.03
	(0.43)	(0.37)	(0.36)	(0.01)	(0.02)
Enrolled in School	0.99	0.91	0.96	0.08***	-0.05***
	(0.05)	(0.81)	(0.20)	(0.01)	(0.01)
Prior Summer Participant	0.29	0.21	0.12	0.09***	0.08***
	(0.46)	(0.41)	(0.33)	(0.02)	(0.02)
Number of Applications	3.55	2.71	2.81	0.85***	-0.10
	(4.12)	(3.34)	(4.76)	(0.13)	(0.18)
Avg. # of Applications per Slot	8.38	9.95	8.35	-1.57***	1.61*
	(8.07)	(17.14)	(11.73)	(0.41)	(0.70)
Completed work Question	0.87	0.77	0.71	0.10***	0.06***
	(0.34)	(0.42)	(0.45)	(0.01)	(0.02)
Avg. Work Question Length (in 100s)	2.76	2.21	1.75	0.56***	0.46***
	(2.87)	(2.64)	(2.42)	(0.09)	(-0.12)
Avg. Work Question Flesch Score - Below grade level	0.46	0.50	0.51	-0.04	-0.01
	(0.50)	(0.50)	(0.25)	(0.017)	(0.03)
Avg. Work Question Flesch Score - At grade level	0.28	0.26	0.25	0.03	0.01
	(0.45)	(0.44)	(0.43)	(0.02)	(0.02)
Avg. Work Question Flesch Score - Above grade level	0.24	0.24	0.25	-0.01	0.00
	(0.42)	(0.43)	(0.43)	(0.02)	(0.02)
Employer selected	0.69	0.60	0.00	0.09***	0.69***
	(0.46)	(0.49)	(0.00)	(0.02)	(0.02)
NU Algorithm selected	0.12	0.09	0.01	0.029**	0.08***
	(0.33)	(0.29)	(0.11)	(0.011)	(0.01)
We Hire Event selected	0.05	0.09	0.44	-0.03***	-0.35***
	(0.23)	(0.28)	(0.50)	(0.01)	(0.02)
Observations	2,380	1,382	737		

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: The sample includes youth who submitted at least one valid job application. Youth who submitted at least one valid application between March and April 30th are categorized as 'Early Applicants' while youth whose earliest application was submitted between May 1st and June 15th are categorized as 'Late Applicants'. Those who submitted a job application after June 15th are categorized as 'Very Late Applicants'. Columns (1) through (3) report the means and standard deviations (in parentheses) for each group. Columns (4) and (5) report the difference in means between each group. Statistical significance is indicated at the following levels: *p<0.1, **p<0.05, ***p<0.01.

Table 8: Characteristics of Youth Selected for a Job:
Employer versus Event ("We Hire") Selections

	(1) Employer Selected	(2) Event Selected	(3) Employer & Event Selected	(4) Youth Applicants	(5) Difference: (2) - (1)	(6) Difference: (3)-(4)
Age	16.7	16.0	16.6	16.56	-0.69***	0.06
	(1.96)	(2.21)	(2.02)	(2.10)	(0.09)	(0.05)
African American	0.42	0.60	0.45	0.44	0.19***	0.01
	(0.49)	(0.49)	(0.50)	(0.50)	(0.02)	(0.01)
White	0.18	0.056	0.16	0.15	-0.13***	0.02*
	(0.39)	(0.23)	(0.37)	(0.35)	(0.02)	(0.01)
Hispanic or Latino	0.21	0.20	0.20	0.23	-0.01	-0.02**
	(0.40)	(0.40)	(0.40)	(0.42)	(0.02)	(0.01)
Asian	0.091	0.030	0.081	0.091	-0.06***	-0.01
	(0.29)	(0.17)	(0.27)	(0.29)	(0.01)	(0.01)
Other Race	0.11	0.11	0.11	0.095	0.01	0.01
	(0.31)	(0.32)	(0.31)	(0.29)	(0.01)	(0.01)
Female	0.48	0.46	0.48	0.49	-0.03	-0.01
	(0.50)	(0.50)	(0.50)	(0.50)	(0.02)	(0.01)
Fluent in Another Language	0.30	0.26	0.29	0.32	-0.04*	-0.023**
	(0.46)	(0.44)	(0.45)	(0.47)	(0.02)	(0.01)
First Language English	0.81	0.88	0.82	0.82	0.06***	0.01
	(0.39)	(0.33)	(0.38)	(0.39)	(0.02)	(0.01)
enrolled	0.95	0.97	0.96	0.96	0.02	-0.02*
	(0.21)	(0.17)	(0.21)	(0.19)	(0.01)	(0.01)
Attends Exam School	0.26	0.14	0.24	0.23	-0.12***	0.01
	(0.44)	(0.34)	(0.42)	(0.42)	(0.02)	(0.01)
Previously Participated	0.31	0.20	0.29	0.26	-0.11***	0.03**
	(0.46)	(0.40)	(0.45)	(0.44)	(0.02)	(0.01)
Number of applications of all time	3.42	4.13	3.43	3.24	0.72***	0.19*
	(4.27)	(6.06)	(4.54)	(3.88)	(0.22)	(0.10)
Avg # of Applications per Slot	6.75	7.53	6.85	8.96	0.78**	-2.11***
	(7.43)	(6.82)	(7.35)	(12.2)	(0.34)	(0.25)
Completed Work Question	0.81	0.85	0.81	0.83	0.037**	-0.019**
	(0.39)	(0.36)	(0.39)	(0.37)	(0.02)	(0.01)
Avg. Work Question Length	2.70	2.05	2.57	2.56	-0.65***	0.01
	(2.92)	(2.26)	(2.82)	(2.80)	(0.13)	(0.07)
Avg. Work Question Flesh Score - Below grade level	0.49	0.51	0.49	0.49	0.02	0.00
	(0.50)	(0.50)	(0.50)	(0.50)	(0.03)	(0.01)
Avg. Work Question Flesh Score - at grade level	0.27	0.25	0.26	0.28	-0.01	-0.01
	(0.44)	(0.43)	(0.44)	(0.45)	(0.02)	(0.01)
Avg. Work Question Flesh Score - above grade level	0.25	0.24	0.25	0.24	-0.00	0.01
	(0.43)	(0.43)	(0.43)	(0.43)	(0.02)	(0.01)
Late Applicant	0.33	0.21	0.31	0.37	-0.12***	-0.06***
	(0.47)	(0.41)	(0.46)	(0.48)	(0.02)	(0.01)
Very Late Applicant	0	0.56	0.11	0	0.56***	0.11***
	(0)	(0.50)	(0.31)	(0)	(0.01)	(0.06)
Observations	2495	572	3067	3762		

