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Where the Rubber Meets the Road: Examining Barriers to Job Placement in Summer Youth Employment Programs

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1 Introduction and Motivation

Summer Youth Employment Programs (SYEP) have been shown to have significant impacts on youth outcomes such as reducing violent crime, increasing high school graduation, and boosting subsequent employment and wages (Heller, 2014; Gelber et al., 2016; Leos-Urbel, 2014; Modestino, 2019; Schwartz et al., 2021; Kessler et al., 2022; Modestino and Paulsen, 2023). Much of this research is based on lotteries from oversubscribed programs where participants are picked at random from a pool of applicants allowing for an experimental design within which to evaluate outcomes by comparing the experiences of the treatment and control groups. This assignment mechanism works well when both the job applicants and the job attributes are fairly uniform. For example, prior to the pandemic, two of the Boston SYEP intermediaries used a simple lottery design with only one round of assignment to place mostly low-income youth aged 14 and 15 years into largely one type of job (e.g., summer camp counselor) that yielded a very high take-up rate (about 85 percent).

However, when there is a high degree of heterogeneity among both job applicants and job attributes, simple random assignment is often not feasible. This is because the matching process is more complex so that the program needs to balance both youth and employer interests to ensure participation. Even prior to the pandemic, 20 out of 27 SYEP programs across the largest U.S. cities using an allocation mechanism other than random assignment such as first come first serve or merit or income based (Heller and Kessler, 2019). 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.[1]

Why not use random assignment? On the job filling side of the market, heterogeneity across basic job requirements in terms of skills, experience, and certifications may reduce participation rates among employers if filled completely at random, ignoring their desired qualifications. This is especially true when there are many youth seeking a job beyond those applying through the program, as was the case early on in the pandemic.[2] On the job seeking side of the market, heterogeneity across basic job amenities in terms of employer type, location, and occupation/industry may reduce take-up rates among youth if placed completely at random, ignoring their preferences. This is especially true when other job opportunities for youth are plentiful during boom times, as has been the case during the summers of 2021 and 2022.[3]

Even when random assignment is used, two issues arise that may still lead to inequitable outcomes. First SYEPs often conduct random assignment at the employer level as opposed to the program level. For example, prior to the pandemic, the New York City program 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). We show that the distribution of applications to positions can be quite imbalanced (e.g., jobs are either over- or under-subscribed). As a result, youth and/or employers may not get their first choice, often resulting in large numbers of youth left

[1] 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] According to the Bureau of Labor Statistics, the employment to population ration 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).

[3] 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.

without a job and a large number of jobs that are not filled. Second, it is often the case that multiple rounds of random assignment may be required to fill all of the jobs that are available either because of rolling application deadlines or the need to backfill positions when youth fail to accept job offers or produce the necessary documentation to make it through the hiring process (Valentine et al., 2017).[4] In both cases, if the distribution or timing of applications across positions is skewed by race, such assignment mechanisms may additionally harm BIPOC applicants.

Given the intended goal of most SYEPs is to level the playing field for low-income youth living in marginalized communities, one might be concerned about both the efficiency and the equity of how these assignments are made in response to the complexity of the matching problem. We explore this intersection between efficiency (e.g., the rubber) and equity (e.g., the road) using a novel dataset collected by the City of Boston during the summer of 2022, that includes daily data snapshots from the hiring platform used by the program to match youth to summer jobs. These data provide a unique glimpse into both applicant and employer behavior to better understand youth labor market dynamics and document how the job matching process unfolds within a youth workforce development program. More specifically, we observe all of the applications from each youth across all employer partners as well as the selection and hiring outcome of each application. This includes timestamps throughout the job flow process, including when youth submit applications, when employers make selections, and when hiring is completed.

[4] 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 (Valentine et al., 2017).

Our findings inform three particular design challenges facing workforce development programs that seek to match participants to employers with the goal of increasing access and maximizing skill development. First, programs need to create a "thick" job market among applicants. 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 leaving many youth without a job and a large number of jobs that are not filled each summer.

Second, programs need to reduce the ability of employers to replicate many of the implicit biases that we observe in the labor market when making youth selections. Given that the City's 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. Employers also selected a larger proportion of native English speakers and students from Boston's prestigious "exam" schools relative to their representation in the overall pool of applicants. This disparity persisted even when controlling for when the application was submitted, previous participation in the program, the number of job applications, and having uploaded a resume as a signal of interest. We demonstrate that applying a simple job matching algorithm stratified by the race of the overall applicant population after the initial round of employer selections can eliminate racial disparity and is even quite efficient relative to other, more sophisticated, methods.

Third, we document that a substantial percentage of youth who are selected fail to make it through the hiring process—an issue similar to that of "summer melt" among low-income college applicants. As a result, even oversubscribed programs continually need to back-fill job placement slots using multiple waves of hiring to employ as many youth as possible. This inefficiency leaves SYEP funding unspent, community-based organizations without the help they needed, and youth unemployed each summer. For example, City of Boston leaves 300-800 summer jobs (10 to 15 percent) unfilled each summer due to both matching and hiring inefficiencies. In addition, BIPOC youth are overrepresented among later applicants such that additional rounds of assignment may be needed to achieve a more diverse set of placements.

Overall, our results indicate that despite having honorable goals to reduce inequality, workforce development programs that face heterogeneity on both sides of the job matching process often find random assignment infeasible, which may result in job placements that are inequitable. It is eye-opening to see these disparities even though SYEP 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 suggests cities can be more intentional about matching youth to jobs while maximizing both employer and youth participation. For example, instituting a 50-50 rule with half of the program slots filled by employer selection and half filled by a lottery could be a feasible solution going forward. However, even with equitable selections, programs will need to also reduce paperwork barriers and convert more selections into actual hires if we are to truly create a level-playing field for low-income BIPOC youth.

2 Literature Review

Designing an optimal matching protocol within a universal workforce development program that seeks to place participants into job opportunities at scale faces several challenges in terms of both efficiency and equity. First, the match must be of sufficient quality such that both participants and employers will accept the placement—and accept it quickly rather than waiting around for a better offer. For summer jobs programs in cities such as Boston, this can actually be a sizeable problem when placing upwards of 6,000 participants during the span of about 8 weeks. Second, if the goal of the program is to increase opportunity and reduce inequality, then matches must be made such that those who ultimately get selected are at least representative of the pool of applicants, or in many cases, intentionally over-representative of traditionally marginalized groups. Again, this is not a trivial problem for summer jobs program operating at scale. Boston SYEP data from prior years indicate that white applicants are 10 percentage points more likely to be selected relative to their representation within the pool of applicants, accounting for several hundred youth placements every summer.

Designing an efficient and optimal matching system has been intensively studied in several related settings, such as school choice allocations, with some useful lessons that could provide insights for summer jobs programs. For example, Roth (2008) emphasizes the need for marketplaces, including labor markets, to have "thickness", i.e., they need to attract a sufficient proportion of the potential participants on both side of the market to be able to make matches efficiently. On the other hand, labor markets need to overcome the congestion that thickness can bring, by making it possible to consider enough alternatives to arrive at good matches. And finally, they need to make it sufficiently simple to participate in the market, as opposed to transacting outside of the market, or having to engage in costly strategic behavior.

However, because most summer jobs programs operate more like the real-world labor market, it's difficult to directly apply the algorithms used in school choice or residency matching programs when matching youth to jobs. Unlike traditional matching protocols, youth do not submit a rank ordering of their job applications from most to least preferred. Instead, youth submit job applications to each employer separately, similar to the traditional labor market. Summer jobs programs are also dependent on employer participation, for which there are many outside options, unlike public schools and medical residency programs that have no outside option for recruitment. These differences seem to drive some of the inequities that we observe in less-regulated programs such as those in workforce development. For example, Heckman and Smith (2004) found substantial inequity in participation among Job Partnership Training Act (JTPA) programs across various stages (i.e., awareness, application, acceptance, and enrollment). They found that applicants with a low level of schooling resulted in a higher probability of being eligible for the program, but a lower probability of awareness, application, and acceptance.

Substantial heterogeneity on both side of the match (e.g., for both employers and job-seekers) also contributes to the difficulty of making efficient and equitable matches within summer jobs programs. On the employer side, prior research shows that job titles play an important role in understanding worker application patterns with substantial heterogeneity across occupations and even within job titles (Marinescu and Wolthoff, 2020). Moreover, workforce practitioners specifically highlight the need for maintaining sufficient heterogeneity on the employer side of the market 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 requires some slots be preserved for youth with greater advantages who can provide positive peer interactions to other participants (Opper et al., forthcoming).

Another challenge that many workforce development programs face is the shift towards online job search platforms that can reduce some types of search frictions yet introduce others that can still lead to inequitable outcomes. On the worker side, unequal access to the internet for job search can limit the opportunity set and exacerbate wage differentials between race, education, or age of workers (Sanchez Cumming et al., 2022). On the firm side, posting jobs online can produce large numbers of applicants, incentivizing employers to use job requirements (Modestino et al. 2020) or other means as a way to screen applications. For example, anecdotal evidence from the Boston SYEP suggests that some employers use the program as a funding mechanism and direct youth with whom they have a pre-existing relationship to apply through the City portal, thereby creating “phantom” vacancies (vacancies which are filled and not withdrawn) that are not truly open to other applicants. Using a directed search model, Vroman at al. (2015) show that the existence of such “phantom” vacancies lead to large search frictions and discouragement from the perspective of job seekers.

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 demonstrate the potential for more widespread use of job matching algorithms in the labor market such as matching health care workers to long-term care facilities to improve staff-to-resident ratios (Zarei et al., 2023). 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).

Given that so much of what happens in the matching process depends on behavior that occurs on both sides of the market, we would be remiss if we did not discuss the potential for nudging participants into certain behaviors that lead to greater efficiency and equity. For example, sending youth reminders to complete applications positively influenced application take-up rates in the Chicago SYEP (Bhanot and Heller, 2022). In other work, we similarly implemented an application nudge within the City of Boston's Learn and Earn summer program which significantly increased application rates among youth from Boston public high schools with low college enrollment rates.

3 Policy Context and Background

Introduced in the early 1980s, the Boston SYEP relies on approximately 10 million in city, state, and private funding to connect about 10,000 youth each summer with roughly 900 local employers (Modestino, 2019). For six weeks, from early July through mid-August, SYEP youth work a maximum of 25 hours per week and all participants are paid the Massachusetts minimum wage. Youth also receive 20 hours of job-readiness training, which includes evaluating learning strengths, skills, and interests; developing soft skills, such as communication, collaboration, and conflict resolution; and learning how to search for a job, draft a resume and cover letter, and answer typical interview questions. Youth apply through one of the four intermediary organizations under contract with the Boston Mayor's Office of Workforce Development (OWD) and most typically apply to the intermediary in their immediate neighborhood.[5] The intermediaries are responsible for reviewing applications, matching applicants with jobs, supervising job placements, and delivering the career-readiness curriculum.

Our analysis is restricted to one of the four intermediaries that the City contracts with: the Office of Youth Employment and Opportunity (OYEO), a city department that works in all of Boston's 23 neighborhoods and serves the City's youth population with a variety of programming. Through its SuccessLink program, OYEO places upwards of 6,000 young people every summer across roughly 500 employer partners, depending on the level of funding that is available, making it the largest Boston SYEP intermediary. We focus on OYEO because it serves a broad population of youth who are Boston residents aged 14 to 24 years with a high degree of heterogeneity across race and socioeconomic status, unlike other summer jobs intermediaries that serve a particular group (e.g., low-income or court-involved). In addition, OYEO offers a wide range of employment options from summer camp positions to nonprofit opportunities to private sector jobs compared to other intermediaries that focus on only one type of employer.

4. Job Application, Selection, and Hiring Process

Since 2017, OYEO has shifted their youth placement process away from random assignment and towards a system that allows for 100 percent employer selection. Prior to 2017, OYEO was one of two Boston SYEP intermediaries that had made use of

[5] The four intermediates include the Boston Department of Youth Engagement and Employment, Action for Boston Community Development, Boston Private Industry Council, Youth Options Unlimited, and John Hancock MLK Scholars Program.

random assignment. During that time assignments were made according to a 60-40 rule where employers were allowed to select youth for 60 percent of their OYEO-funded openings and the remaining 40 percent filled by OYEO using simple random assignment within job type/location. In 2017, OYEO discontinued random assignment due to capacity constraints and has since allowed employers to select 100 percent of their youth with the caveat that 40 percent of those youth are new to the organization—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 employers to participate in the summer jobs program either as a “grant” partner that simply receives funding to cover youth wages or as a “direct” partner that also makes use of the City’s hiring platform and payroll process. Each year, OYEO allocates a certain number of job slots to both direct and grant partners based on a combination of capacity, job quality, and prior performance. In 2022, our analysis focuses on the 3,500 job slots allocated to “direct” employer partners who advertised their positions, received youth applications, and made youth selections through the OYEO online application portal.[6]

A timeline of the job application, selection, and hiring process during the 2022 season 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, and conducting online information sessions. The application portal opened on March 18th at

[6] OYEO granted out another 1,500 job slots to grant partners and about 500 job slots to City college and career readiness programs including the Boston Mayor’s Office of Workforce Development’s Learn and Earn program that supports youth enrolling in community college courses, the City’s Dreamers Fellowship that supports skill and leadership development for immigrant youth regardless of status, ABCD’s Summerworks Program, and YOU Boston’s Summer Youth Employment program.

which time youth were able to search and apply to multiple jobs. 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 by employer in terms of quality. Each job required a separate application and like the real-world labor market, there was no information provided regarding the number of openings per employer nor the number of applicants.

Employers could start reviewing applications and interviewing youth in late March, although the bulk of the applications are received during April. Employers were able to submit their youth selections starting April 29th and were required to submit all of their youth selections by the end of May. However, this deadline was extended through June 2nd as is often the case each year, with some City departments allowed to select youth even beyond this date (through June 15th). The application portal remained open until June 20th due to the need to backfill remaining open positions even after the employer selection period was over.

