# Where the Rubber Meets the Road: Examining Inequities in Summer Youth Employment Programs

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**Abstract**

Abstract: Summer Youth Employment Programs 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. Much of this research is based on lotteries from oversubscribed programs. But what happens when jobs cannot be allocated using simple random assignment due to heterogeneous preferences of employers and youth participants? During the summer of 2022, we obtained daily data snapshots from the hiring platform used by the City of Boston to match youth to summer jobs. Using this novel administrative data set, we explore both youth application and employer selection behavior to better understand youth labor market dynamics and document how the job matching process unfolds within a youth workforce development program. We find that roughly one-third of youth fail to complete the application process, suggesting significant barriers to accessing the program. Among youth completing at least one valid job application, there was a high degree of mismatch between the distribution of applicants versus openings, leaving upwards of 25 percent (830) of positions unfilled as of 2021. Finally, employers were nearly twice as likely to select white youth relative to the percentage of whites in the overall pool of applicants and significantly less likely to select Black and Hispanic applicants. This racial disparity persisted even when controlling for other demographics, number and timing of applications submitted, and previous participation in the program. Implementing a job matching algorithm that was stratified by race improved both the equity and efficiency of the program. Our findings demonstrate that despite having stated goals of reducing inequality, workforce development programs that face heterogeneity on both sides of the job matching process are likely to result in job placements that perpetuate inequities found in the broader labor market. In the absence of a simple random selection mechanism, instituting some kind of 50-50 rule with half of the job openings are filled by employer selection and the remaining half are filled by a lottery run by the public agency could be a feasible solution to improve both equity and efficiency.

***Keywords***— Youth, Workforce Development, Summer Jobs, Job Matching

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# 1 Introduction and Motivation

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

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

Yet most cities do not use random assignment when making SYEP job placements. Even prior to the pandemic, 20 out of 27 SYEP programs across the largest U.S. cities used an allocation mechanism other than random assignment such as first come first serve, merit, or income based (Heller and Kessler, 2017). Since 2020, another three programs have moved away from using lotteries due shifts in the population of youth who apply, the number and types of employers who participate, and the nature of the job opportunities that are available.[1] These programs are often faced with a high degree of heterogeneity among both job applicants and job attributes, creating a complex job

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

matching process each summer that needs to balance both youth and employer interests to ensure participation. Moreover, even among programs that use random assignment, many run their lotteries at the employer level among those who applied to each job site rather than using simple random assignment across all available jobs.[2] Although some cities intentionally target certain groups of youth,[3] most cities have open access programs where the lack of random assignment may restrict access for low-income youth living in marginalized communities, thereby unintentionally failing to meet their intended goals of leveling the playing field.

In this paper we show that using an allocation mechanism other than random assignment results in both large inefficiencies in the number of jobs filled as well as sizeable inequities by race and ethnicity that run counter to the stated objectives of many SYEPs. 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 their hiring platform that is used 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–as well as detailed information for each youth applicant.

Our findings inform three particular design challenges facing workforce development programs that seek to match participants to employers with the goal of increasing equitable access while maximizing the number of jobs filled. First, programs need to create a "thick" job market among applicants to make matches efficiently and equitably. We find that roughly one-third of youth fail to complete the City of Boston application process, suggesting that there are significant barriers to participating. Among those who do complete an application, about half of all youth apply to only one job and many apply to the same employer, often resulting in a high degree of mismatch leaving many youth

[2]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).

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

without a job and a large number of jobs unfilled each summer. When the distribution of applications to positions is imbalanced (e.g., jobs are either over- or under-subscribed), even programs that run lotteries within employers can end up with assignments that are inefficient and inequitable.

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

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

Overall, our results indicate that the complexity of the job matching process may prevent many workforce development programs from meeting their goals to reduce inequality. In particular, the racial and ethnic disparities are eye-opening, especially when 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 presents one solution by which cities can be more intentional about matching youth to jobs while maximizing both employer and youth participation. For example, instituting a 50-50 rule with half of the program slots filled by employer selection and half filled by a lottery could be a feasible approach going forward. However, even with equitable selections, programs will also need to reduce paperwork barriers and convert more selections into actual hires to ensure a that marginalized youth have access to these early employment experiences that have been shown to have meaningful impacts on a rnage of long-term academic, employment, and behavioral outcomes.