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: Column (1) reports means standard deviations (in parentheses) for youth who were ever selected by an employer partner, conditional on having applied prior to the June 15th cut-o↲ date. Column (2) reports means standard deviations (in parentheses) for youth who were selected during the "We Hire" event which includes youth who "walked in" and applied after the June 15th cut-o↲ date. Column (3) reports the differences in means between the two groups. The variable "Late Applicant" is an indicator which equals one if the youth's first job application was submitted between May 1st and June 15th. The variable "Very Late Applicant" is an indicator variable which is equal to one if the youth's first job application was submitted after June 15th. Note that since the sample now includes youth who submitted their first application after the June 15th deadline, the number of applications and average number of applications per slot is adjusted to consider all job applications, regardless of submission date. Statistical significance is indicated at the following levels: *p<0.1, ** p < 0.05, *** p< 0.01.

Table 9: Relationship between Youth Characteristics and Hired Status Conditional on Selection

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.07**	-0.07**	-0.14***	-0.14***	-0.13***	-0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black or African American	-0.15***	-0.14***	-0.12***	-0.12***	-0.13***	-0.13***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Hispanic or Latino	-0.17***	-0.16***	-0.15***	-0.14***	-0.15***	-0.15***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Asian	-0.03	-0.04	-0.03	-0.03	-0.04	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Other Race	-0.06**	-0.06**	-0.06**	-0.05**	-0.06**	-0.06**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Female	-0.22**	-0.22**	-0.25**	-0.25**	-0.26**	-0.26**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Fluent in Another Language	-0.06**	-0.06**	-0.06**	-0.05**	-0.05**	-0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
First Language English	0.07***	0.06**	0.06**	0.06**	0.05**	0.05**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Attends Exam School		0.02	0.03	0.02	0.02	0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Enrolled in School		0.06	0.06	0.06	0.06	0.06
		(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Prior Summer Participant			0.12***	0.12***	0.13***	0.13***
			(0.02)	(0.02)	(0.02)	(0.02)
Earliest App Submitted in March				-0.15**	-0.15**	-0.15**
				(0.06)	(0.06)	(0.06)
Earliest App Submitted in April				-0.14**	-0.14**	-0.14**
				(0.06)	(0.06)	(0.06)
Earliest App Submitted in May				-0.11**	-0.11**	-0.11**
				(0.06)	(0.06)	(0.06)
Employer partner selected after May 30th				-0.07**	-0.07***	-0.07***
				(0.03)	(0.03)	(0.03)
Completed Work Question					0.03	0.03
					(0.03)	(0.03)
Avg. Work Question Length (in 100s)					-0.00	-0.00
					(0.00)	(0.00)
Avg. Work Question Flesh Score - At grade level					-0.01	-0.01
					(0.02)	(0.02)
Avg. Work Question Flesh Score - Above grade level					0.04	0.04
					(0.03)	(0.03)
Observations	2079	2079	2079	2079	2079	2079
Application Controls	No	No	No	No	Yes	Yes
Zip Code Controls	No	No	No	No	No	Yes

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: The dependent variable is equal to 1 if the youth was ever hired conditional on being selected and is equal to 0 otherwise. To ensure youth have sufficient time to complete the onboarding paperwork, the sample is restricted to youth who submitted at least one valid application by June 15th and were either selected by an employer partner, the Northeastern University algorithm, or at the OYEO 'We Hire'" event. The relevant omitted category is youth selected by an employer partner by the May 30th deadline. The 'Other Race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race. Although not reported here, we include controls for zip code, earliest application month as well as dummy variables for missing data for each demographic characteristic, school enrollment status and name, and previous SYEP participation. Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: *p <0.10, **p <0.05, ***p < 0.01.

Appendix Materials

A. Analytical Dataset

During the summer of 2022, youth could apply to the SuccessLink program between March 18th and June 19th and could be selected for a position through June 24th. Youth applied for each job separately through the City's hiring platform and all youth-job applications were tracked by the Office of Youth Employment and Opportunity (OYEO) in their daily recruiting report. This report provides a daily snapshot of the status of each job application that the youth submitted corresponding to the application flow illustrated in Figure A1 below:

- Incomplete: If the youth did not complete the job application, then they were recorded as such and sent an automated message to encourage them to return to the hiring portal and finish it. A nonnegligible portion of applications were incomplete or invalid. See section B for an analysis of application behavior.
- Initial DNQ: If the youth did not answer one or more of the screening questions correctly indicating that did not meet the eligibility criteria they were flagged as potential "do not qualify." For example, youth might enter the wrong year for their birthdate which would result in an age that was either younger than 14 or older than 24, potentially disqualifying them from the program. OYEO staff contacted these youth to verify the correct information and update the youth's status if they qualified.
- Does Not Qualify (DNQ): If OYEO verified that the youth entered the correct information but they were not eligible, then they would be assigned this status.
- Applied: If the youth completed the application, then they received a confirmation and their application was visible to the employer on the hiring platform with a status of applied for each particular position.
- Onboarding (Selected): If the youth was selected for the position, then they were sent an email notifying them to complete the paperwork needed to be hired onto the City's payroll. They were assigned this status for the particular position they were selected for while they completed the paperwork. Hundreds of youth were observed to be "stuck in onboarding" and did not complete the hiring paperwork despite having been selected for a job.

- Hired: If the youth completed the hiring paperwork, then they were ready to start work and were assigned a status of hired for this particular position.
- Self-Withdrew (Portal): If the youth chose to withdraw their application before being selected by the employer (e.g., they had already accepted another job offer), then they were assigned this status for that particular position. Only a handful of youth chose to withdraw their applications.
- Self-Withdrew (Recruiter): If the youth notified the recruiter that they withdrew their application (e.g., they turned down the employer's offer), then they were assigned this status for that particular position. A total of 43 youth-applications which were self-withdrawn had been placed into onboarding.