Once an employer selection was made, an automated email was sent notifying youth that they had been selected for the position and needed to complete the hiring process by submitting documentation of eligibility and other information for the payroll system. The hiring process included upwards of 10 different steps, including uploading multiple documents to prove age, residency, and school status such as a social security card, household utility bill, and school report card (see Appendix E). As one might suspect, a nontrivial number of youth failed to make it through the hiring process, leaving some jobs unfilled and some youth unemployed - despite being selected during the application process.

Any remaining openings were back-filled by OYEO directly placing youth into jobs. Typically, this process occurs during several in-person hiring events that take place just before the start of the program. Placing youth in positions that match their individual interests and also meet the employer requirements in real-time takes significant personalized attention and effort, for which OYEO staff do not have the capacity, which often means leaving jobs unfilled. To address this inefficiency, we implemented a job matching algorithm between June 2nd and June 20th to place youth into unfilled positions after the employer selection deadline but before the first OYEO in-person hiring event. We were restricted to filling positions where (1) there were more open slots than applicants (e.g., the job was undersubscribed) or (2) slots had opened up because youth had declined positions. At the end of June, OYEO invited youth that had applied but were not yet placed in a job to their usual in-person "We Hire" event as well as drop-in office hours during which they could be assigned to any remaining open position, including those slots where selected applicants had failed to make it through the onboarding process.

Examining application and hiring data from prior years reveals that the matching and hiring processes often produce outcomes that are both inefficient and inequitable. Despite having selected a youth for each position, City of Boston left 300-600 summer youth jobs unfilled between 2017 and 2020 (see Table 1). Moreover, these job opportunities were not distributed equitably across racial and ethnic groups. For example, white youth were disproportionately placed into summer jobs compared to Black and Hispanic youth such that 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 (see Table 2). Although the differences between application and placement rates may seem small (e.g., about 5 percentage points), when applied to the total number of youth applicants each year (e.g., upwards of 6,000), this translates into several hundred slots per summer being disproportionately assigned, contradicting the program's stated goal of reducing inequality.

5. Data Collection

Our analytical data set was created by appending daily recruiting reports provided by OYEO from the City of Boston's online job matching portal during the summer of 2022.[7] These daily reports consisted of each youth's application for a particular job, as well as the status of each application. The data also include timestamps for when the application was submitted, when the youth was selected by an employer, when the youth was first notified to complete the hiring process, when the youth declined (if applicable), and when the youth was finally hired into the position.[8] When a youth logs into the portal, 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.[9] If a youth does not complete a job application or is not eligible for the position, they are listed in the recruiting snapshot as having an 'Incomplete' or 'Do Not Qualify' status for that particular position.[10]

The daily recruiting snapshots have a few irregularities which required some cleaning prior to analysis. First, we drop the handful of observations with exact duplicate information in terms of first name, last name, system ID, job posting title,

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[7] The daily snapshots of the recruiting reports for our analysis begin on May 19th and end on August 10th, capturing most of the day-to-day activity along with prior timestamps of when youth applied, and when employer selections were made.

[8] See Appendix E for a diagram of how a youth's application status changes throughout the application and hiring process.

[9] There are some instances where a youth created more than one system ID although this occurrence is rare with approximately 2.67 percent (200 youth) having duplicative portal accounts.

[10] Only one youth had the highest status of "Not Qualified" and 281 youth had "Initial DNQ"

status, and report date. There were also a handful of observations which had identical first name, last name, system ID, report date, and job posting title, but varied by status so we kept the record with the higher status (e.g., hired over applicant). In addition, some youth had a status of "Continuing Candidate" which mean that they had worked for the employer during OYEO's school year program and were selected to continue working with the same employer through the summer. We keep these observations and treat these youth as being selected by an employer.

We use the resulting analytical dataset to explore three particular design challenges facing workforce development programs and SYEPs in particular. These include creating a "thick" labor market among youth applicants, limiting disproportionate selections on the part of employers, and backfilling positions over multiple waves of hiring to employ as many youth as possible. The goal of this analysis is to answer the following research questions:

- **Youth application behavior:** *Which youth choose to apply to the City's program from among the broader youth population? 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? Which job characteristics (e.g., distance, industry/occupation) are correlated with oversubscription? How does application behavior differ by age, gender, race, ethnicity, and school type?*

- **Employer selection behavior:** *Which youth characteristics (e.g., age, gender, race/ethnicity, language spoken, school type) appear to drive employer selections? Can these disparities be explained by differences in youth application* *behaviors across groups? To what degree can a simple job matching algorithm reduce these disparities?*

- **Hiring over multiple waves:** *What are the differences between youth who apply to the program early compared to those who apply later? Once selected, how many youth fail to complete the hiring process? How do the characteristics of youth who are selected compare to those who complete the hiring process?*

6. Results

To answer our research questions, we explore the pathway by which youth move through each phase of the City's SuccessLink application and hiring process. In phase 1, youth apply for SuccessLink positions through the City's online portal. In phase 2, employers select youth from that applicant pool and make offers. In phase 3, youth complete the hiring process through the online portal to become fully 'hired'. As youth move through each of these phases, systematic disparities may arise, leading to unequal outcomes in job placements.

6.1 Youth Application Behavior: Creating a "Thick" Labor Market

In this section we explore several aspects of youth application behavior to understand which youth choose to apply to the Boston SYEP, potential barriers that youth face in completing an application, and the number and types of jobs that youth apply to. Throughout we explore differences in application by age, gender, and racial/ethnic groups to apply an equity lens to the application process.

6.1.1 Incomplete and Invalid Applications

During the 2022 summer job cycle, we observed unique 5,488 youth in our analytical dataset who had created a profile before the employer selection deadline of

June 2^{nd}. Of those youth, approximately one-third (1,726) failed to complete a valid job application or had their application deemed invalid, suggesting that there are significant barriers to participating that start with the application process. Unfortunately, it is difficult to assess which youth characteristics may be correlated with not completing an application due to the large among of missing data (hence the incompleteness).[11] As a result, for the remainder of the analysis, we focus exclusively on youth who have submitted at least one valid job application.

6.1.2 Completed Applications

Using data collected from the youth's application profile, we examine the usual demographic variables of interest such as age, gender, and race as well as additional variables that proxy for certain characteristics. 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 immigrant status. We also observe school name and construct a variable for whether youth attended an open enrollment school or exam school in the Boston Public School (BPS) system or another type of (e.g., private, parochial, or suburban), and use this variable as a proxy for academic preparation.[12] Finally, we use whether youth have previously participated in the OYEO summer youth employment program as a proxy for work experience.

Table 3 provides some basic descriptive statistics for the 3,762 youth who

[11] Roughly 78 percent (1,865) of youth are missing either their date of birth or self-reported race or gender compared to only 5 percent (257) of youth with at least one valid application. Oftentimes, youth received an "Initial DNQ" status because they did not answer one or more of the screening questions correctly, such as age, which disqualified them from a particular position. OYEO staff worked with these youth to either correct their information so that they could move ahead in the application process (N=281) or verify that they were indeed ineligible resulting in a status of "Does Not Qualify."
[12] There are three exam schools within the Boston Public School system (Boston Latin Academy, Boston Latin School, and the John D. O'Bryant School of Mathematics and Science) that have entrance exams and GPA requirements.

successfully completed an application. Youth who apply to OYEO are on average 17 years old, slightly less likely to be female (49 percent), and the majority are youth of color (67 percent identify as Black or Hispanic). Compared to Census data, this is largely representative of the City's population of youth. In addition, about 33 percent are fluent in another language although only 16 percent report that English is not their first language. Just under one-quarter (23 percent) attend an exam school and just over one-quarter (26 percent) previously participated in the City's summer youth employment program.

Using the rich data provided by the online job portal, we are also able to observe many aspects of youth application behavior. On average, youth submit three applications, typically apply to jobs that are competitive (e.g., have 9 applications per opening), and don't submit their first application until April. A little more than half submit a resume and only a quarter choose to respond to the open-ended question "Why do you want to participate in the SYEP this summer?" which we take as an indication of job readiness and motivation respectively.

6.1.3 Number of Applications per Youth

We further explore youth behavior by examining the number of job applications submitted by youth. Figure 2 shows that despite most positions being fairly competitive, over 50 percent of youth apply for only one position.[13] Although this might seem like a bad strategy on the part of youth, many employers to hand-pick youth in advance and direct them to the online portal to get on the City payroll. Thus, having fewer applications does not necessarily correlate with lower odds of landing a

[13] Note that we only include applications submitted prior to the cut-off date of June 15th, when employer lists were last accepted by OYEO.

job.

Given the potential mismatch between youth and positions, it's important to determine whether this behavior varies across groups to understand the equity implications of youth falling through the cracks. Table 4 further explores this by estimating the relationship between the number of job applications submitted across groups by sequentially adding in demographic characteristics such as basic demographics, school enrollment and type, timing of the youth's earliest application, prior participation, and residential ZIP code.

The results indicate that there are important differences exist regarding how many job applications youth complete based on their observable characteristics. Older youth submit fewer applications, likely because they have more outside options in comparison to those 15 years old or younger. In addition, youth who have previously participated also submit fewer applications, probably because they have a pre-existing relationship with the employer. Female and non-white youth submit more applications than white males. Including youth residential zip code does little to change the estimates, suggesting that racial disparities in the number of applications submitted is not driven by geographical mismatch with youth living in low-income neighborhoods where fewer jobs are located.

6.1.4 Distribution of Applications across Positions

How does the distribution of youth applications compare to the distribution of openings across employers? If most youth are chasing a small number of positions, then this can result in severe mismatch during the application process, such that youth fail to get selected into any position. Figure 3 indicates that the distribution of job applications is indeed concentrated among a few employer postings, even when we account for employers having multiple slots available (e.g., the average number of openings per employer is around 17). Employer sites receive anywhere from 0 to 10 applications per slot, with roughly 10 employers receiving as many as 15 to 40 applications per available slot. This disparity in the number of applications across employer partners, combined with at least half of the youth applying to only one job, means that the OYEO labor market is lacking "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 are available. Indeed, the online portal is only searchable by location and employer name, meaning that youth would largely need to know where they want to apply or face the daunting task of paging through hundreds of positions. [14] Given that youth apply to about 3 positions on average and the distribution of applications across positions is skewed to a few highly favored positions, for some youth the prospect of being selected for a job is very slim unless they have a pre-existing relationship with the employer. As such, the City's selection process essentially replicates that of the broader labor market where "it's not just what you know, but who you know."

6.2 Employer Selection Behavior: Limiting Disproportionate Selections

In this next section, we explore the correlation between youth demographics and employer selections to explore the disparities in terms of who gets offered a position that were observed in prior years. Employers were asked to select youth for jobs by June 15th so we categorize a youth as "selected by employer" based on the timestamp of when

[14] Parents have indicated on open ended survey responses that the lack of searchability is a problem for youth.

the youth's status changed.[15] Of the 5,488 valid youth applicants, 3,762 youth applied before the June 15th 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. This implies that just under one-third (33 percent or 1,254) of valid applicants were not selected by an employer for a summer job. However, after the deadline, youth could also be selected by either the job matching algorithm or at the We Hire in-person event. By the end of the selection process about 75 percent of youth were offered at least one job from any source, with 61 percent (2,495) selected by an employer, 11 percent (420) selected by the research team using the job matching algorithm and 3 percent (129) selected by OYEO at the We Hire event.

6.2.1 Differences in Employer Selection Behavior by Youth Characteristics

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. A simple comparison of youth selected versus not selected by an employer reveals that employers were twice as likely to hire white youth relative to their representation with the applicant pool (see Table F1). Table 7 estimates this relationship between whether or not the youth was selected by an employer and their demographic characteristics, controlling for our measures of job readiness (e.g., having uploaded a resume) and motivation (e.g., having answered the "Why Work" question on the application).[16] Across all specifications, Black and

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[15] Several employer-partners were allowed to select youth beyond the deadline (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). In those cases, 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."

[16] Note that this analysis is at the youth-level and application-level data such as resume text length were averaged

Hispanic youth had significantly ***lower*** rates of being selected by an employer compared to white youth, even when controlling for application quality. Although the intensity of the youth's job search (measured by the number of applications submitted) and the competitiveness of a position (captured by the average number of applications submitted per position the youth applied) is significantly correlated with the probability of being selected, this still cannot explain why Black youth are less likely to be selected by an employer.

Interestingly, we see a negative relationship between ever submitting a resume in an application and the probability of being selected by a site. OYEO noted that it is not uncommon for employers to have a pre-existing relationship with youth such that employers are able to base their selections on factors that we cannot observe in the OYEO online portal. Additionally, anecdotal evidence suggests that in these cases employers simply direct the youth to upload a resume and apply through the OYEO portal to gain access to funding that covers the youth's wages.[17]

6.2.2 NU Selected: Job Matching Algorithm

After employers made their selections in early June, OYEO implemented several mechanisms to match youth to employers with the explicit goal of improving equity and minimizing the number of jobs left unfilled. The first mechanism was the job matching algorithm which was designed by the Northeastern University (NU) research team and piloted between June 2nd and June 21st. To implement the job matching algorithm, each day our team received a daily snapshot of the data in the application

across all of the youth's applications.

[17] This means that there are some jobs that have "phantom postings" that are not actually open to all youth. We further explore this pre-selection dynamic in the appendix.

portal to determine which jobs remained open and which youth had not yet been selected. We then used the algorithm to place youth into undersubscribed jobs first and then randomly assign youth to the oversubscribed jobs, stratifying by race and ethnicity.

After 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 placed into hiring for the position. For our analysis, we identify youth who were selected 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 employer selection deadline to ensure that youth were able to have been selected by the employer prior to the deadline. In total, the research team suggested placements for 420 youth. However, in practice there were 111 youth who were selected both by an employer and the job matching algorithm so that ultimately only 309 youth were placed solely by the algorithm.

To investigate whether our job matching pilot improved equity, we compare the demographic characteristics of youth who applied, those who were selected by an employer, and those who were selected by the job matching algorithm in Table 6. Not surprisingly, the job matching algorithm was more likely to select youth who were female, Black, Hispanic and fluent in another language, as would be the case when using random assignment stratified by race. However, these youth also had applied to more jobs, more competitive jobs, and uploaded a resume. In comparison, employers disproportionately selected youth who were white, English speaking, and attending exam schools.