## 2 Designing for Efficiency and Equity

Designing an optimal job matching protocol within a universal workforce development program that seeks to place participants into job opportunities at scale faces several challenges. These challenges arise from complex interactions across youth application behavior, employer selection behavior, and hiring processes over multiple waves with implications for both efficiency and equity. For summer jobs programs in cities such as Boston, this can actually be a sizeable problem when sifting through upwards of 12,000 applications to place as many as 9,000 participants during the span of 8 weeks leading up to the program's start (Modestino and Cope, 2023).

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

As a result, the City abandoned its lottery system in 2017 and allowed employer-partners to select youth from among the pool of applicants that had applied to their job, resulting in a matching and hiring process that produced inefficient and inequitable outcomes. For example, there were 300-800 SYEP jobs (10 to 25 percent) left unfilled between 2017 and 2021 (see Panel A of Table 1). Moreover, these job opportunities were not distributed equitably across racial and ethnic groups. 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 Panel B of Table 1). Although these differences between application and placement rates may seem small, when applied to the total number of youth applicants each year (e.g., upwards of 7,000-10,000), this translates into several hundred jobs per summer being disproportionately assigned, contradicting the program's stated goal of reducing inequality across different racial, ethnic, and socioeconomic groups.

Designing an efficient and optimal matching system has been intensively studied in several related settings, such as school choice allocations, with some useful insights for summer jobs programs. The first set of insights from the literature pertains to application behavior, emphasizing the need for marketplaces to have "thickness", i.e., they need to attract a sufficient proportion of the potential participants on both sides of the market to be able to make matches efficiently (Roth, 2008b). Indeed even when SYEPs conduct random assignment at the employer level, as opposed to the program level, the distribution of applications to positions can be quite imbalanced (e.g., jobs are either over- or under-subscribed). Without a sufficiently "thick" labor market, youth and/or employers may not get their first choice or even any choice, potentially resulting in large numbers of youth left without a job and large numbers of jobs that are left unfilled.

Prior research suggests that raising awareness and behavioral nudges can help improve application behavior and create a thicker market. For example, Heckman and Smith (2004) found substantial inequity in participation among Job Partnership Training Act (JTPA) programs across various stages (i.e., awareness, application, acceptance, and enrollment). Applicants with a lower level of schooling resulted in a higher probability of being eligible for the program, but a lower probability of awareness, application, and acceptance. In the broader labor market, Marinescu and Wolthoff (2020) showed that job titles play an important role in understanding worker application patterns with substantial heterogeneity across occupations and even within job titles. Finally, sending youth reminders to complete applications has been demonstrated to positively influence application take-up rates among SYEPs. In an experiment conducted in Philadephia Bhanot and Heller (2022) find that reminder emails increased application completion by 12.3 percent, with bigger effects from emphasizing short-term monetary gains. . In other work, we similarly implemented an experimental application nudge within the City of Boston's Learn and Earn summer program which doubled application rates among youth from Boston public high schools with low college enrollment rates (Marks and Modestino., 2022)

The second set of insights from the literature focuses on selection behavior, highlighting that markets also need to overcome the congestion that thickness can bring, by making it possible to consider enough alternatives to arrive at good matches Roth (2008b). In settings such as the medical residency match, this problem has been resolved by using a deferred acceptance (DA) algorithm where actors make offers and/or applications in order of preference until there are no rejected agents who wish to make any additional proposed matches Roth (2008a). However, it's difficult to apply these type of algorithms when matching youth to summer jobs. This is because unlike DA 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 real-world labor market.

Selections must also 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 or taking an outside option Roth (2008b). Unlike charter schools and medical residency programs where there is no outside market, summer jobs programs are dependent on both employer and youth participation. On the employer side, differences across basic job requirements in terms of skills, experience, and certifications may reduce their participation in the program if jobs are filled completely at random, ignoring their desired qualifications. This is especially true when the supply of youth outside the program is plentiful, as was the case early on in the pandemic during the summer of 2020[4]. On the applicant side, differences across basic job amenities in terms of employer type, location, and responsibilities may reduce take-up rates among youth if placed completely at random, ignoring their preferences. This is especially true when the supply of job opportunities outside the program are plentiful, as has been the case more recently during the summers of 2021 and 2022[5].