Our analytical data set was created by appending these daily recruiting reports provided by OYEO between May 19th and end August 10th where each row is a job application (whether complete or incomplete). The information in each row includes each youth's profile information which contains their personally identifying information (name, date of birth, address, phone number, and email), basic demographics (gender, race/ethnicity, language spoken at home, and school name), and work readiness (prior participation in the program, open-ended response for why they wanted a job, and a resume if they chose to upload one). For each job application, we also observe the employer's name, the status of the application (e.g., incomplete, do not quality, applied, onboarding (selected), hired, self-withdrew), and timestamps corresponding to each status for that day's recruiting report. We use the employer's name to merge in data from OEYO's daily requisition report which includes information such as the number of openings, the industry and occupation, and a brief job description for each position.

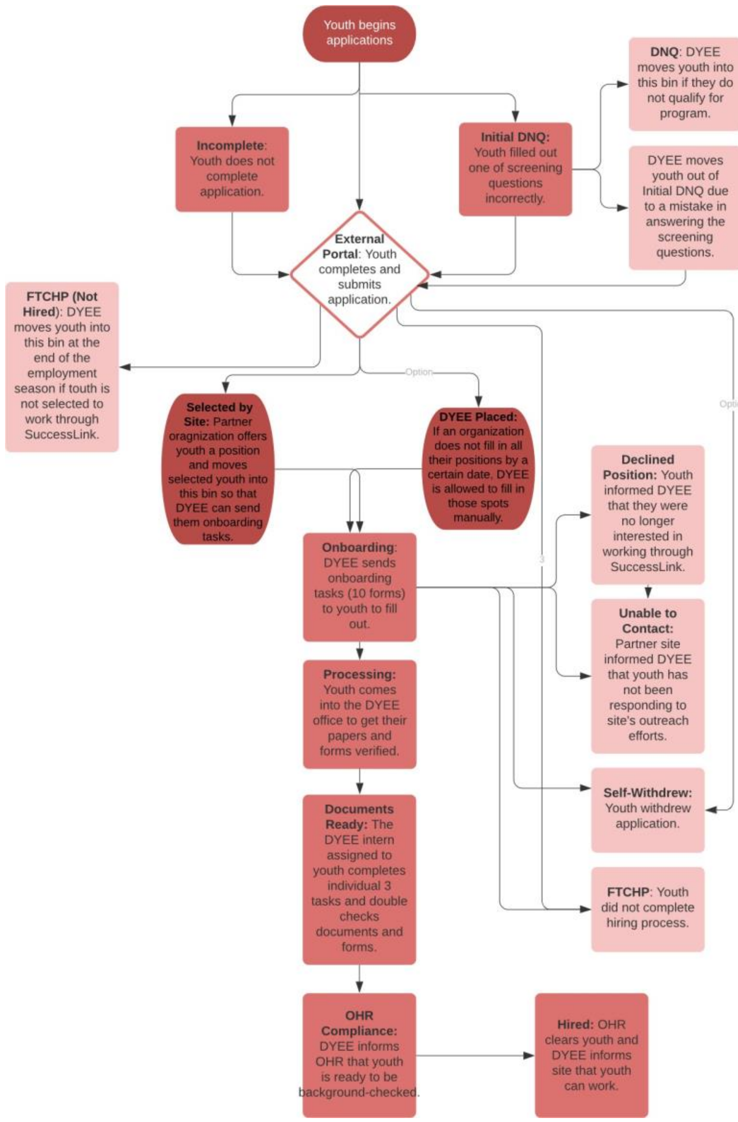
The daily recruiting snapshots have a few irregularities which required processing prior to analysis. First, when a youth created a profile within the City's hiring portal, they were assigned a unique system ID that identified each youth throughout the application and hiring process. Among the youth-job records in the recruiting report, 2.67 percent of youth had created more than one system ID by using more than one email address (either accidentally or intentionally). For youth with duplicate IDs where the profile has the same first name, last name, and date of birth (N=200), we reassigned their records to have one unique ID. For youth where the profiles had identical first and last name, but one had a valid birth date and the other was missing birth date information (N=164), we kept the profile with the valid birth date field. Finally, for youth where first name and last name matched but the birth date varied, we identified duplicate observations by matching non-missing middle name, address, and email address (N=29).

Second, some youth applied to the same job multiple times, either intentionally or accidentally. Of these, some youth had received the same status for that job within the same recruiting snapshot (e.g., identical system ID, first and last name, job posting title, and status). For these cases, we kept only one of the duplicate observations. There were also a handful of youth who applied to the same job multiple times but received a different status within the same recruiting snapshot (e.g., identical system ID, first and last name, and job posting title but different status). For these cases, we kept the observation with the higher status in that recruiting snapshot (e.g., hired over applicant).

Third, there were also some youth who applied to SuccessLink because they wanted to continue working with the same employer during the summer that had employed them during the school year. We identified these youth in two ways. First, there were a handful of youth-job observations with the status "School Year Participant" (N=6). Second, there are approximately 300 youth who applied to a job posting titled "Summer 2022 Continuing Candidates" which was created as a means to onboard youth who were continuing employment with a year-round employer partner. In the paper we categorize both these groups as School Year Participants and treat these youth as having been selected by an employer since the employer had allowed them to continue working in the same position during the summer.

Using the rich data collected through the recruiting snapshots, our final analytical dataset allows us to construct variables capturing the total number of applications a youth submitted, the date of a youth's earliest application (e.g., when a youth first entered the application system), and the competitiveness of the position they applied to (e.g., the ratio of total youth applications to total openings for a given position). We also constructed variables measuring the youth's characteristics in terms of basic demographics (e.g., age, gender, race/ethnicity, language spoken at home), school type (e.g., regular public school, prestigious exam public school, parochial or private school), and work readiness (e.g., prior participation in the program, length and Flesch readability score for the open- ended question which asked youth "why do they want to participate in the SYEP this summer").

Figure A1: Job Application Flow



Source: Authors' illustration based on information from the City of Boston's Office of Youth Employment and Opportunity.

B. Youth Application Behavior

Submitting a valid job application may pose a barrier for youth with roughly one-third failing to submit a valid application. During the 2022 summer job cycle, we observed 5,488 unique SuccessLink profiles created by youth prior to the employer selection deadline of June 2nd. Of those users, 66.8 percent (N=3,762) successfully submitted at least one job application, while approximately 33.2 percent (N=1,726) never completed a valid job application, (i.e. their assigned system ID only received an 'Incomplete', 'Initial DNQ', or 'Did Not Qualify (DNQ)' status). Table B1 contains the average age, racial composition, and gender composition for users who have at least one valid job application and those who only have invalid job applications. However, it is difficult to assess which youth characteristics may be correlated with not completing an application due to the large amount of missing data (hence the incompleteness). For youth who have at least one valid application, only less than one percent (N=30) are missing date of birth, gender, or race/ethnicity. Among youth who do not complete at least one valid application, 75.9 percent (N=1,141) youth are missing that basic demographic information. Slightly more than half of youth without at least one valid application (55 percent) did not enter their street address and nearly all (95 percent) did not enter their social security number. As a result, we focus our analysis exclusively on youth who have submitted at least one valid job application.