One drawback of the random assignment algorithm is that it does not maximize youth-job matches. To measure this, we retroactively applied the Ford–Fulkerson algorithm and compared our results.[18] We found that our simple job matching pilot was actually slightly more efficient while also producing greater equity across racial groups than the Ford–Fulkerson algorithm (see Appendix g).

6.3 Hiring over Multiple Waves: Backfilling Positions

In this section we explore the equity and efficiency implications of conducting multiple waves of hiring leading up to and through the start of the program.[19] 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, including at an in-person at the 'We Hire' event. This multi-day event was held in person June 21st to June 24th and all youth who had yet to be selected for a summer job were invited to the OYEO offices. During this event, the youth were matched in real-time with any position that was still available. In contrast to the suggested job matches created by our research team, OYEO staff could verify with youth that they were still interested in the position and also notify them immediately of their placement so that the hiring process could begin immediately. After the initial "We Hire" event, OYEO also accepted walk-ins on a rolling basis until July 22nd.

6.3.1 Timing of Youth Applications

The timing of youth applications varied considerably as shown in Figure 4 which plots the number of "first-time" applications by youth over time. The number of first-time applications is quite high when the SuccessLink portal first opens in April but

[18] The Ford–Fulkerson algorithm finds the maximum number of "matches" between youths and job slots (or flow network). See Appendix G for details.
[19] Note that for this section of the analysis, we no longer impose the June 15th submission deadline for our observations of interest.

then drifts down over time until May 29th when we see a spike as late applicants respond to the deadline. We can see also spike in applications during the We Hire event on June 24th when OYEO is able to place even later applicants in real-time.

Not surprisingly, youth who submit applications later differ in terms of key demographic traits. To document the extent of late applications. We categorize youth as being either an "early" applicant who submitted their first application in March or April, a "late" applicant who submitted their first job application in May through June 15th, and an even "later" applicant who submitted their first application after June 15th. Table 7 reveals that later applicants are significantly more likely to be African American, less likely to be white or Asian, and less likely to attend an exam school. As such, providing an opportunity for youth to apply later appears to be quite important for ensuring diversity among youth placed into positions.

6.3.2 OYEO Selections: We Hire Event

We identified youth who participated in the 'We Hire' event using one of two methods. The first method was observing youth with an application status of 'Recruiter Submitted' in any daily snapshot that occurred after June 20th. Note that as was the case with the job matching algorithm, it is possible that a youth was selected by an employer, declined the position, and was subsequently placed during the 'We Hire' event into a different position. We again code these observations as being selected by an employer and not by OYEO 'We Hire'.

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. Youth selected during the event were more likely to be Black and less likely to attend an exam school. Unlike those selected by the job matching algorithm, youth selected at the event had submitted fewer applications and were less likely to have uploaded a resume—most likely because they were applying for the first time in-person at the event.

6.3.3 Improving Equity and Efficiency

Finally, to assess whether the overall impact of the placements made using the job matching algorithm and through the We Hire event, 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 OYEO selected youth (either through the pilot job matching algorithm or through the 'We Hire' event) were less likely to be white, more likely to be Black and more likely to be white compared to those selected by employers. We find that the combination of these two mechanisms moved the needle on equity, reducing the disparities in placements across race, ethnicity, and school type (see Table G2 in the Appendix).

We also checked whether OYEO achieved greater overall efficiency in their job placements by combining the two mechanisms (job matching algorithm pilot plus in-person We Hire placements). 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 better part of 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.

6.4 Remaining Barriers to the Hiring Process

In this final section of our results, we examine how youth complete the hiring process once being selected by either an employer, the job matching algorithm or

OYEO. Once a youth is selected, the recruitment system automatically sends an email to the youth notifying them that they need to begin the hiring process which involves 10 different steps, including the submission of official documents such as a school report card, proof of residency, and a social security card. Parent surveys and youth focus groups confirm that navigating this process and obtaining and submitting all of the required documentation presents a barrier for some youth.

Our analysis focuses on those who were selected for a position and then proceeded to the hiring stage, but ultimately did not get hired. Note that we only include those who were selected by an employer in this analysis. We code youth as reaching the hiring stage if we observe an "Onboarding" status and those as being hired if their last status update for a particular job posting was "Hired". This includes youth who were hired and later self-withdrew from the position. Unsurprisingly, those who reached onboarding but did not get hired were more likely to be Black, Hispanic, and female (see Table H1 in the appendix). Controlling for other demographics (e.g., fluent in another language, attends an exam school), the number and timing of applications, and the methods of selection (e.g., employer versus OYEO) does not eliminate these racial disparities. This includes youth placed in-person during the We Hire event, suggesting that programs need to consider how to eliminate paperwork and administrative barriers to hiring even once youth are selected if equity is the goal.

7. Conclusion

While the Boston summer jobs ecosystem was able to expand the types of opportunities available during summer 2020 and serve a more diverse youth population, these changes made matching youth to jobs more complex. This is because intermediaries needed to balance both the diverse career interests of youth as well as employer needs for each of the many types of positions, making random assignment no longer feasible.

However, the hiring platforms used by the intermediaries 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 complete paperwork in a timely manner. As a result, the post-COVID selection and hiring process across the Boston summer jobs ecosystem has become inefficient, serving to slow down or even derail the hiring process for some youth. Moreover, the employer selection process, left unchecked, replicates many of the inequities that we see 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 BIPOC youth, 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 are not maximizing 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 receive hundreds of applications for only a few positions while other employers receive only a handful, signaling a lack of information. The combination of youth submitting too few applications and many applying to the same employers creates a severe mismatch that can leave youth unemployed and jobs unfilled.

Employers tend to select the same youth for multiple positions while other youth are not selected for any positions and these selections often show disparities by race and ethnicity. Employers are nearly 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 school type, previous participation, the timing and number of applications, and having uploaded a resume. Fortunately, our pilot job matching algorithm, along with the OYEO "We Hire" event, was able to greatly reduce these disparities by race and ethnicity.

However, the hiring paperwork poses significant barriers such that up to 15% of youth who are matched to a job do not complete the onboarding process. In particular, Black and Hispanic and female youth are less likely to make it through onboarding to get hired. Youth took 25 days on average to complete onboarding with most taking upwards of 5-6 weeks, potentially delaying their start date.

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. It is eye-opening to see these disparities even though SYEP employers have signed on to be part of a six-week developmental program and youth applicants have little real-world experience to differentiate themselves. However, our job matching algorithm suggests that cities can be more intentional about matching youth to jobs while maximizing both employer and youth participation. Instituting some kind of 50-50 rule with half of the program slots filled by employer selection and the remaining half filled by a lottery run by the city 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 room for youth self-selection to perpetuate systemic inequality. Greater outreach and marketing of opportunities could help reduce the disparity in applicants across jobs, creating a thicker market and improving the matching process in terms of both efficiency and equity. During summer 2023 we will test several behavioral nudges aimed at getting youth to apply earlier and to more jobs. Additional research evidence is needed to ensure that the City of Boston is ready to improve the hiring process, increase job quality, and expand opportunities for young people by building a more holistic youth workforce development system for Boston's youth.

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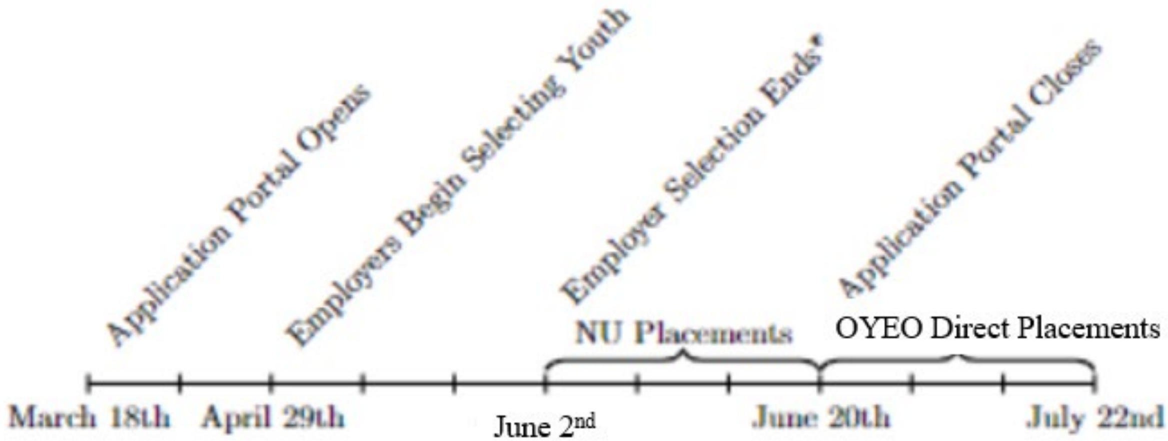
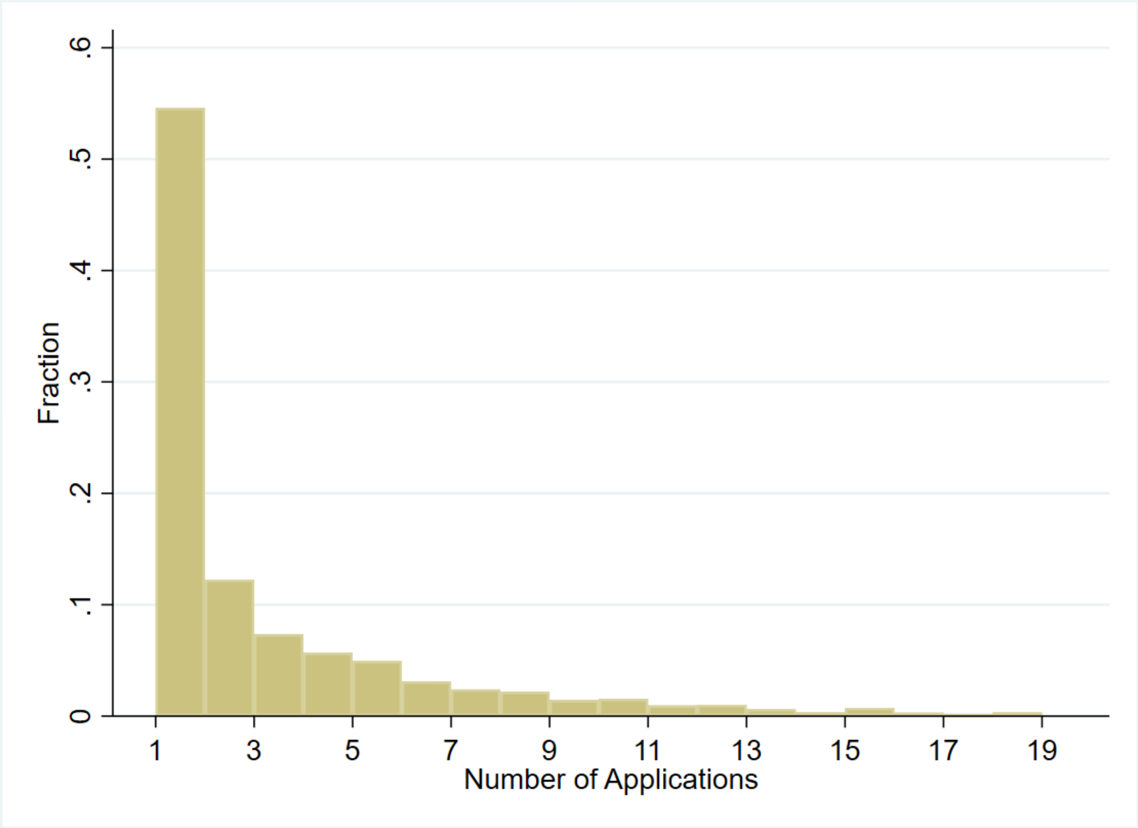
Figure 1: DYEE Job Application Timeline, Summer 2022



Source: Authors' depiction 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.

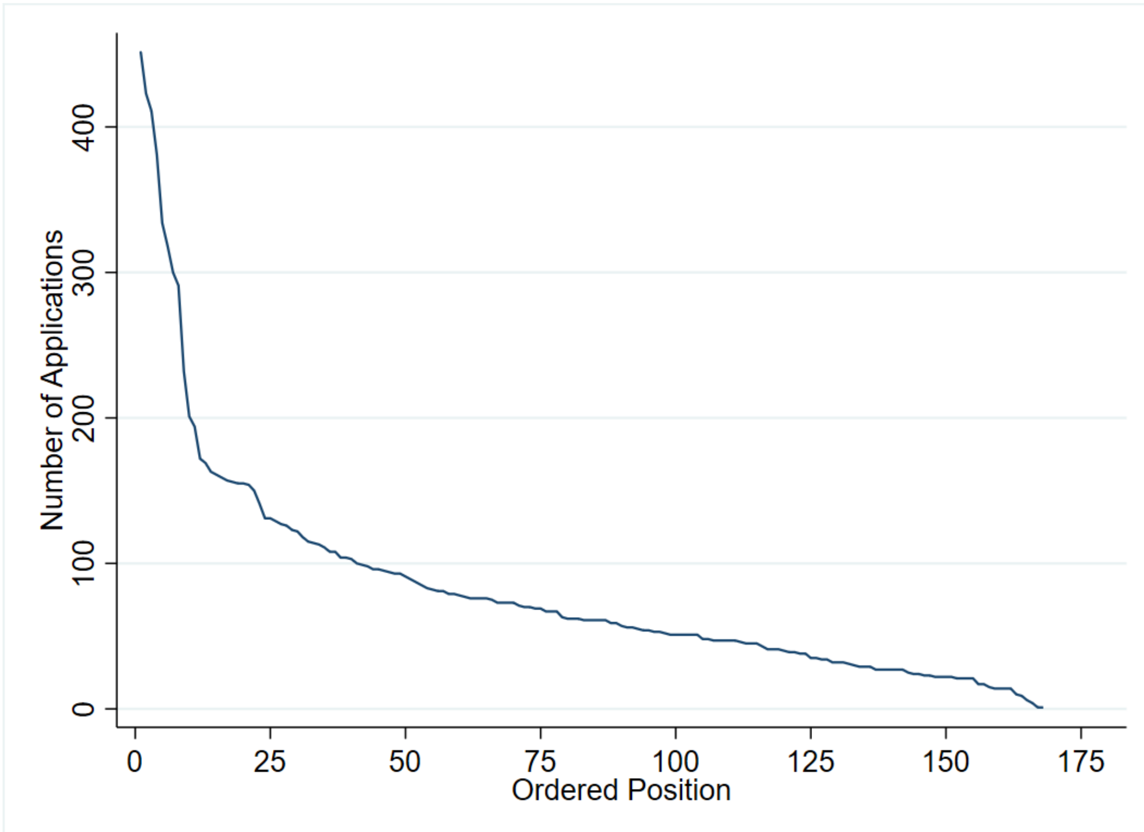
Notes: *Some employers were allowed to make selections after the June 2nd deadline. These included STRIVE Madison, STRIVE Wentworth Training Program, BCYF - SOAR Boston, Hawthorne Youth and Community Center, WriteBoston, STRIVE: Document Imaging Service Center, and Boston Parks and Recreation departments.