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

The third set of insights from the literature can help address the need to conduct multiple rounds of assignment due to late applicants as well as the need to back-fill positions when youth fail to accept job offers or produce the necessary documentation to make it through the hiring process (Valentine et al., 2017)[6]. These market frictions have important implications for equity when hiring over multiple waves, as the distribution and timing of applications across positions is often skewed by race, ethnicity, and school type. As such, programs need to make it sufficiently simple for both applicants and employers to participate in the market without having to engage in costly strategic behavior (Roth, 2008b).

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

[4]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).

[5]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.

[6]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).

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

Finally, 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). However, if the goal of the program is to increase opportunity and reduce inequality, then having a certain share of automated placements may be the only way to ensure that those who ultimately get selected are at least representative of the pool of applicants if not targeted towards marginalized groups.

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

- **Youth application behavior: How can programs create a "think" labor market?** *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? How does application behavior differ by age, gender, race, ethnicity, and school type?*

- **Employer selection behavior: How can programs limit disproportionate selections?** *Which youth characteristics (e.g., age, gender, race/ethnicity, 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 programs use automated placements (e.g., algorithm) to reduce these disparities?*

- **Hiring over multiple waves: How can programs back-fill positions equitably and efficiently?** *What are the characteristics of youth who apply to the program "late"? What are the equity implications of imposing strict deadlines? Once selected, how many youth fail to complete the hiring process? What are the characteristics of youth who fail to complete the hiring process?*

# 3 Program Background: Job Application, Selection, and Hiring Process

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

In this paper, we focus our analysis on the City's SuccessLink program operated by the Office of Youth Employment and Opportunity (OYEO). As the largest provider of summer jobs within the Boston ecosystem, providing open access to all youth, yielding a high degree of heterogeneity across both race and socioeconomic status. The program serves upwards of 6,000 youth aged 14-18 years from all 23 of the City's neighborhoods with greater representation among low-income communities of color such as Dorchester, Roxbury, and Mattapan.[7] The SuccessLink program also offers a wide range of job opportunities at upwards of 200 employer partners include city agencies, local nonprofits, community-based organizations, and private-sector employers. Youth work a maximum of 25 hours per week for up to 7 weeks during July and August and are paid the minimum wage.[8] Survey data consistently show that more than half of SuccessLink participants use their earnings to pay some type of household bill, such as groceries, housing, utilities or transportation—making the program an important source of support for low-income households during the summer (Modestino and Blakely, 2023).

The SuccessLink selection and matching process has undergone several changes since the City moved away from random assignment in 2017. Prior to that, assignments were made according to a 60-40 rule where employers were allowed to select youth for 60 percent of their SuccessLink openings and the remaining 40 percent were filled by OYEO using simple random assignment. Since then, OYEO has allowed employers to select 100 percent of their youth with the caveat that 40 percent of those youth should be new participants—somewhat in the spirit of the prior 60-40 rule. Our analysis focuses on the 3,500 job slots allocated to SuccessLink's "direct" employer partners who used the OYEO online application portal to advertise their positions, review their youth applications, and make their youth selections[9].

A timeline of the SuccessLink job application, selection, and hiring process during 2022 is depicted in Figure 1. In early March, OYEO began its usual outreach efforts to youth which included advertising on public transportation, reaching out to schools, job fairs, and conducting online information sessions. The application portal opened on March 18th at which time youth were able to search for jobs and were encouraged to apply to as many as 15 positions. However, the City's portal was only searchable by

[7] There is also a smaller program for youth leaders age 19-24 who are often prior participants and are paid slightly above the minimum wage.

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

[9] 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

employer name and location making it difficult for youth to identify particular occupations or industries without reading through each job ad, which often varied considerably by employer in terms of quality. Each job required a separate application and like the real-world labor market, there was no information provided to the youth regarding the number of openings per employer nor the number of applicants.

Employers could start reviewing applications and interviewing youth in late March, although the bulk of the applications were received during April. Unlike typical job application data, employers also receive access to the youth profile with information that includes their name, address, and phone number, demographic information including age, gender, race, and ethnicity, language fluency, school name, prior participation, an optional statement about why they want to work this summer, and a resume if they chose to upload one. Employers were able to view all of this information and contact youth for interviews in real-time, submitting their youth selections through the portal between April 30th and May 30th.[10]

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

Once a youth was selected for a position through any of these methods (employer, job

[10]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).

matching algorithm, 'We Hire' event), an automated email notified 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 application and hiring process included upwards of 10 different steps (see Appendix B1), most notably uploading multiple documents to prove age, citizenship, residency, and school status such as a social security card, household utility bill, and school report card. As one might suspect, a nontrivial number of youth failed to make it through this complex onboarding process, leaving some jobs unfilled and some youth unemployed–despite having selected a youth for each opening prior to the program's start.