Youth also vary in terms of when they apply to the program and this behavior differs in terms of key demographic traits. To explore this further, tables A2 through A6 report descriptive statistics for youth applicants by their earliest application date for each month (e.g., March through July). Later applicants are significantly more likely to be older, Black, and female. They are also less likely to speak English as their first language, to be enrolled in school at all or attend a prestigious exam school, or to have previously participated in the SuccessLink program.

Finally, youth vary in terms of which jobs they choose to apply for. Figure A2 shows that youth tend to apply to the same employer and that the concentration of applications among few employers also varies considerably by race. In particular, Black and Hispanic youth are more likely than White and Asian youth to apply to the same employer, suggesting that they may lack information on the wide variety of positions that are available beyond their neighborhood (e.g.,YMCA) or other popular sites they may have visited before (e.g., New England Aquarium).

Table A1: Comparison of Descriptive Statistics for Youth with No Valid Job Applications versus Youth with at Least One Valid Job Application

	No Valid Job Application Mean/Num. Obs	At Least One Valid Application Mean/Num. Obs.	Diff in Means/ Std.Err. of Diff	p-value Diff in Means
Age	17.78	16.71	1.064	0.0000
	434	3,727	(0.076)	
Black African American	0.47	0.44	0.027	0.2061
	636	3,761	(0.021)	
White	0.17	0.15	0.021	0.1777
	636	3,761	(0.015)	
Hispanic or Latino	0.21	0.23	-0.014	0.4251
	636	3,761	(0.018)	
Asian	0.06	0.09	-0.034	0.0043
	636	3,761	(0.012)	
Other Race	0.10	0.09	0.001	0.9372
	636	3,761	(0.013)	
Missing Race	0.63	0.00	0.631	0.0000
	1,726	3,762	(0.008)	
Missing Birth Date	0.75	0.01	0.739	0.0000
	1,726	3,762	(0.007)	
Female	0.57	0.49	0.087	0.0000
	636	3,761	(0.021)	
Male	0.41	0.50	-0.098	0.0000
	636	3,761	(0.021)	
Missing Gender	0.63	0.00	0.631	0.0000
	1,726	3,762	(0.008)	
Observations	1,726	3,762	5,488	

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Note: Column 1 reports means for youth who only submitted applications that were incomplete or did not qualify. Column 2 reports means for youth who submitted at least one valid job application. Column 3 reports the differences in the reported means. Column 4 contains the p-value from a two-sampled t-test. The 'other race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race.

Table A2: Descriptive Statistics for Youth who Applied in March 2022

	Mean	Std. Dev.	Count
Age	16.6	1.129	1,032
Black or African American	0.40	0.490	1,038
White	0.20	0.399	1,038
Hispanic or Latino	0.22	0.415	1,038
Asian	0.087	0.282	1,038
Other Race	0.092	0.290	1,038
Female	0.48	0.500	1,038
Fluent in Another Language	0.31	0.463	1,036
First Language English	0.87	0.338	1,036
Attends Exam School	0.24	0.427	972
Prior Summer Participant	0.33	0.471	1,038
Number of Applications	3.67	4.482	1,038
Avg. # of Other Applications Per Slot	6.82	4.570	1,038
Avg. Why Work Question Character Length	317.9	286.0	901
Avg. Why Work Question Flesch Score	69.5	15.55	901
Employer Selected	0.70	0.460	1,038
NU Algorithm Selected	0.082	0.274	1,038
Selected by OYEO	0.16	0.363	1,038

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table A3: Descriptive Statistics for Youth who Applied in April 2022

	Mean	Std. Dev.	Count
Age	16.6	1.088	1,341
Black or African American	0.44	0.497	1,351
White	0.15	0.358	1,351
Hispanic or Latino	0.22	0.413	1,351
Asian	0.11	0.309	1,351
Other Race	0.080	0.271	1,351
Female	0.45	0.498	1,351
Fluent in Another Language	0.32	0.468	1,349
First Language English	0.84	0.364	1,349
Attends Exam School	0.26	0.437	1,271
Previous Summer Participant	0.26	0.441	1,351
Number of Applications	3.03	3.504	1,351
Avg. # of Other Applications Per Slot	6.51	3.762	1,351
Avg. Why Work Question Character Length	318.7	286.3	1,187
Avg. Why Work Question Flesch Score	66.9	38.16	1,187
Employer Selected	0.65	0.478	1,351
NU Algorithm Selected	0.088	0.284	1,351
Selected by OYEO	0.17	0.379	1,351

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table A4: Descriptive Statistics for Youth who Applied in May 2022

	Mean	Std. Dev.	Count
Age	16.6	1.536	855
Black or African American	0.47	0.499	866
White	0.10	0.304	866
Hispanic or Latino	0.26	0.440	866
Asian	0.075	0.264	866
Other Race	0.091	0.288	867
Female	0.51	0.500	866
Fluent in Another Language	0.35	0.478	829
First Language English	0.81	0.392	829
Attends Exam School	0.18	0.381	772
Prior Summer Participant	0.19	0.392	867
Number of Applications	2.73	3.397	867
Avg. # of Other Applications Per Slot	5.94	3.742	867
Avg. Why Work Question Character Length	266.8	253.2	730
Avg. Why Work Question Flesch Score	69.0	21.70	730
Employer Selected	0.54	0.499	867
NU Algorithm Selected	0.093	0.291	867
Selected by OYEO	0.19	0.391	867

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table A5: Descriptive Statistics for Youth who Applied in June 2022