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



Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: The histogram shows the distribution of youth by the number of job applications they submitted as of June 15th.

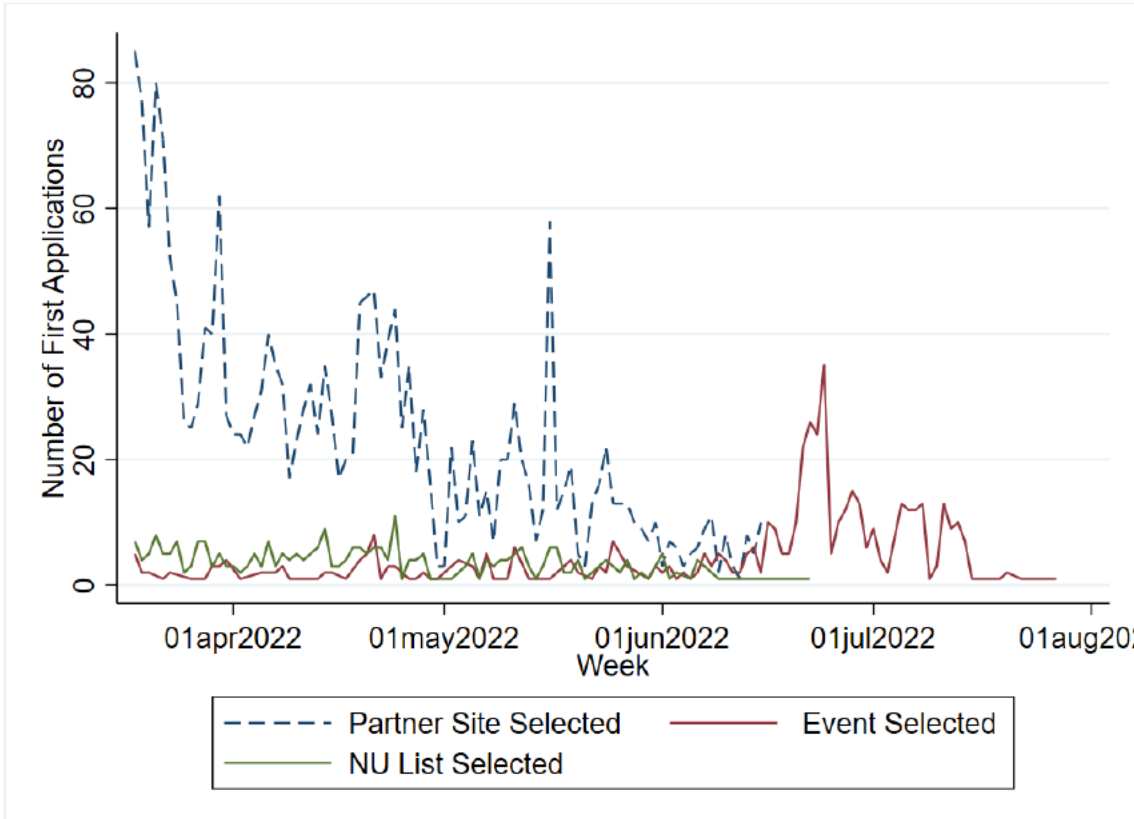
Figure 3: Distribution of Number of Youth Applications per Job Slot



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

Note: As of June 15th, the top 6 partner sites who received the greatest number of applications were YMCA Dorchester (354), YMCA Roxbury (344), Boy & Girls Clubs of Dorchester (324), YMCA Hyde Park (312), YMCA West Roxbury (259), and Zoo New England (234). The bottom 6 sites who received the least number of applications were STRIVE: DISC (4), WriteBoston (1), Boston Public Library Roxbury (1), Immigrant Family Services Institute (0), Boston Public Library Codman Square (0), and Boston Public Library Parker Hill (0).

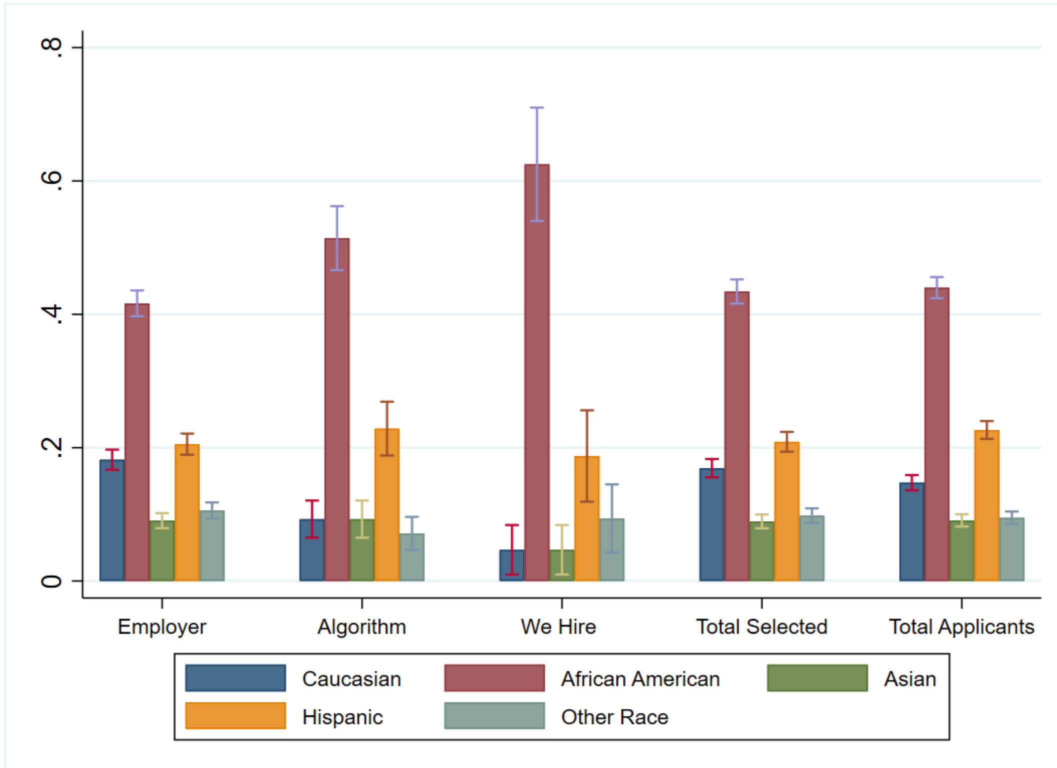
Figure 4: Number of Youth Applying to the Program by Date of First Application



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, 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 Composition of Selected Youth by Employer versus DYEE versus Total Applicants



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 a valid application by June 15th.

Table 1: Estimated Number of City of Boston SuccessLink Jobs Left Unfilled each Summer

	2017	**2018**	**2019**	**2020**
Number of Positions Available	3133	3189	3025	4057
Number of Positions Filled	2848	2587	2637	3477
Number of Positions Unfilled	285	602	388	580
Percent of Positions Unfilled	9.1%	18.9%	12.8%	14.3%

Source: Office of Youth Employment and Opportunity.

Table 2: Difference in the Racial Distribution of Youth Applicants versus Hires for SuccessLink Jobs

	Percentage Point Difference: Share of hiring pool minus share of applicant pool			
	2017	**2018**	**2019**	**2020**
White (Not Hispanic or Latino)	5.47	4.01	3.75	2.56
Asian (Not Hispanic or Latino)	-1.51	-1.77	-0.61	1.99
Black or African American (Not Hispanic or Latino)	0.15	1.40	-0.85	-1.77
Hispanic or Latino	-3.53	-3.26	-1.71	-2.46
Two or More Races (Not Hispanic or Latino)	0.13	-0.06	-0.27	0.00

Source: Office of Youth Employment and Opportunity.

Table 3: Descriptive Statistics for Youth who have Completed at Least One Valid Job Application

	Mean	Std. Dev.	Count
Age	16.7	1.366	3,727
African American	0.44	0.496	3,761
White	0.15	0.355	3,761
Hispanic or Latino	0.23	0.419	3,761
Asian	0.091	0.288	3,761
Other Race	0.095	0.293	3,761
Female	0.49	0.500	3,761
Fluent in Another Language	0.33	0.469	3,652
First Language English	0.84	0.363	3,652
Attends Exam School	0.23	0.420	3,418
Continuing Candidate	0.097	0.296	3,762
Previously Participated	0.26	0.440	3,762
Number of Applications	3.04	3.744	3,762
Avg Num of Other Apps Per Slot	8.92	12.32	3,762
Earliest App Submitted in March	0.28	0.447	3,762
Earliest App Submitted in April	0.36	0.479	3,762
Earliest App Submitted in May	0.23	0.420	3,762
Earliest App Submitted in June	0.14	0.346	3,762
Recorded Resume Response	0.53	0.499	3,762
Avg Resume Character Length	5976.8	3629.1	3,027
Avg Work Question Length	308.4	280.4	3,143

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.

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

	(1)	(2)	(3)	(4)
Age 15	-0.48*	-0.50*	-0.51*	-0.54*
	(-1.73)	(-1.78)	(-1.81)	(-1.92)
Age 16	-0.83***	-0.85***	-0.80***	-0.81***
	(-2.95)	(-3.02)	(-2.80)	(-2.82)
Age 17	-1.28***	-1.29***	-1.21***	-1.25***
	(-4.43)	(-4.47)	(-4.12)	(-4.18)
Age 18	-1.38***	-1.39***	-1.30***	-1.35***
	(-4.57)	(-4.59)	(-4.16)	(-4.28)
Age 19	-1.53***	-1.50**	-1.43**	-1.35**
	(-2.62)	(-2.56)	(-2.39)	(-2.21)
Age 20 or Older	-1.32**	-1.28**	-1.22**	-1.21*
	(-2.20)	(-2.12)	(-1.97)	(-1.90)
African American	1.12***	1.22***	1.20***	1.20***
	(6.12)	(6.44)	(6.29)	(5.51)
Hispanic or Latino	0.95***	1.05***	1.02***	1.02***
	(4.39)	(4.73)	(4.55)	(4.21)
Asian	0.68**	0.61**	0.58**	0.74**
	(2.54)	(2.25)	(2.16)	(2.55)
Other Race	1.42***	1.48***	1.47***	1.50***
	(5.65)	(5.86)	(5.76)	(5.56)
Female	0.40***	0.38***	0.38***	0.38***
	(3.31)	(3.14)	(3.14)	(3.08)
Fluent in Another Language	-0.09	-0.09	-0.10	-0.07
	(-0.60)	(-0.65)	(-0.66)	(-0.45)
Enrolled in School		0.63	0.64	0.53
		(0.85)	(0.86)	(0.69)
Attends Exam School		0.33*	0.33*	0.27
		(1.95)	(1.95)	(1.58)
Previously Participated			-0.26*	-0.26*
			(-1.69)	(-1.65)
Continuing Candidate			0.19	0.18
			(0.61)	(0.59)
Constant	2.39	2.33	2.36	2.11
	(0.64)	(0.62)	(0.63)	(0.39)
Observations	3,762	3,762	3,762	3,762
Postal Code Controls	No	No	No	Yes

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

Note: Age fourteen or younger, male, and white are omitted categorical variables. Although not reported here, we also include the following variables as controls: a dummy variable for whether or not the youth reported their gender and race (columns 1-4), a dummy variable if the youth chose to opt out of reporting their gender (columns 1-4), a dummy variable indicating if the youth recorded a secondary language (columns 1-4), a dummy variable indicating if the youth recorded their school enrollment status (columns 2-4), a dummy variable indicating if the youth recorded their school name (columns 2-4), a dummy variable indicating if the youth recorded previous SYEP status (columns 3-4), a set of dummy variables for earliest application date (columns 1-4), and a set of dummy variables for youth ZIP code (column 4).