	Mean	Std. Dev.	Count
Age	16.3	1.360	611
Black or African American	0.57	0.496	623
White	0.074	0.262	623
Hispanic or Latino	0.22	0.416	623
Asian	0.055	0.227	623
Other Race	0.082	0.274	623
Female	0.46	0.499	623
Fluent in Another Language	0.33	0.470	617
First Language English	0.86	0.345	617
Attends Exam School	0.15	0.356	553
Prior Summer Participant	0.14	0.352	623
Number of Applications	0.11	0.718	623
Avg. # of Other Applications Per Slot	5.69	3.722	623
Avg. Why Work Question Character Length	244.7	229.0	526
Avg. Why Work Question Flesch Score	68.9	16.50	526
Employer selected	0.29	0.453	623
NU Algorithm Selected	0.026	0.158	623
Selected by OYEO	0.31	0.463	623

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table A6: Descriptive Statistics for Youth who Applied in July 2022

	Mean	Std. Dev.	Count
Age	16.2	1.384	276
Black or African American	0.58	0.495	281
White	0.096	0.295	281
Hispanic or Latino	0.19	0.389	281
Asian	0.032	0.176	281
Other Race	0.11	0.313	282
Female	0.52	0.501	281
Fluent in Another Language	0.24	0.429	277
First Language English	0.90	0.307	277
Attends Exam School	0.16	0.367	256
Prior Summer Participant	0.13	0.334	282
Number of Applications	0	0	282
Avg. # of Other Applications Per Slot	4.91	3.432	282
Avg. Why Work Question Character Length	249.4	263.4	238
Avg. Why Work Question Flesch Score	70.2	16.46	238
Employer Selected	0.21	0.405	282
NU Algorithm Selected	0	0	282
Selected by OYEO	0.21	0.405	282

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

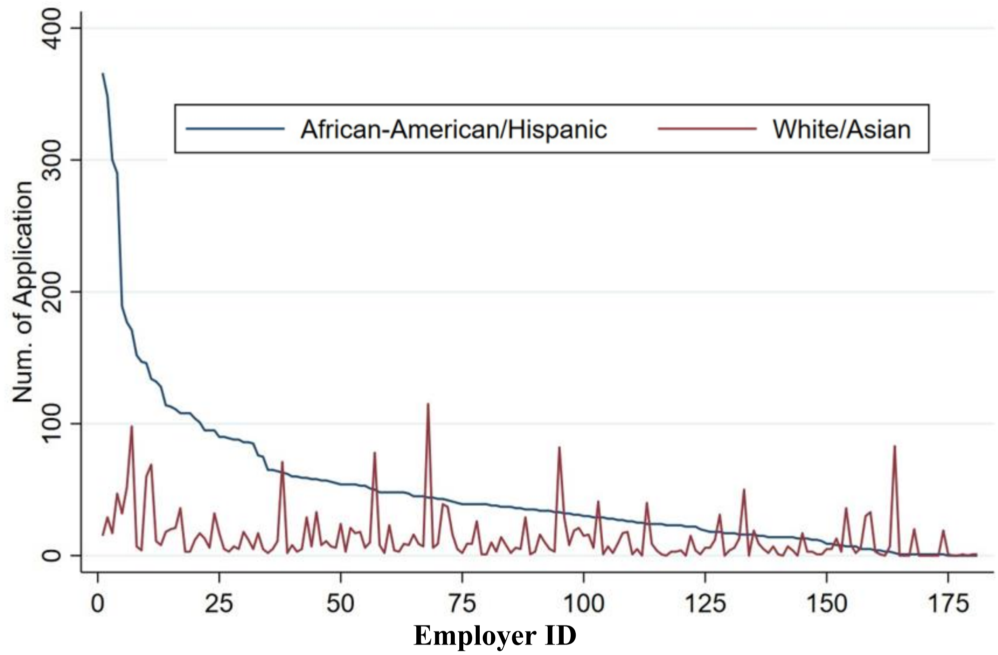
Table A7: Relationship between Youth Characteristics and Number of Applications Submitted – Poisson Specification

	(1)	(2)	(3)	(4)	(5)
Age 15	-0.16***	-0.16***	-0.16***	-0.16***	-0.17***
	(-3.88)	(-3.84)	(-3.93)	(-3.94)	(-4.19)
Age 16	-0.26***	-0.26***	-0.27***	-0.25***	-0.25***
	(-6.24)	(-6.21)	(-6.37)	(-5.80)	(-5.85)
Age 17	-0.42***	-0.42***	-0.43***	-0.40***	-0.40***
	(-9.55)	(-9.48)	(-9.57)	(-8.78)	(-8.84)
Age 18	-0.47***	-0.46***	-0.47***	-0.43***	-0.45***
	(-9.82)	(-9.74)	(-9.83)	(-8.88)	(-9.11)
Age 19	-0.72***	-0.58***	-0.58***	-0.54***	-0.51***
	(-6.30)	(-4.92)	(-4.96)	(-4.62)	(-4.26)
Age 20 or Older	-0.81***	-0.54***	-0.54***	-0.50***	-0.49***
	(-6.89)	(-4.12)	(-4.09)	(-3.75)	(-3.60)
Missing Birth Date	0.26***	0.30***	0.28***	0.29***	0.26***
	(2.89)	(3.31)	(3.16)	(3.20)	(2.91)
African American	0.39***	0.40***	0.43***	0.43***	0.43***
	(12.48)	(12.56)	(13.18)	(12.95)	(11.59)
Hispanic or Latino	0.33***	0.35***	0.38***	0.37***	0.38***
	(9.40)	(9.38)	(10.04)	(9.75)	(9.17)
Asian	0.23***	0.25***	0.23***	0.22***	0.27***
	(5.37)	(5.53)	(4.97)	(4.81)	(5.59)
Other Race	0.49***	0.49***	0.51***	0.51***	0.52***
	(11.84)	(11.84)	(12.24)	(12.21)	(11.86)
Female	0.13***	0.13***	0.13***	0.13***	0.13***
	(6.85)	(6.80)	(6.50)	(6.56)	(6.49)
Continuing Candidate	0.02	0.02	0.03	0.05	0.04
	(0.37)	(0.49)	(0.50)	(0.90)	(0.77)
Fluent in Another Language		-0.03	-0.03	-0.03	-0.02
		(-1.30)	(-1.36)	(-1.37)	(-0.90)
Enrolled in School		0.23*	0.22	0.23	0.19
		(1.65)	(1.57)	(1.63)	(1.34)
Attends Exam School			0.11***	0.11***	0.09***
			(4.17)	(4.19)	(3.48)
Previously Participated				-0.08***	-0.08***
				(-3.27)	(-3.16)
Observations	3762	3762	3762	3762	3762
Zip Code Controls	No	No	No	No	Yes

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Note: White, male, and work question Flesch Score - below grade level are omitted categorical variables. The 'Other Race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race. Although not reported here, we also include controls a set of dummy variables for missing data on the application for each of the demographic characteristics (columns 1-5), school enrollment status and school name (columns 2-5), and previous SYEP participation (columns 3-5). Column (5) also includes a set of dummy variables for youth ZIP code. Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: *p<0.10, **p<0.05, ***p<0.01.

Figure A2: Distribution of Applications by Race



Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Notes: Number of total applications per employer across all possible job openings (not applications per opening).

C. Employer Site Selection

Employers were asked to select youth for jobs by June 2nd so we categorize a youth as "selected by employer" based on the timestamp of when the youth's status changed from 'Applied' to 'Onboarding.' Of the 5,488 valid youth applicants, 3,762 youth applied before the June 2nd cut-off date for which they could be observed by an employer. Of these 3,762 youth, over two-thirds (66 percent) were selected by an employer.

Table A7 compares the descriptive statistics for youth who were selected versus not selected by an employer. In terms of demographic characteristics, youth who were selected by an employer were on average older, white, male, attended an exam school, and also indicated that they had previously participated in the OYEO program. In contrast, youth who were Black, Hispanic, or fluent in another language and/or did not have English as their first language were less likely to be selected by an employer.

In terms of labor market dynamics, youth who showed greater job readiness, as measured by the number of submitted job applications and week of earliest job application submitted, were more likely to be selected by an employer. Furthermore, youth who apply to less competitive jobs, as measured by the average number of applications per slot, were more likely to be selected. Although youth selected by an employer were less likely to have answered the open-ended "Why Work" question on the application, this is likely due to applicants who had a pre-existing relationship with the employer. That said, among youth who answered the open-ended question, those with longer text responses and higher readability scores were more likely to get selected by an employer. We test whether these characteristics account for the racial disparities in both selection and hiring using a regression framework. Table A8 shows that the OLS results in the paper are robust to using a Logit specification.

Table A8: Relationship between Youth Characteristics and Likelihood of being Selected by an Employer – Logit Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Age 15	0.16	0.15	0.13	0.12	0.37**	0.40**
	(0.93)	(0.87)	(0.77)	(0.72)	(2.08)	(2.18)
Age 16	0.35**	0.35**	0.31*	0.17	0.55***	0.62***
	(2.08)	(2.04)	(1.85)	(1.01)	(3.02)	(3.27)
Age 17	0.40**	0.40**	0.37**	0.18	0.58***	0.68***
	(2.29)	(2.26)	(2.10)	(0.99)	(3.08)	(3.42)
Age 18	0.50***	0.48***	0.46**	0.22	0.65***	0.69***
	(2.68)	(2.59)	(2.46)	(1.17)	(3.25)	(3.27)
Age 19	1.89***	1.43***	1.42***	1.12**	1.54***	1.80***
	(3.99)	(2.88)	(2.85)	(2.22)	(2.63)	(2.95)
Age 20 or Older	2.13***	1.08**	1.09**	0.79	1.18*	1.58**
	(4.46)	(2.00)	(2.00)	(1.43)	(1.95)	(2.37)
Female	-0.02	-0.01	-0.03	-0.04	0.03	0.05
	(-0.22)	(-0.10)	(-0.41)	(-0.52)	(0.32)	(0.56)
Black or African American	-0.85***	-0.85***	-0.76***	-0.73***	-0.71***	-0.62***
	(-5.91)	(-5.85)	(-5.15)	(-4.91)	(-4.55)	(-3.80)
Hispanic or Latino	-0.97***	-1.00***	-0.91***	-0.86***	-0.80***	-0.60***
	(-6.45)	(-6.25)	(-5.61)	(-5.29)	(-4.70)	(-3.41)
Asian	-1.00***	-1.03***	-1.16***	-1.13***	-1.13***	-0.98***
	(-5.54)	(-5.41)	(-5.94)	(-5.79)	(-5.52)	(-4.62)
Other Race	-0.38**	-0.35*	-0.30	-0.32*	-0.35*	-0.27
	(-2.08)	(-1.95)	(-1.63)	(-1.72)	(-1.81)	(-1.35)
Fluent in Another Language		0.01	0.01	0.01	0.01	-0.00
		(0.14)	(0.13)	(0.13)	(0.12)	(-0.02)
Enrolled in School		0.98**	0.87*	0.78*	0.58	0.40
		(2.18)	(1.91)	(1.72)	(1.17)	(0.77)
Attends Exam School			0.38***	0.38***	0.40***	0.39***
			(3.32)	(3.37)	(3.32)	(3.12)
Prior Summer Participant				0.56***	0.57***	0.42***
				(5.56)	(5.33)	(3.75)
Number of Applications					0.16***	0.16***
					(10.59)	(10.26)
Avg. # of Other Applications Per Slot					-0.08***	-0.07***
					(-11.88)	(-10.99)
Avg. Why Work Question Character Length						0.00**
						(2.48)
Avg. Why Work Question Flesch Score						0.00
						(0.20)
Observations	3723	3723	3723	3723	3723	3723

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Note: The sample conditions on those who submitted at least one complete and valid job application prior to the June 15th cut-off date. The dependent variable is equal to one if the youth was selected for employment by at least one partner site and is equal to zero otherwise. Omitted categorical variable is aged fourteen or youth, white, and male. The 'other race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race. Although not reported here, we include the following as controls in the regression: a dummy variable indicating if the youth reported their birth date (columns 1-6), a dummy variable for whether or not the youth reported their gender and race (columns 1-6), a dummy variable if the youth chose to opt out of reporting their gender (columns 1-6), a dummy variable indicating if the youth recorded being fluent in a secondary language (columns 2-6), a dummy variable indicating if the youth recorded enrollment status (columns 2-6), a dummy variable indicating if the youth recorded their school name (columns 3-6), a dummy variable indicating if the youth recorded previous SYEP status (columns 4-6), a set of dummy variables for earliest application date (columns 1-6), and a dummy variable indicating if the youth completed the open-ended text question (column 6). Statistical significance indicated at the *p<0.10, **p<0.05, ***p<0.01 levels.