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

	(1)	(2)	(3)	(4)	(5)	(6)
African American	-0.15***	-0.15***	-0.13***	-0.12***	-0.12***	-0.08***
	(-5.64)	(-5.57)	(-4.84)	(-4.55)	(-4.46)	(-3.29)
Hispanic or Latino	-0.17***	-0.18***	-0.16***	-0.15***	-0.13***	-0.08***
	(-6.23)	(-5.98)	(-5.33)	(-4.95)	(-4.47)	(-2.94)
Asian	-0.17***	-0.18***	-0.20***	-0.19***	-0.17***	-0.13***
	(-5.12)	(-4.98)	(-5.49)	(-5.28)	(-5.01)	(-3.93)
Other Race	-0.05*	-0.05	-0.04	-0.05	-0.05*	-0.03
	(-1.66)	(-1.56)	(-1.27)	(-1.38)	(-1.66)	(-0.91)
Age 15	0.03	0.03	0.03	0.03	0.07**	0.07**
	(0.97)	(0.95)	(0.83)	(0.84)	(2.02)	(2.14)
Age 16	0.08**	0.08**	0.07**	0.04	0.10***	0.11***
	(2.16)	(2.17)	(1.96)	(1.19)	(2.94)	(3.26)
Age 17	0.09**	0.09**	0.08**	0.04	0.11***	0.12***
	(2.39)	(2.41)	(2.25)	(1.20)	(3.20)	(3.57)
Age 18	0.10***	0.10***	0.10**	0.05	0.11***	0.11***
	(2.71)	(2.68)	(2.55)	(1.30)	(3.03)	(3.12)
Age 19	0.30***	0.22***	0.22***	0.17**	0.24***	0.26***
	(4.36)	(3.05)	(2.98)	(2.26)	(3.33)	(3.79)
Age 20 or Older	0.30***	0.16**	0.16**	0.11	0.17**	0.21***
	(4.70)	(2.06)	(2.06)	(1.38)	(2.32)	(2.88)
Female	-0.00	0.00	-0.00	-0.01	-0.00	0.00
	(-0.15)	(0.02)	(-0.29)	(-0.40)	(-0.08)	(0.26)
Fluent in Another Language		0.00	-0.00	-0.00	-0.00	-0.01
		(0.04)	(-0.00)	(-0.02)	(-0.24)	(-0.31)
Enrolled in School		0.21**	0.18**	0.17*	0.11	0.08
		(2.28)	(1.97)	(1.82)	(1.25)	(0.93)
Attends Exam School			0.07***	0.07***	0.07***	0.06***
			(3.28)	(3.32)	(3.38)	(3.32)
Previously Participated				0.10***	0.09***	0.06***
				(5.37)	(5.12)	(3.49)
Number of Applications					0.02***	0.02***
					(10.54)	(10.44)
Avg Num of Other Apps Per Slot					-0.01***	-0.01***
					(-13.98)	(-12.76)
Recorded Resume Response						-0.28***
						(-8.90)
Avg Resume Character Length						0.00***
						(10.04)
Avg Resume Flesch Score						0.01***
						(14.54)
Avg Work Question Length						0.00***
						(2.83)
Avg Work Question Flesch Score						-0.00
						(-0.01)
Constant	0.29	0.08	0.11	0.07	-0.06	1.00
	(0.44)	(0.13)	(0.17)	(0.10)	(-0.09)	(1.62)
Observations	3,762	3,762	3,762	3,762	3,762	3,762

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

Note: The sample includes youth who submitted at least one complete and valid job application prior to the employer selection 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 youth aged fourteen, 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, their gender and race, their enrollment status, their school name, their previous SYEP status, being fluent in a secondary language, their earliest application date, whether they completed the open-ended text question. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 6: Descriptive Statistics by Selection Method: Employer versus NU Job Matching Algorithm

	(1) Employer Selected	(2) NU Selected	(3) Employer + NU Selected	(4) Total Applicants	(5) Diff. Employer and NU	(6) Diff. Selected and Applied
Age	16.8	16.8	16.8	16.7	0.088	0.121***
	(1.392)	(1.181)	(1.370)	(1.366)	(0.083)	(0.034)
White	0.18	0.094	0.17	0.15	0.088***	0.025**
	(0.386)	(0.292)	(0.378)	(0.355)	(0.023)	(0.009)
African American	0.42	0.52	0.43	0.44	-0.108***	-0.012
	(0.493)	(0.500)	(0.495)	(0.496)	(0.030)	(0.012)
Asian	0.091	0.087	0.090	0.091	0.003	-0.001
	(0.287)	(0.283)	(0.287)	(0.288)	(0.017)	(0.007)
Hispanic or Latino	0.21	0.25	0.21	0.23	-0.041	-0.017
	(0.404)	(0.431)	(0.407)	(0.419)	(0.025)	(0.010)
Other Race	0.11	0.049	0.100	0.095	0.057**	0.005
	(0.308)	(0.215)	(0.299)	(0.293)	(0.018)	(0.007)
Female	0.48	0.47	0.48	0.49	0.012	-0.005
	(0.500)	(0.500)	(0.500)	(0.500)	(0.030)	(0.012)
Attends Exam School	0.26	0.22	0.25	0.23	0.038	0.025*
	(0.437)	(0.415)	(0.435)	(0.420)	(0.028)	(0.011)
Fluent in Another Language	0.31	0.34	0.31	0.33	-0.034	-0.012
	(0.462)	(0.475)	(0.464)	(0.469)	(0.028)	(0.012)
Number of Applications	3.33	3.62	3.37	3.04	-0.288	0.325***
	(4.188)	(3.088)	(4.082)	(3.744)	(0.246)	(0.097)
Avg. Num of Other Apps Per Slot	6.65	9.82	7.00	8.92	-3.178***	-1.924***
	(7.165)	(9.598)	(7.536)	(12.32)	(0.451)	(0.263)
Earliest App Submitted in March	0.31	0.23	0.30	0.28	0.078**	0.023*
	(0.462)	(0.421)	(0.458)	(0.447)	(0.028)	(0.011)
Earliest App Submitted in April	0.36	0.43	0.37	0.36	-0.073*	0.009
	(0.479)	(0.496)	(0.482)	(0.479)	(0.029)	(0.012)
Earliest App Submitted in May	0.19	0.29	0.20	0.23	-0.094***	-0.025*
	(0.395)	(0.454)	(0.403)	(0.420)	(0.024)	(0.010)
Earliest App Submitted in June	0.14	0.052	0.13	0.14	0.089***	-0.008
	(0.348)	(0.222)	(0.337)	(0.346)	(0.020)	(0.009)
Recorded Resume Response	0.51	0.58	0.52	0.53	-0.065*	-0.014
	(0.500)	(0.495)	(0.500)	(0.499)	(0.030)	(0.012)
Completed Work Question	0.81	0.87	0.82	0.83	-0.064**	-0.016
	(0.393)	(0.333)	(0.387)	(0.373)	(0.023)	(0.009)
Avg. Resume Character Length	5493.0	7271.6	5721.8	5977.0	-1.8e+03***	-255.287**
	(3071.4)	(4124.6)	(3279.6)	(3629.3)	(201.884)	(96.621)
Avg. Resume Flesch Score	-9.14	-37.3	-12.8	-18.5	28.156***	5.725***
	(40.11)	(47.55)	(42.20)	(44.77)	(2.575)	(1.212)
Avg. Work Question Length	333.8	310.4	331.0	308.4	23.384	22.608**
	(289.1)	(313.1)	(292.1)	(280.4)	(18.919)	(7.833)
Avg. Work Question Flesch Score	67.9	66.0	67.7	68.3	1.892	-0.669
	(29.48)	(37.82)	(30.58)	(27.57)	(1.981)	(0.793)
Observations	2,495	309	2,804	3,762		

Source: Authors' calculations based on data from the Boston Department of Youth Engagement and Employment.

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 selected youth) and column 4 (all applicants). Standard errors are reported below in parentheses. This sample conditions on those who have submitted at least one valid application by the cut-off date of June 15th. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 7: Comparison of Descriptive Statistics by Timing of Application

	Early Applicants	Late Applicants	Very Late Applicants	Diff in Means	Std.Err. in Diff	p-value
Age	16.62	16.82	16.2	0.200	(0.046)	0.0000
African American	0.43	0.46	0.57	0.039	(0.017)	0.0199
White	0.17	0.10	0.08	-0.065	(0.012)	0.0000
Hispanic or Latino	0.22	0.25	0.22	0.029	(0.014)	0.0421
Asian	0.10	0.08	0.03	-0.020	(0.010)	0.0376
Other Race	0.00	0.11	0.01	0.017	(0.010)	0.0807
Female	0.47	0.52	0.45	0.059	(0.017)	0.0005
Fluent in Another Language	0.32	0.34	0.30	0.026	(0.016)	0.1170
First Language English	0.85	0.82	0.86	-0.029	(0.013)	0.0208
Attends Exam School	0.25	0.18	0.15	-0.065	(0.015)	0.0000
Previously Participated	0.29	0.21	0.12	-0.084	(0.015)	0.0000
Number of Applications	3.55	2.73	2.81	-0.818	(0.132)	0.0000
Avg Num of Other Apps Per Slot	8.38	10.17	8.35	1.792	(0.417)	0.0000
Recorded Resume Response	0.46	0.60	0.47	0.137	(0.017)	0.0000
Avg Resume Character Length	5828.2	6208.18	6622.4	379.982	(134.743)	0.0048
Avg Resume Flesch Score	-20.22	-16.33	-27.80	3.886	(1.663)	0.0195
Avg Work Question Length	318.23	288.12	244.8	-30.114	(10.559)	0.0044
Avg Work Question Flesch Score	68.05	68.86	69.50	0.810	(1.039)	0.4359
Selected by Employer	0.69	0.59	0.00	-0.100	(0.016)	0.0000
Selected by Northeastern University List	0.12	0.10	0.01	-0.026	(0.011)	0.0139
We Hire Event Selected	0.05	0.09	0.44	0.033	(0.008)	0.0001
Observations	737	1,382	2,380			

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

Notes: The sample includes youth who submitted at least one valid job application. Youth who submitted at least one valid application in either March or April are categorized as `Early Applicants' while youth whose earliest application was submitted in May or up to June 15th are categorized as `Late Applicants'. Those who submitted a job application after the June 15th deadline are categorized as `Very Late Applicants'. Column 4 contains the difference in means between column 2 and column 3. Column 5 contains the standard error in differences. Column 5 contains the p-value for the two-sample t-test.

Table 8. Descriptive Statistics by Selection Method: Employer versus We Hire Event

	Employer Selected Mean	We Hire Mean	Difference	p value
Age	16.84	16.24	0.607	0.000
White	0.18	0.06	0.126	0.000
African American	0.42	0.60	0.185	0.000
Asian	0.09	0.03	0.061	0.000
Hispanic or Latino	0.21	0.20	0.005	0.781
Other Race	0.11	0.11	0.006	0.652
Female	0.48	0.46	0.025	0.277
Attends Exam School	0.26	0.14	0.120	0.000
Fluent in Another Language	0.31	0.27	0.044	0.042
Number of Applications	3.34	1.86	1.477	0.000
Avg Num of Other Apps Per Slot	6.75	7.53	0.777	0.022
Earliest App Submitted in March	0.31	0.10	0.210	0.000
Earliest App Submitted in April	0.36	0.13	0.230	0.000
Earliest App Submitted in May	0.19	0.12	0.076	0.000
Earliest App Submitted in June	0.14	0.46	0.316	0.000
Recorded Resume Response	0.50	0.41	0.089	0.000
Completed Work Question	0.81	0.85	0.037	0.040
Avg Resume Character Length	5491.28	6580.61	1089.325	0.000
Avg Resume Flesch Score	9.22	25.35	16.126	0.000
Avg Work Question Length	333.71	242.06	91.659	0.000
Avg Work Question Flesch Score	67.91	68.24	0.331	0.825

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

Notes: The sample includes youth who submitted at least one valid job application.

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

	(1)	(2)	(3)
African American	-0.12***	-0.11***	-0.04**
	(-4.61)	(-3.93)	(-2.09)
Hispanic or Latino	-0.16***	-0.14***	-0.06**
	(-5.85)	(-4.72)	(-2.55)
Asian	-0.05	-0.04	0.01
	(-1.57)	(-1.14)	(0.37)
Other Race	-0.03	-0.01	-0.03
	(-0.77)	(-0.36)	(-1.21)
Female	-0.04***	-0.04***	-0.03**
	(-2.84)	(-2.60)	(-2.46)
Earliest App Submitted in March	-0.32***	-0.31***	-0.09***
	(-8.96)	(-8.63)	(-2.86)
Earliest App Submitted in April	-0.32***	-0.31***	-0.08***
	(-9.16)	(-8.82)	(-2.60)
Earliest App Submitted in May	-0.26***	-0.25***	-0.03
	(-7.49)	(-7.28)	(-1.17)
Earliest Onboarding in April	0.36***	0.35***	0.20***
	(5.17)	(4.91)	(3.68)
Earliest Onboarding in May	0.29***	0.27***	0.17***
	(4.29)	(4.02)	(3.17)
Earliest Onboarding in June	0.22***	0.20***	0.15***
	(3.24)	(3.07)	(2.91)
Selected by Northeastern University List	-0.28***	-0.28***	-0.15***
	(-10.21)	(-10.26)	(-6.74)
We Hire Event Selected	0.00	0.00	0.02
	(0.08)	(0.08)	(0.75)
Fluent in Another Language		-0.04**	-0.04**
		(-2.09)	(-2.34)
Enrolled in School		0.32***	0.14
		(2.71)	(1.53)
Attends Exam School		0.03	0.04**
		(1.26)	(2.16)
Previously Participated			0.07***
			(4.59)
Continuing Candidate			0.45***
			(14.44)
Constant	0.71	0.57	1.79***
	(1.16)	(0.92)	(3.64)
Observations	2,884	2,884	2,884
Application Controls	No	No	Yes

Source: Authors' calculations based on data from the Boston Office of Youth Employment and Opportunity.
Note: The sample includes youth who submitted at least one valid application * p<0.1, ** p<0.05, *** p<0.01.

Appendix A. Data Appendix

The analytical data set was created by appending daily reports provided by DYEE from the online job matching portal. These daily reports at are the youth-job level and consist of all applications (both complete and incomplete), along with employer characteristics and youth demographics. For each application for a particular job, we observe the status of the application (i.e., applied, selected, hired). The data also includes timestamps for when the application was submitted, when the youth was selected by an employer, when the youth was first notified to complete the hiring process, and when the youth was finally hired into the position. When a youth logs into the portal, they are assigned a unique system ID.

This ID identifies each youth throughout the application and hiring process. There are some instances where a youth created more than one system ID. Of all the youths observed in the system, approximately 2.67% (200) made duplicative portal accounts. If a set of users shared the same first name, last name, and date of birth but varied on system ID, we assume that the youth created a duplicative account. For these users, we reassigned their system ID such that one unique ID is assigned to the youth. In instances where observations were identical on first name and last name, but one set of system ID observations had a valid birth date and another set of system ID observations were missing birth date information, we removed observations where the birth date field is missing. There were 164 instances of this occurring. Finally, there were some cases in which the first name and last name matched but varied on system ID or birth date. We identified duplicative observations by matching non-missing middle name, address, and email address. There was a total of 29 instances of this occurring.

Youth must apply for each job separately and as such, we observe all youth-job applications in a particular recruiting report. The snapshots recruiting reports in this analysis begin on May 19th and end August 10th. The earliest date youth could apply was March 18th and last date a youth can apply for a position through SuccessLink was June 19th. The last data a youth could be selected was July 24th 2022. If a youth does not complete a job application or is not eligible for the position, they will receive an 'Incomplete' or 'Do Not Qualify' status.

The daily recruiting snapshots have a few irregularities which required processing prior to analysis. First, we drop duplicate observations in terms of first name, last name, system ID, job posting title, status, and date of the snapshot (or report date). There were a handful of observations which had identical first name, last name, system id, report date, and job posting title, but varied by recruiting report status. For these observations, we select the higher status (e.g., hired over applicant).

We observe some youth-job observations with a "Continuing Candidate" status. All observations associated with this status are with the City of Boston Office of Human Resources. For these youth-application observations, we only see the "Continuing

Candidate" status, as as such, we cannot determine the date in which these youth applied or were selected for employment by status alone. There are 6 youth who are associated with the "Continuing Candidate" status. For these handful of observations, we utilize only timestamp data to determine these youth's application and employer selection decisions. Furthermore, there are approximately 300 youth who applied to a job posting titled "Summer 2022 Continuing Candidates". Discussions with DYEE determined that this job posting was created as a means to onboard youth who were continuing employment with a year-round employer partner. We keep these observations and treat these youth as being selected by an employer.

Finally, the Self-Withdrew (Portal) and Self-Withdrew (Recruiter) status implies that the youth rescinded the particular job application. A total of 156 youths or 537 youth-applications were only observed with a "Self-Withdrew" status. Since an employer may have seen the youth's application prior to being withdrawn, we include these observations within our analysis that follows. A total of 43 youth-applications which were self-withdrawn were placed into onboarding. A nonnegligible portion of applications were incomplete or invalid. This data appendix includes an analysis on this subsample of youth.

Using the rich data provided by the online job portal, we are also able to observe the total number of applications a youth submitted, the date of a youth's earliest application (i.e. when a youth first entered the application system), and whether or not a youth has ever submitted a resume to any job application and construct a measure of resume quality based on a count of the number of characters. Youth were also asked an open-ended question which asked youth "why do they want to participate in the SYEP this summer" from which we also constructed quality measures including a character count. We also computed a Flesch reading score for both the resume and response to the open-ended question. The Flesch reading score provides a metric of reading ease with higher values denoting easier readability.

Table A1. tabulates the number of applications by age, race, gender, exam school status, and language fluency of the applicant. We can see that older youth are also more likely to submit only one job application. Older youth also have more outside options in comparison to those 15 years old or younger. We also report the total number of applications submitted per position averaged over all a youth's applications. From this metric, we can see that youth submitting only one application are not selecting unpopular positions but rather are more likely to be applying to jobs that are oversubscribed.

Table A1: Applicant Demographics by Number of Applications

	(1) Apply to 1 Job Mean/SD/N	(2) Apply to 2 to 3 Jobs Mean/SD/N	(3) Apply to 4 to 10 Jobs Mean/SD/N	(4) Apply to 11+ Jobs Mean/SD/N
Age	16.9	16.6	16.4	16.2
	(1.506)	(1.140)	(1.131)	(1.058)
	2,037	759	782	181
White	0.17	0.15	0.088	0.092
	(0.377)	(0.357)	(0.284)	(0.290)
	2,053	764	791	185
African American	0.43	0.40	0.49	0.52
	(0.495)	(0.491)	(0.500)	(0.501)
	2,053	764	791	185
Asian	0.089	0.089	0.11	0.043
	(0.285)	(0.285)	(0.310)	(0.204)
	2,053	764	791	185
Hispanic or Latino	0.22	0.24	0.23	0.22
	(0.417)	(0.426)	(0.419)	(0.413)
	2,053	764	791	185
Other Race	0.086	0.12	0.090	0.13
	(0.281)	(0.324)	(0.286)	(0.337)
	2,053	764	791	185
Female	0.45	0.53	0.51	0.55
	(0.498)	(0.499)	(0.500)	(0.499)
	2,053	764	791	185
Attends Exam School	0.20	0.26	0.25	0.22
	(0.403)	(0.441)	(0.434)	(0.414)
	1,809	720	741	174
Fluent in Another Language	0.32	0.36	0.32	0.30
	(0.466)	(0.481)	(0.465)	(0.461)
	1,943	762	791	185
Avg Num of Other Apps Per Slot	7.47	10.4	11.2	9.99
	(13.20)	(12.85)	(9.415)	(4.887)
	2,054	764	791	185
Continuing Candidate	0.13	0.10	0.021	0.043
	(0.335)	(0.305)	(0.145)	(0.204)
	2,054	764	791	185

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

Note: This sample includes youth who submitted at least one valid application by June 15th. The `other race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or youth who opt out of reporting their race.

Appendix B. Incomplete and Invalid Applications

During the 2022 summer job cycle, we observed unique 5, 488 youth-users who had applied prior to the employer selection deadline of June 2nd. Of those these users, a majority of them (3,762) successfully submitted at least one job application, while approximately 33.2% of all users (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). In the 'Initial DNQ' status, the youth did not answer one or more of the screening questions correctly, for example, reported age disqualified them from a particular position. DYEE staff have the ability to move youth applications out of this bin after the applicant change their answers and alert DYEE of these changes. Importantly, potential site employers had the ability to see these applicants, but not the responses to the screening questions and thus why the youth received an 'Initial DNQ' status. If someone was assigned a 'Does Not Qualify (DNQ)' status, this means that a DYEE intern verified that the youth is not eligible for the position.

The frequency of missing information varies by whether a user has ever submitted a valid application or only has incomplete applications. For those who have at least one valid application, 0.91% (30) of youth are missing either their date of birth or self-reported race or gender. For those who only have invalid applications, 75.86% (1,141) youth are missing such information.

It appears that entering one's social security number may be a barrier for applicants as a significant number of invalid users are missing such information. Of invalid users, 63.43% are missing race information, 63.43% are missing gender information, 94.55% are missing social security numbers, 94.55% are missing phone numbers, and 55.05% are missing street addresses.

It may also be the case that incomplete or do not qualify users do not have social security numbers and thus are not eligible for the program. 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. Column 3 reports the differences in means between these two groups, along with the standard error below in parentheses. Column 4 reports the p-value resulting from a two-sample t-test for differences i n means. We find that youths that only have invalid job applications are statistically more likely to be older.

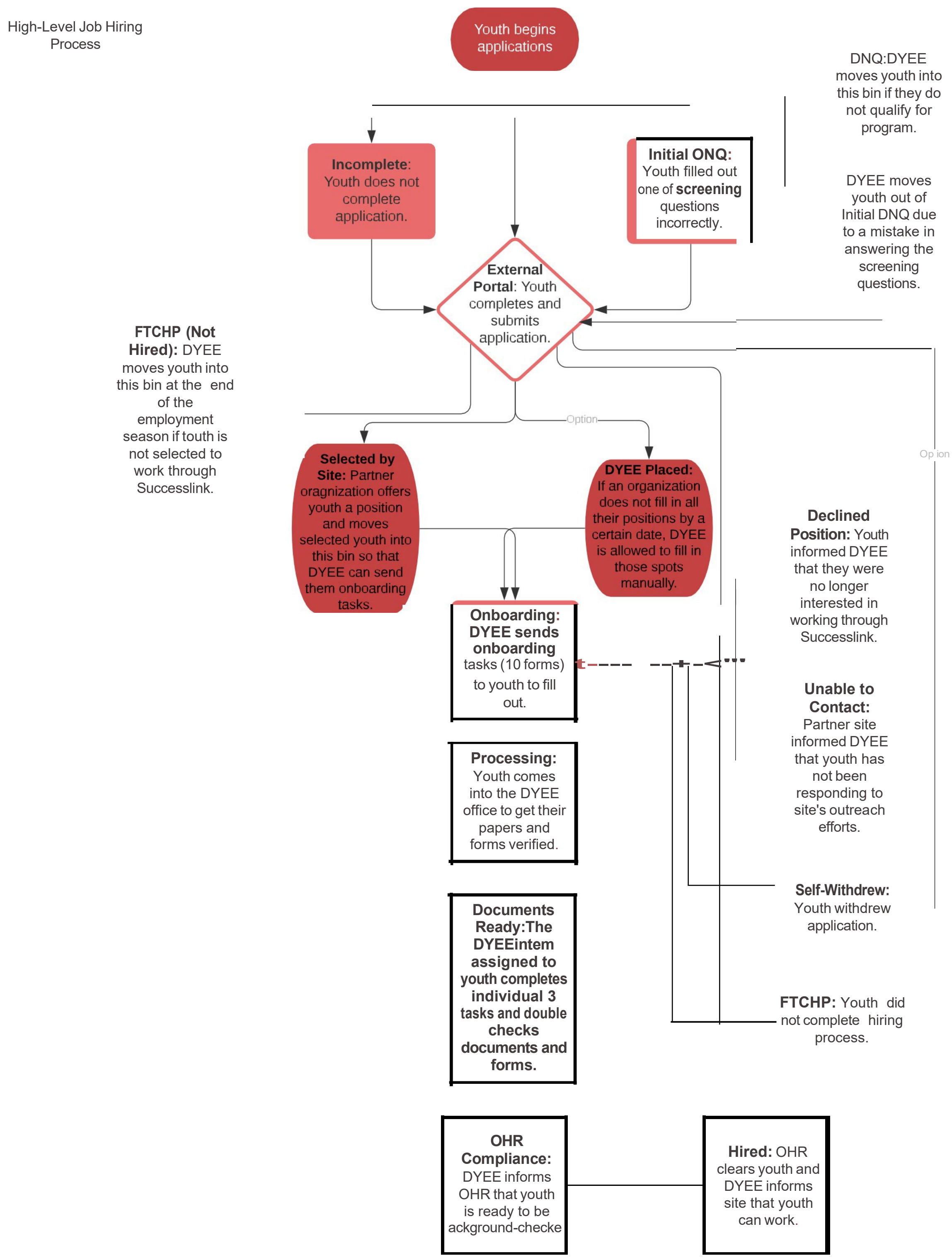
Creating and submitting a valid job application may pose as a barrier for youths with roughly one-third failing to submit an application. However, it is difficult to assess which youth characteristics may be correlated with not completing an application due to the large among of missing data (hence the incompleteness). As a result, for the remainder of the analysis, we focus exclusively on youths who have submitted at least one valid job application.

Table B1: Descriptive Statistics between Valid and Invalid Users

	Invalid Mean/Obvs.	Valid Mean/Obvs.	Diff in Means/Std.Err. in Diff	p-value
Age	17.78	16.71	1.064	0.0000
	434	3,727	(0.076)	
Missing Birth Date	0.75	0.01	0.739	0.0000
	1,726	3,762	(0.007)	
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)	
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	5488			

Notes: This sample conditions on youth who have submitted at least one valid application by June 15th. Column 1 reports the averages for youths who only submitted incomplete or does not qualify job applications. Column 2 reports the average for youths who submitted at least one valid job application. Column 3 reports the differences in the reported averages. 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.

Figure B1. Job Application Flow



Appendix C. Youth Interest Areas

In the following section, we report distribution of youth's reported interest areas and compare them to the number of job listings within the particular interest area. Interest areas are self-reported at the youth level. A vast majority of youth (93 percent) did not report their industry interest area.

The distributions of youth interest areas are contained in Figure C1. Youth interests are spread out across numerous areas, from the arts, health care, and STEM-related fields. However, a majority of the positions available through the SYEP are concentrated among the areas of camp counselors, education, or human services. Given these two distributions, there is a clear mismatch between youth interests and jobs available. In addition, Figure C2 plots youth's 'revealed' preferences, that is, the distribution of all of the youth's applications by job area type.

Figure C1: Distribution of Job Interests to Jobs Available

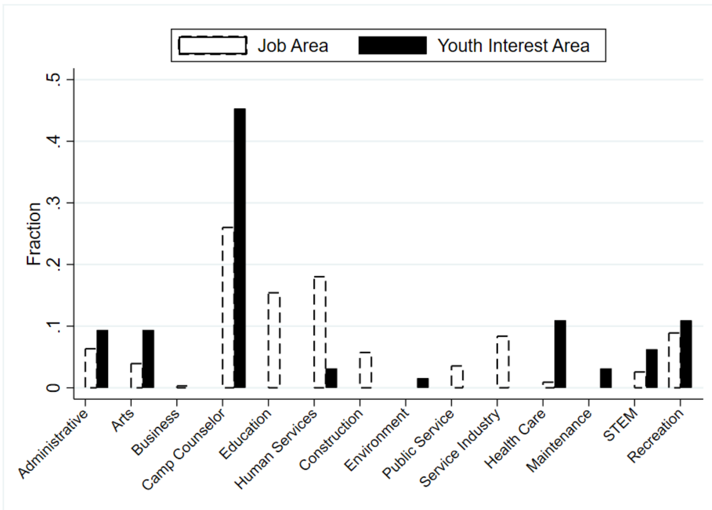
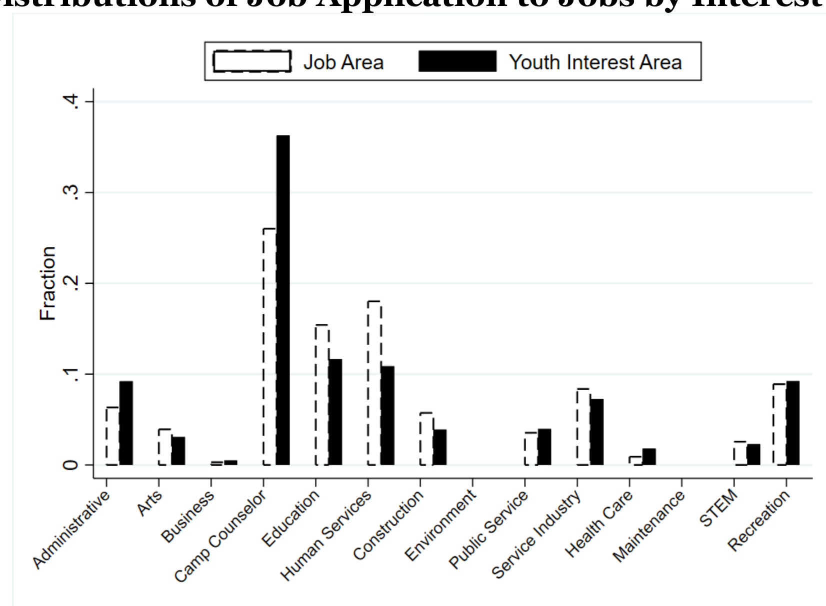


Figure C2: Distributions of Job Application to Jobs by Interest Area



Appendix D. Number of Applications

Table D1. Number of Submitted Applications to a Job Site by Industry

	(1)
Slots Requested	0.49***
	(6.15)
Fraction of Youth Living in Same Zipcode	442.15***
	(3.66)
Childcare Industry	32.69
	(1.31)
Community/Social Assist. Industry	-12.88
	(-0.53)
Construction Industry	46.06
	(1.21)
Education Industry	-8.35
	(-0.34)
Food Service Industry	44.13
	(0.90)
Healthcare Industry	0.11
	(0.00)
Information Finance and Insurance Industry	-21.30
	(-0.44)
Protection Industry	93.87**
	(2.25)
Public Administration Industry	40.52
	(1.39)
Recreation Industry	5.85
	(0.20)
Science Industry	-6.61
	(-0.17)
Sports Industry	7.32
	(0.28)
Constant	28.61
	(1.28)
Observations	163

Note: This table presents results of an OLS regression with the num- ber of applications received by June 15th. Observations are at the employer-level. Omitted categorical variable is the Arts and Enter- tainment Industry. Of the 168 employers, one was missing an industry field.