D. Job Matching Algorithm

One drawback of the job matching algorithm that we were able to implement with OYEO is that it maximizes youth-job matches in a very simple way. Specifically, the algorithm fills undersubscribed jobs first and then runs lotteries within oversubscribed jobs starting with the positions with the most remaining openings. To test how efficient our algorithm was at filling jobs, we retroactively applied the Ford–Fulkerson algorithm and compared our results. The Ford–Fulkerson algorithm finds the maximum number of "matches" between youths and job slots (or flow network). For this exercise, we consider all youth who submitted at least one job application and were not hired by June 15th.

We completed a direct one-to-one comparison between the job matching pilot algorithm and the Ford-Fulkerson algorithm. For this comparison, we considered the same set of available youth and job slots which were used by the pilot algorithm in the June 2nd snapshot. To compute the number of job opening edges within the graph, we compute the number of openings still available for each employer by taking their total allocation of openings and subtracting the number of youth hired by June 2nd. There were a total of 350 remaining openings available and 661 unplaced youth. The Ford–Fulkerson algorithm made 256 youth-job matches while the pilot algorithm made 309 matches. Thus, our simple job matching pilot was slightly more efficient than the Ford–Fulkerson algorithm.

We also compared the descriptive statistics of the youth applicants selected by the Ford-Fulkerson and the job matching pilot using a two-sample t-test. Table A9 shows that the Ford-Fulkerson selected younger, less Black or African American, more White, more other race, and less youth who indicated they were fluent in another language. Recall that the pilot algorithm took into account the race and language fluency of youth applicants and gave priority to those who were underrepresented within the pool of employer-selected youth. As such, the results of racial and language-fluency differences across algorithms should be expected. Overall, our simple job matching pilot appeared to enhance equity to a greater degree than the Ford–Fulkerson algorithm.

Table A9: Comparison of Ford–Fulkerson Algorithm versus Job Matching Algorithm

	Ford-Fulkerson Algorithm Selected Mean	Job Matching Algorithm Selected Mean	Difference	p-value
Black or African American	0.44	0.60	0.162	0.000
Hispanic or Latino	0.28	0.24	0.039	0.304
White	0.09	0.02	0.069	0.001
Asian	0.09	0.07	0.012	0.600
Other Race	0.10	0.06	0.042	0.072
Age	16.52	16.84	0.315	0.003
Female	0.55	0.52	0.024	0.576
Fluent in Another Language	0.34	0.44	0.102	0.015
First Language English	0.83	0.85	0.025	0.437
Attends Exam School	0.20	0.19	0.009	0.792
Missing School Name	0.07	0.09	0.017	0.475
Prior Summer Participant	0.22	0.28	0.058	0.117
Number of Applications	4.19	4.44	0.255	0.458
Avg Num of Other Apps Per Slot	10.17	9.84	0.330	0.667
Earliest App Submitted in March	0.25	0.25	0.001	0.973
Earliest App Submitted in April	0.38	0.40	0.021	0.616
Earliest App Submitted in May	0.34	0.31	0.028	0.495
Earliest App Submitted in June	0.03	0.03	0.001	0.959
Avg Work Question Length	285.42	302.23	16.805	0.500
Avg Work Question Flesch Score	68.94	66.31	2.632	0.333

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table A10: Comparing the Distributional Impacts of SuccessLink Alternative Placement Mechanisms

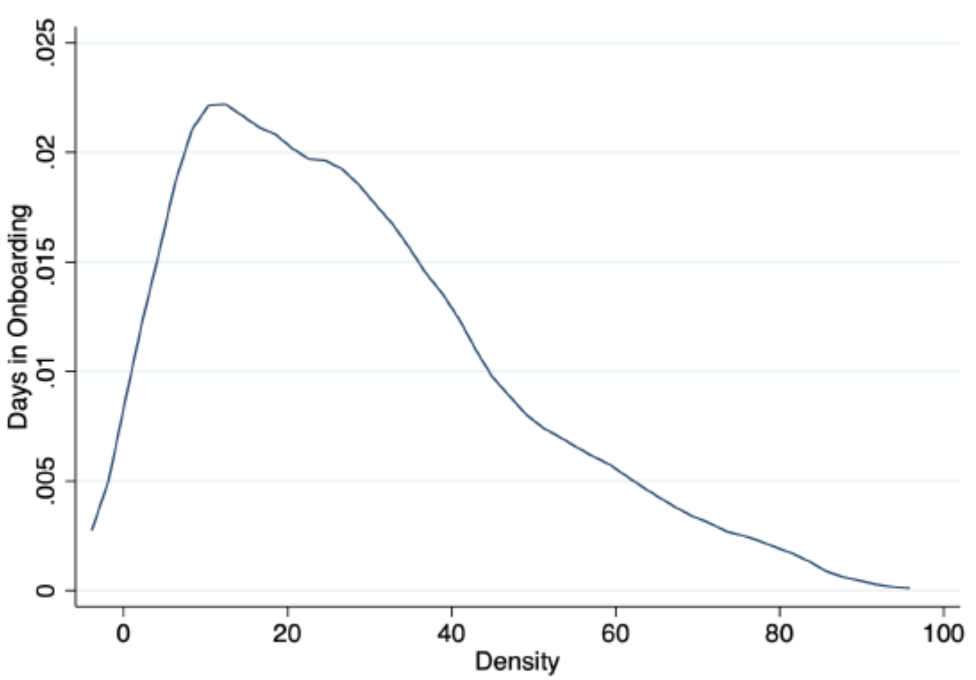
	(1) Employer	(2) NU Algorithm	(3) We Hire Event	(4) NU Algorithm + We Hire Event	(5) Total Selected	(6) Total Applicants	(7) Total Selected – Total Applicants	(8) *p-value*
Black or African American	0.42	0.51	0.63	0.54	0.43	0.44	-0.121	0.0000
	(0.493)	(0.500)	(0.486)	(0.499)	(0.496)	(0.496)	(0.023)	
Hispanic or Latino	0.21	0.23	0.19	0.22	0.21	0.23	-0.013	0.4895
	(0.404)	(0.420)	(0.392)	(0.414)	(0.407)	(0.419)	(0.019)	
White	0.18	0.093	0.047	0.083	0.17	0.15	0.099	0.0000
	(0.386)	(0.291)	(0.212)	(0.277)	(0.375)	(0.355)	(0.018)	
Asian	0.091	0.093	0.047	0.083	0.089	0.091	0.007	0.5924
	(0.287)	(0.291)	(0.212)	(0.277)	(0.285)	(0.288)	(0.014)	
Other Race	0.11	0.071	0.094	0.078	0.098	0.095	0.028	0.0498
	(0.308)	(0.258)	(0.293)	(0.268)	(0.298)	(0.293)	(0.014)	
Age	16.8	16.8	16.3	16.7	16.8	16.7	0.176	0.0068
	(1.392)	(1.185)	(1.228)	(1.210)	(1.372)	(1.366)	(0.065)	
Female	0.48	0.49	0.47	0.49	0.48	0.49	-0.006	0.8110
	(0.500)	(0.501)	(0.501)	(0.500)	(0.500)	(0.500)	(0.024)	
Attends Exam School	0.26	0.23	0.20	0.23	0.25	0.23	0.030	0.1656
	(0.437)	(0.422)	(0.402)	(0.420)	(0.434)	(0.420)	(0.022)	
Fluent in Another Language	0.31	0.34	0.30	0.33	0.31	0.33	-0.019	0.3932
	(0.462)	(0.474)	(0.459)	(0.470)	(0.464)	(0.469)	(0.022)	
Number of Applications	3.34	4.33	5.65	4.62	3.37	3.04	-1.278	0.0000
	(4.191)	(3.604)	(6.364)	(4.442)	(4.101)	(3.744)	(0.201)	
Avg Num. of Other Apps Per Slot	6.65	9.54	9.66	9.55	7.07	8.92	-2.899	0.0000
	(7.163)	(8.999)	(7.307)	(8.678)	(7.565)	(12.32)	(0.354)	
Earliest App Submitted in March	0.31	0.28	0.25	0.27	0.29	0.28	0.036	0.0972
	(0.462)	(0.449)	(0.434)	(0.445)	(0.455)	(0.447)	(0.022)	
Earliest App Submitted in April	0.36	0.41	0.32	0.39	0.36	0.36	-0.034	0.1369
	(0.479)	(0.493)	(0.467)	(0.489)	(0.481)	(0.479)	(0.023)	
Earliest App Submitted in May	0.19	0.26	0.24	0.25	0.21	0.23	-0.060	0.0018
	(0.395)	(0.439)	(0.429)	(0.435)	(0.405)	(0.420)	(0.019)	
Earliest App Submitted in June	0.14	0.048	0.19	0.083	0.14	0.14	0.058	0.0003
	(0.348)	(0.213)	(0.397)	(0.276)	(0.342)	(0.346)	(0.016)	
Completed Work Question	0.81	0.86	0.93	0.88	0.82	0.83	-0.070	0.0001
	(0.392)	(0.345)	(0.256)	(0.325)	(0.384)	(0.372)	(0.018)	
Avg Work Question Length	333.7	327.1	284.1	318.4	329.3	308.4	15.300	0.3036
	(289.1)	(313.1)	(274.9)	(305.3)	(291.7)	(280.4)	(14.871)	
Avg Work Question Flesch Score	67.9	66.2	70.4	67.2	67.8	68.3	0.726	0.6299
	(29.48)	(33.53)	(13.49)	(30.04)	(30.20)	(27.57)	(1.506)	
Observations	2,495	420	129	541	2,884	3,762		

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

E. Onboarding Barriers

We code youth as being selected if we ever observe that they have a status of 'Onboarding' and code youth as being hired if we ever observe that they have a status of 'Hired.' This includes youth who were selected and/or hired and later self-withdrew from the position. Figure A3 presents the distribution of number of days a youth spent in the onboarding status. Youth took on average 25 days to complete onboarding with a standard deviation of 19 days. Table A11 compares the characteristics of youth who reached the onboarding status but did versus did reach a status of hired. Not surprisingly, these youth were often Black and Hispanic or fluent on another language. Table A12 shows that the disparity in hiring non-white youth persists even when controlling for the lower likelihood of the groups making it through the onboarding process.

Figure A3: Distribution of Days Youth Spent in Onboarding Status for a Job



Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Table A11: Comparing Characteristics of Youth who were Hired versus Youth who Failed to Make it through the Onboarding Process (Not Hired)

	Not Hired Mean/Num. Obs.	Hired Mean/Num. Obs.	Diff in Means/ Std.Err. of Diff	p-value
Black or African American	0.49 812	0.41 2,071	0.080 (0.020)	0.0001
Hispanic or Latino	0.29 812	0.18 2,071	0.107 (0.017)	0.0000
White	0.08 812	0.20 2,071	-0.122 (0.015)	0.0000
Asian	0.08 812	0.10 2,071	-0.020 (0.012)	0.0907
Other Race	0.07 812	0.11 2,071	-0.044 (0.012)	0.0003
Age	16.68 801	16.87 2,062	-0.192 (0.057)	0.0008
Female	0.53 812	0.46 2,071	0.065 (0.021)	0.0015
Fluent in Another Language	0.39 809	0.28 1,968	0.103 (0.019)	0.0000
First Language English	0.80 809	0.87 1,968	-0.069 (0.015)	0.0000
Attends Exam School	0.20 744	0.27 1,866	-0.070 (0.019)	0.0002
Prior Summer Participant	0.21 813	0.33 2,071	-0.123 (0.019)	0.0000
Continuing Candidate	0.00 813	0.18 2,071	-0.174 (0.013)	0.0000
Number of Applications	3.99 813	3.12 2,071	0.873 (0.169)	0.0000
Avg Num. of Other Apps Per Slot	8.53 813	6.49 2,071	2.041 (0.311)	0.0000
Earliest App Submitted in March	0.30 813	0.29 2,071	0.011 (0.019)	0.5540
Earliest App Submitted in April	0.41 813	0.35 2,071	0.065 (0.020)	0.0012
Earliest App Submitted in May	0.24 813	0.19 2,071	0.046 (0.017)	0.0058
Earliest App Submitted in June	0.05 813	0.17 2,071	-0.122 (0.014)	0.0000
Avg Work Question Length	304.21 710	340.05 1,662	-35.843 (13.062)	0.0061
Avg Work Question Flesch Score	67.68 710	67.84 1,662	-0.153 (1.354)	0.9098
Observations	813	2,071		

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.

Notes: Column 1 reports means for youth who were selected by an employer-partner but never made it to the "Hired" status. Column 2 reports means for youth who were selected by an employer successfully reached the "Hired" status. Column 3 reports the difference in the means. Column 4 contains the p-value from a two-sampled t-test of the difference in means.