Table D2. Number of Submitted Applications to a Job Site by Neighborhood

	(1)
Slots Requested	0.60***
	(6.94)
Fraction of Youth Living in Same Zipcode	419.69**
	(2.53)
Chinatown	7.40
	(0.14)
Dorchester	-5.19
	(-0.10)
Downtown	-7.01
	(-0.14)
East Boston	-20.53
	(-0.38)
Fenway	-3.85
	(-0.06)
Hyde Park	-9.48
	(-0.18)
Jamaica Plain	-11.63
	(-0.23)
Mattapan	2.03
	(0.04)
Mission Hill	8.84
	(0.16)
Roslindale	42.11
	(0.74)
Roxbury	1.85
	(0.04)
South Boston	5.46
	(0.11)
South End	-4.02
	(-0.07)
West Roxbury	42.93
	(0.65)
Constant	37.60
	(0.81)
Observations	163

Note: This table presents results of an OLS regression with the number of applications received by June 15th. Observations are at the employer-level. Omitted categorical variable is the Allston Neighborhood. Of of the 168 employers, one was missing a neighborhood location.

Table D3. Number of Submitted Applications to a Job Site by Occupation

	(1)
Slots Requested	0.67***
	(4.09)
Fraction of Youth Living in Same Zipcode	432.07***
	(3.45)
Community and Social Services Occupation	-26.05**
	(-2.13)
Early Childhood Education Occupation	9.99
	(0.74)
Art and Design Occupation	-4.97
	(-0.38)
Architecture and Engineering Occupation	-11.97
	(-0.31)
Maintenance Occupation	1.35
	(0.08)
Protective Services Occupation	43.98
	(1.62)
Education Occupation	-17.49
	(-1.34)
Office and Administration Occupation	22.53*
	(1.67)
Recreation Occupation	2.31
	(0.20)
Sciences Occupation	29.62
	(1.05)
Computer and Mathematical Occupation	-5.03
	(-0.24)
Food Services Occupation	-11.06
	(-0.35)
Legal Occupation	66.11
	(0.99)
Agriculture Occupation	-26.70
	(-0.73)
Healthcare Occupation	-36.58
	(-0.93)
Business and Finance Occupation	-55.46
	(-1.47)
Construction Occupation	39.02
	(0.88)
Constant	46.62***
	(3.65)
Observations	163

Note: This table presents results of an OLS regression with the num- ber of applications received by June 15th. Observations are at the employer-level. Omitted categorical variable is Recreation Occupa- tions. Of of the 168 employers, one was missing occupation coding.

Table D4. Number of Submitted Applications to a Job Site by Employer Characteristics

	(1)
Slots Requested	1.35***
	(3.73)
Fraction of Youth Living in Same Zipcode	418.98***
	(3.36)
YMCA Job	-234.31**
	(-2.27)
Parks and Recreation Job	-19.79
	(-0.87)
Boston Public Library Job	-26.91
	(-1.22)
Additional Application	-11.26
	(-0.83)
Hybrid Position	-18.02
	(-1.45)
Remote Position	-32.85
	(-0.85)
Works with Vulnerable Population	9.94
	(0.77)
Accommodate Summer School	12.26
	(0.94)
Require Youth Orientation	3.38
	(0.18)
Regular Evaluations	-34.25*
	(-1.74)
Provide Training	3.07
	(0.23)
Measures Outcomes	15.15
	(0.97)
Provide Mentoring	1.14
	(0.08)
Constant	43.82
	(1.61)
Observations	163

Note: This table presents results of an OLS regression with the number of applications received by June 15th. Observations are at the employer-level.

Table D5. Number of Submitted Applications to a Job Site by Location

	(1)
Slots Requested	0.58***
	(7.36)
Recorded Location on Application	-11.56
	(-0.24)
Distance to T Station or Stop in Feet (100s)	0.58
	(0.52)
T Station	-10.06
	(-0.78)
Constant	72.33
	(1.50)
Observations	166

Note: This table presents results of an OLS regression with the number of applications received by June 15th. Observations are at the employer-level.

Table D6. Poisson Regression on Number of Applications Submitted

	(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)
Constant	0.61	0.56	0.58	0.59	0.83
	(0.60)	(0.56)	(0.57)	(0.58)	(0.58)
Observations	3762	3762	3762	3762	3762
Postal Code Controls	No	No	No	No	Yes

Note: This table reports the results of a Poisson regression with the number of applications submitted as the dependent variable. Age fourteen or younger, male, and white 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 include the following as controls in the regression: a dummy variable for whether or not the youth reported their gender and race, secondary language, school enrollment status, school name, previous SYEP status, earliest application date, and a set of dummy variables for youth ZIP code.

Appendix E. Timing of Applications

Table E1. Youth who Applied in March 2022 - Descriptive Statistics

	(1)		
	Mean	Std. Dev.	Count
Age	16.6	1.129	1,032
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
Previously Participated	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
Recorded Resume Response	0.41	0.493	1,038
Avg. Resume Character Length	5903.1	3786.8	820
Avg. Resume Flesch Score	-22.7	45.12	820
Avg. Why Work Question Character Length	317.9	286.0	901
Avg. Why Work Question Flesch Score	69.5	15.55	901
Selected by Employer	0.70	0.460	1,038
NU List Selected	0.082	0.274	1,038
Selected by DYEE	0.16	0.363	1,038

Table E2. Youth who Applied in April 2022 - Descriptive Statistics

	(1) Mean	Std. Dev.	Count
Age	16.6	1.088	1,341
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
Previously Participated	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
Recorded Resume Response	0.49	0.500	1,351
Avg. Resume Character Length	5744.0	3646.2	1,077
Avg. Resume Flesch Score	-19.4	43.88	1,077
Avg. Why Work Question Character Length	318.7	286.3	1,187
Avg. Why Work Question Flesch Score	66.9	38.16	1,187
Selected by Employer	0.65	0.478	1,351
NU List Selected	0.088	0.284	1,351
Selected by DYEE	0.17	0.379	1,351

Table E3. Youth who Applied in May 2022 - Descriptive Statistics

	(1) Mean	Std. Dev.	Count
Age	16.6	1.536	855
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
Previously Participated	0.19	0.392	867
Number of Applications	2.73	3.397	867
Avg. # of Other Applications Per Slot	5.94	3.742	867
Recorded Resume Response	0.50	0.500	867
Avg. Resume Character Length	6306.7	3971.9	684
Avg. Resume Flesch Score	-23.2	49.46	684
Avg. Why Work Question Character Length	266.8	253.2	730
Avg. Why Work Question Flesch Score	69.0	21.70	730
Selected by Employer	0.54	0.499	867
NU List Selected	0.093	0.291	867
Selected by DYEE	0.19	0.391	867

Table E4. Youth who Applied in June 2022 - Descriptive Statistics

	(1) Mean	Std. Dev.	Count
Age	16.3	1.360	611
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
Previously Participated	0.14	0.352	623
Number of Applications	0.11	0.718	623
Avg. # of Other Applications Per Slot	5.69	3.722	623
Recorded Resume Response	0.56	0.497	623
Avg. Resume Character Length	5925.1	3919.3	518
Avg. Resume Flesch Score	-19.8	49.17	518
Avg. Why Work Question Character Length	244.7	229.0	526
Avg. Why Work Question Flesch Score	68.9	16.50	526
Selected by Employer	0.29	0.453	623
NU List Selected	0.026	0.158	623
Selected by DYEE	0.31	0.463	623

Table E5. Youth who Applied in July 2022 - Descriptive Statistics

	(1) Mean	Std. Dev.	Count
Age	16.2	1.384	276
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
Previously Participated	0.13	0.334	282
Number of Applications	0	0	282
Avg. # of Other Applications Per Slot	4.91	3.432	282
Recorded Resume Response	0.55	0.499	282
Avg. Resume Character Length	7393.1	4685.0	220
Avg. Resume Flesch Score	-37.5	54.23	220
Avg. Why Work Question Character Length	249.4	263.4	238
Avg. Why Work Question Flesch Score	70.2	16.46	238
Selected by Employer	0.21	0.405	282
NU List Selected	0	0	282
Selected by DYEE	0.21	0.405	282

Appendix F. Employer Site Selection

Employers were asked to select youth for jobs by June 15th so we categorize a youth as "selected by employer" based on the timestamp of when the youth's status changed. Of the 5,488 valid youth applicants, 3,762 youth applied before the June 15th 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. This implies that just under one-third (33 percent or 1,254) of valid applicants were not selected by an employer for a summer job. However, after the deadline, youth could also be selected by either the job matching algorithm or at the We Hire in-person event. By the end of the selection process about 75 percent of youth were offered at least one job from any source, with 61 percent (2,495) selected by an employer, 11 percent (420) selected by the research team using the job matching algorithm and 3 percent (129) selected by OYEO at the We Hire event.

Table F1 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, we also find evidence that youth who exhibit higher levels of effort in their job search, 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. Youth selected by an employer were less likely to have uploaded resume or answered the open-ended "Why Work" text question, although those with longer text responses to the open-ended question were more likely to get selected by an employer.

Table F1. 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	*p-value*
Age	16.45	16.84	-0.390	0.0000
	(1.283)	(1.377)	(0.047)	
African American	0.49	0.42	0.070	0.0000
	(0.500)	(0.494)	(0.017)	
White	0.08	0.18	-0.102	0.0000
	(0.258)	(0.382)	(0.012)	
Hispanic or Latino	0.27	0.21	0.063	0.0000
	(0.446)	(0.406)	(0.014)	
Asian	0.09	0.09	0.001	0.9161
	(0.288)	(0.287)	(0.010)	
Other Race	0.07	0.11	-0.032	0.0014
	(0.270)	(0.302)	(0.010)	
Female	0.49	0.48	0.012	0.5040
	(0.500)	(0.500)	(0.017)	
Fluent in Another Language	0.36	0.31	0.049	0.0027
	(0.482)	(0.463)	(0.016)	
First Language English	0.83	0.85	-0.018	0.1444
	(0.376)	(0.357)	(0.013)	
Attends Exam School	0.17	0.26	-0.087	0.0000
	(0.367)	(0.436)	(0.015)	
Previously Participated	0.18	0.31	-0.131	0.0000
	(0.366)	(0.460)	(0.015)	
Continuing Candidate	0.00	0.15	-0.146	0.0000
	(0.000)	(0.341)	(0.010)	
Number of Applications	2.46	3.34	-0.881	0.0000
	(2.384)	(4.114)	(0.128)	
Avg. Num of Other Apps Per Slot	13.40	6.65	6.751	0.0000
	(18.986)	(7.484)	(0.411)	
Earliest App Submitted in March	0.21	0.31	-0.094	0.0000
	(0.409)	(0.459)	(0.015)	
Earliest App Submitted in April	0.35	0.36	-0.004	0.7936
	(0.476)	(0.480)	(0.017)	
Earliest App Submitted in May	0.30	0.19	0.104	0.0000
	(0.455)	(0.403)	(0.014)	
Earliest App Submitted in June	0.13	0.14	-0.006	0.6318
	(0.357)	(0.341)	(0.012)	
Recorded Resume Response	0.58	0.51	0.065	0.0002
	(0.496)	(0.500)	(0.017)	
Avg. Resume Character Length	6899.11	5493.35	1405.758	0.0000
	(4318.965)	(3291.955)	(136.514)	
Avg. Resume Flesch Score	-36.31	-9.15	-27.160	0.0000
	(46.445)	(42.466)	(1.640)	
Avg. Work Question Length	262.46	333.67	-71.211	0.0000
	(237.948)	(292.795)	(10.377)	
Avg. Work Question Flesch Score	69.14	67.91	1.232	0.2306
	(24.974)	(28.577)	(1.028)	
Observations	1,267	2,495		

Source: Authors' calculations based on data from the Boston Department of Youth Engagement and Employment.

Notes: 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 a employer. Column 3 reports the differences in the reported averages. Column 4 contains the p-value from a two-sampled t-test.

Table F2. Predict Site Selection - 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)
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)
Previously Participated				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)
Recorded Resume Response						-1.57***
						(-8.44)
Avg. Resume Character Length						0.00***
						(9.82)
Avg. Resume Flesch Score						0.04***
						(12.91)
Avg. Why Work Question Character Length						0.00**
						(2.48)
Avg. Why Work Question Flesch Score						0.00
						(0.20)
Constant	1.95	4.41***	4.29***	4.46***	3.57**	2.84**
	(1.55)	(3.11)	(3.07)	(3.23)	(2.55)	(1.99)
Observations	3723	3723	3723	3723	3723	3723
Has Gender/Race + Has Gender/Race × African-American	-0.85	-0.85	-0.76	-0.73	-0.71	-0.62
p-value	0.000	0.000	0.000	0.000	0.000	0.000

*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). * p<0.1, ** p<0.05, *** p<0.01.*

Table F3. Predict Site Selection - Random Effects Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Age 15	-0.04	-0.04	-0.04	-0.04	-0.03	-0.02
	(-1.30)	(-1.33)	(-1.35)	(-1.40)	(-1.14)	(-0.84)
Age 16	0.00	0.00	0.00	-0.02	-0.02	-0.00
	(0.15)	(0.07)	(0.05)	(-0.80)	(-0.75)	(-0.12)
Age 17	0.03	0.02	0.02	-0.01	-0.02	-0.00
	(0.84)	(0.73)	(0.69)	(-0.35)	(-0.63)	(-0.01)
Age 18	0.08**	0.08**	0.08**	0.04	0.02	0.03
	(2.53)	(2.37)	(2.33)	(1.11)	(0.61)	(1.00)
Age 19	0.31***	0.21**	0.21**	0.16*	0.10	0.14**
	(3.78)	(2.56)	(2.56)	(1.95)	(1.46)	(2.15)
Age 20 or Older	0.36***	0.18*	0.18*	0.14	0.05	0.11
	(3.64)	(1.74)	(1.76)	(1.37)	(0.55)	(1.04)
Female	0.00	0.00	0.05	0.03	0.04	0.90***
	(.)	(.)	(0.80)	(0.54)	(0.64)	(11.95)
African American	-0.21***	-0.21***	-0.21***	-0.20***	-0.14***	-0.13***
	(-10.24)	(-10.25)	(-10.21)	(-9.93)	(-7.50)	(-7.64)
Hispanic or Latino	-0.21***	-0.22***	-0.22***	-0.20***	-0.15***	-0.13***
	(-9.32)	(-9.06)	(-9.03)	(-8.59)	(-6.84)	(-6.48)
Asian	-0.17***	-0.18***	-0.18***	-0.17***	-0.14***	-0.11***
	(-6.28)	(-6.19)	(-6.20)	(-5.96)	(-5.45)	(-4.72)
Other Race	-0.20***	-0.20***	-0.20***	-0.20***	-0.13***	-0.12***
	(-7.09)	(-7.16)	(-7.15)	(-7.21)	(-5.42)	(-5.29)
Fluent in Another Language		0.01	0.01	0.01	0.01	0.01
		(0.44)	(0.46)	(0.50)	(0.62)	(0.86)
Enrolled in School		-0.30***	-0.32***	-0.34***	-0.24***	-0.19***
		(-4.07)	(-4.09)	(-4.38)	(-3.52)	(-2.92)
Attends Exam School			0.06	0.04	0.03	0.00
			(0.56)	(0.38)	(0.28)	(0.05)
Previously Participated				0.09***	0.07***	0.06***
				(5.34)	(4.92)	(4.11)
Number of Applications					-0.02***	-0.02***
					(-11.88)	(-11.65)
Number of Job Applications per Slot Available					-0.02***	-0.02***
					(-23.64)	(-23.30)
Recorded Resume Response						-0.26***
						(-10.29)
Character Count of Resume						0.00***
						(12.64)
Resume Flesch Score						0.01***
						(12.98)
Character Count of why work question						0.00
						(0.86)
Why work question Flesch Score						-0.00
						(-1.46)
Constant	0.56***	0.87***	0.82***	0.84***	0.93***	0.00
	(11.30)	(9.51)	(7.50)	(7.67)	(9.50)	(.)
Observations	10335	10335	10335	10335	10335	10335

*Note: The sample conditions on those who submitted at least one complete and valid job application prior to the June 2nd cut-off date. Observations are clustered at the youth-level. The dependent variable is equal to one if the youth was selected for employment 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 if the youth chose to opt out of reporting their gender (columns 1-6), a dummy variable indicating if the youth recorded their school name (columns 3-6), a set of dummy variables for application week (columns 1-6), and a dummy variable indicating if the youth completed the open-ended text question (column 6). * p<0.1, ** p<0.05, *** p<0.01.*

Table F4. Predict Site Selection - Logit Random Effects Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Age 15	-0.10	-0.11	-0.10	-0.11	-0.00	0.04
	(-0.62)	(-0.65)	(-0.64)	(-0.67)	(-0.01)	(0.28)
Age 16	0.14	0.13	0.13	0.02	0.09	0.17
	(0.86)	(0.77)	(0.77)	(0.12)	(0.63)	(1.22)
Age 17	0.27	0.25	0.25	0.12	0.12	0.20
	(1.61)	(1.50)	(1.49)	(0.68)	(0.79)	(1.36)
Age 18	0.55***	0.52***	0.52***	0.35*	0.27	0.33**
	(3.05)	(2.90)	(2.88)	(1.90)	(1.58)	(1.97)
Age 19	1.67***	1.22***	1.22***	1.04**	0.59*	0.81**
	(3.84)	(2.84)	(2.84)	(2.32)	(1.79)	(2.54)
Age 20 or Older	2.20***	1.28**	1.29**	1.13*	0.38	0.68
	(4.12)	(2.24)	(2.26)	(1.96)	(0.79)	(1.11)
Female	-0.18***	-0.18***	-0.19***	-0.19***	-0.01	0.03
	(-2.84)	(-2.88)	(-2.90)	(-3.03)	(-0.16)	(0.48)
African American	-0.96***	-0.97***	-0.97***	-0.95***	-0.49***	-0.48***
	(-9.41)	(-9.43)	(-9.39)	(-9.25)	(-4.68)	(-4.79)
Hispanic or Latino	-0.93***	-0.97***	-0.97***	-0.93***	-0.50***	-0.46***
	(-8.23)	(-7.98)	(-7.97)	(-7.70)	(-4.28)	(-3.96)
Asian	-0.72***	-0.74***	-0.74***	-0.72***	-0.50***	-0.40***
	(-5.36)	(-5.28)	(-5.31)	(-5.15)	(-3.89)	(-3.12)
Other Race	-0.92***	-0.93***	-0.93***	-0.94***	-0.51***	-0.49***
	(-6.62)	(-6.69)	(-6.66)	(-6.74)	(-3.84)	(-3.79)
Fluent in Another Language		0.03	0.04	0.04	0.06	0.07
		(0.45)	(0.48)	(0.53)	(0.85)	(1.01)
Enrolled in School		-1.62***	-1.67***	-1.77***	-0.90**	-0.74**
		(-3.63)	(-3.68)	(-3.90)	(-2.43)	(-1.99)
Attends Exam School			0.47	0.38	0.20	0.05
			(0.92)	(0.74)	(0.45)	(0.12)
Previously Participated				0.36***	0.25***	0.20***
				(4.40)	(3.51)	(2.79)
Number of Applications					-0.11***	-0.10***
					(-8.28)	(-7.81)
Number of Job Applications per Slot Available					-0.24***	-0.23***
					(-18.30)	(-17.58)
Recorded Resume Response						-1.66***
						(-8.79)
Character Count of Resume						0.00***
						(10.54)
Resume Flesch Score						0.04***
						(10.97)
Character Count of why work question						0.00
						(0.55)
Why work question Flesch Score						-0.00
						(-0.57)
Constant	0.18	1.83***	1.81***	1.87***	2.32***	2.02***
	(0.70)	(3.50)	(3.47)	(3.57)	(5.38)	(4.66)
lnsig2u	-0.29**	-0.31**	-0.31**	-0.29**	-1.29***	-1.42***
	(-2.09)	(-2.20)	(-2.21)	(-2.13)	(-4.78)	(-5.11)
Observations	10327	10327	10327	10327	10327	10327

*Note: The sample conditions on those who submitted at least one complete and valid job application prior to the June 2nd cut-off date. Observations are clustered at the youth-level. The dependent variable is equal to one if the youth was selected for employment 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 if the youth chose to opt out of reporting their gender (columns 1-6), a dummy variable indicating if the youth recorded their school name (columns 3-6), a set of dummy variables for application week (columns 1-6), and a dummy variable indicating if the youth completed the open-ended text question (column 6). * p<0.1, ** p<0.05, *** p<0.01*

Appendix G. Job Matching Algorithm

One drawback of the random assignment algorithm is that it does not maximize youth-job matches. To measure this, 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 slot edges within the graph, we compute the number of slots still available for each employer by taking their total slot allocation and subtracting the number of youth hired by June 2nd. There were a total of 350 employment slots available and 661 youth unplaced youth. The Ford–Fulkerson algorithm made 256 youth-job matches while the pilot algorithm made 285 matches. Overall, 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. The Ford-Fulkerson selected younger, less 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 G1. T-test Between Ford–Fulkerson and Pilot Job Matching Algorithm

	F F Algorithm Selected Mean	Pilot Algorithm Mean	Difference	p value
Age	16.52	16.84	0.315	0.003
African American	0.44	0.60	0.162	0.000
White	0.09	0.02	0.069	0.001
Hispanic or Latino	0.28	0.24	0.039	0.304
Asian	0.09	0.07	0.012	0.600
Other Race	0.10	0.06	0.042	0.072
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
Previously Participated	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
Recorded Resume Response	0.53	0.53	0.002	0.954
Avg Resume Character Length	6457.98	6794.25	336.270	0.319
Avg Resume Flesch Score	31.02	34.35	3.334	0.375
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

Note: This table presents the results of a two-sample t-test between youth who were selected by the Ford-Fulkerson algorithm and youth who were selected by the job matching pilot algorithm. Note that since a youth could have been selected by both algorithms, a subset of youth appears in both samples (119 youth in total).

Table G2. T-test Between Ford–Fulkerson and Pilot Job Matching Algorithm

	(1) Employer	(2) NU	(3) We Hire	(4) NU List + We Hire	(5) Total Selected	(6) Total Applicants	(7) Employer - DYEE	(8) *p-value*
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)	
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)	
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)	
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)	
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)	
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)	
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)	
Recorded Resume Response	0.51	0.55	0.40	0.52	0.52	0.53	-0.005	0.8301
	(0.500)	(0.498)	(0.492)	(0.500)	(0.500)	(0.499)	(0.024)	
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 Resume Character Length	5493.3	6742.9	6154.7	6629.2	5748.2	5976.8	-1.1e+03	0.0000
	(3070.4)	(3895.3)	(3632.0)	(3861.4)	(3318.6)	(3629.1)	(161.212)	
Avg Resume Flesch Score	-9.15	-32.8	-26.4	-31.6	-13.2	-18.5	22.447	0.0000
	(40.10)	(44.40)	(44.58)	(44.69)	(42.66)	(44.76)	(2.039)	
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 Boston Office of Youth Employment and Opportunity.

Appendix H. Onboarding Barriers

We code youth as reaching the hiring stage if we observe an "Onboarding" status and those as being hired if their last status update for a particular job posting was "Hired". This includes youth who were hired and later self-withdrew from the position. Table H1 provides descriptive statistics of those who reached an hiring or onboarded-implied status but did not get hired (column 1) and those who were successfully onboarded and hired (column 2).

Table H1. Descriptive Statistics for Youth who were Hired versus Youth who Failed to Make it through the Onboarding Process (Not Hired)

	Not Hired Mean/Obvs.	Hired Mean/Obvs.	Diff in Means/Std.Err. in Diff	p-value
Age	16.68	16.87	-0.192	0.0008
	801	2,062	(0.057)	
African American	0.49	0.41	0.080	0.0001
	812	2,071	(0.020)	
White	0.08	0.20	-0.122	0.0000
	812	2,071	(0.015)	
Hispanic or Latino	0.29	0.18	0.107	0.0000
	812	2,071	(0.017)	
Asian	0.08	0.10	-0.020	0.0907
	812	2,071	(0.012)	
Other Race	0.07	0.11	-0.044	0.0003
	812	2,071	(0.012)	
Female	0.53	0.46	0.065	0.0015
	812	2,071	(0.021)	
Fluent in Another Language	0.39	0.28	0.103	0.0000
	809	1,968	(0.019)	
First Language English	0.80	0.87	-0.069	0.0000
	809	1,968	(0.015)	
Attends Exam School	0.20	0.27	-0.070	0.0002
	744	1,866	(0.019)	
Previously Participated	0.21	0.33	-0.123	0.0000
	813	2,071	(0.019)	
Continuing Candidate	0.00	0.18	-0.174	0.0000
	813	2,071	(0.013)	
Number of Applications	3.99	3.12	0.873	0.0000
	813	2,071	(0.169)	
Avg Num. of Other Apps Per Slot	8.53	6.49	2.041	0.0000
	813	2,071	(0.311)	
Earliest App Submitted in March	0.30	0.29	0.011	0.5540
	813	2,071	(0.019)	
Earliest App Submitted in April	0.41	0.35	0.065	0.0012
	813	2,071	(0.020)	
Earliest App Submitted in May	0.24	0.19	0.046	0.0058
	813	2,071	(0.017)	
Earliest App Submitted in June	0.05	0.17	-0.122	0.0000
	813	2,071	(0.014)	
Recorded Resume Response	0.64	0.47	0.173	0.0000
	813	2,071	(0.020)	
Avg Resume Character Length	7407.89	4909.85	2498.043	0.0000
	787	1,558	(135.679)	
Avg Resume Flesch Score	-47.12	3.94	-51.062	0.0000
	787	1,558	(1.539)	
Avg Work Question Length	304.21	340.05	-35.843	0.0061
	710	1,662	(13.062)	
Avg Work Question Flesch Score	67.68	67.84	-0.153	0.9098
	710	1,662	(1.354)	
Observations	813	2,071		

Source: Authors' calculations based on data from the Boston Department of Youth Engagement and Employment.

Notes: Column 1 reports the averages for youth who were selected for employment by an employer-partner but never made it to the "Hired" status. Column 2 reports the average for youth who were onboarded and reached the "Hired" stage. Column 3 reports the differences in the reported averages. Column 4 contains the p-value from a two-sampled t-test.