## 4 Data Collection and Variable Creation

Our analytical data set was created by appending recruiting reports provided daily by OYEO from the City of Boston's online job matching portal during the summer of 2022.[11] These reports consisted of each youth's profile, their application for each job they applied to, as well as the status of each application. When a youth creates their profile they are assigned a unique system ID which enables us to track youth throughout the application and hiring process at the youth-job application level[12]. This 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, when the youth declined (if applicable), and when the youth was finally hired into the position. Appendix B1 contains a diagram of how a youth's application status changes throughout the application and hiring process For example, if a youth does not complete the application or does not qualify for the position (e.g., younger than 14 years of age), they are listed as having either an 'Incomplete' or 'Initial DNQ' status respectively.

The daily recruiting snapshots have a few irregularities which required some cleaning prior to analysis. First, we dropped the handful of observations with exact duplicate information in terms of first name, last name, system ID, job posting title, status, and report date where youth had applied to the same job multiple times. There were also a handful of observations which had identical first name, last name, system ID, report

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

[12] 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.

date, and job posting title, but varied by status so we kept the record with the higher status (e.g., hired versus onboarding versus applicant). In addition, some youth had a status of "School Year Participant" which mean that they had worked for the employer through OYEO's school year program and were selected to continue working with the same employer through the summer. We kept these observations and treated these youth as being selected by the employer.

Using data collected from the youth's application profile, we examine the usual demographic variables of interest such as age, gender, race and ethnicity 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 and language skills respectively. We also observe school name and construct a variable for whether youth attended one of the prestigious exam schools within the Boston Public School (BPS) system or another type of school (e.g., traditional public school, private, or parochial school), and use this variable as a proxy for academic preparation[13]. We also know whether youth have previously participated in either the OYEO summer or school year youth employment programs as a proxy for prior work experience. We also observe whether youth choose to answer the open-ended question "Why do you want to participate in the SYEP this summer?" as well as whether they uploaded a resume, along with the quality of those responses, and use this information as an indication of job readiness. Finally, we are able to proxy socioeconomic status using the youth's residential ZIP code which largely corresponds to one of the City's 23 different neighborhoods.

# 5 Results

To answer our research questions, we explore the pathway by which youth move through each phase of the City's SuccessLink application, selection, and hiring processes. In phase 1, we document how youth apply to positions through the online portal to determine what barriers might prevent programs from creating a "thick" labor market. In phase 2, we examine how youth are selected by employers from the applicant pool

[13] 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 for admission.

and whether automated assignments can limit disproportionate selections by race and ethnicity. In phase 3, we study which youth fail to complete the hiring process and how programs can back-fill positions over multiple waves to be able to employ as many youth as possible. As youth move through each of these phases, we find that systematic disparities arise, leading to job placement outcomes that are ultimately inefficient and inequitable.

## 5.1 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 rates by age, gender, race/ethnicity, language spoken, and school type to understand ways that programs can overcome barriers to create a thicker labor market that produces more matches and more equitable matches.

### 5.1.1 Incomplete and Invalid Applications

During the 2022 summer job cycle, we observed 5,488 unique youth in our analytical dataset who had created a profile before June 15th. Of those youth, approximately one-third (1,726) failed to complete a job application or had their application deemed invalid.[14] Although this would suggest that there are significant barriers to participating in the Boston SYEP, starting with the application process, 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)[15]. However, prior work comparing Boston SYEP applicants to the 5-Year Population Estimates from the American Community Survey show that youth who apply are largely representative of Boston's

[14]Most of these youth had failed to complete an application. Only 281 youth had a status of "Initial DNQ" indicating that their application was invalid, often because they did not answer one or more of the screening questions correctly, such as their birthdate. OYEO staff worked with these youth to either correct their information so that they could move ahead in the application process (N=281) or verify that they were indeed ineligible resulting in a status of "Does Not Qualify" (N=1)

[15]For youth with valid applications race and gender is observed for all applicants whereas for youth with incomplete applications roughly 63 percent are missing self-reported race and gender. In addition, 75 percent of youth with incomplete application are missing date of birth compared to only 1 percent of youth with at least one valid job application. See Appendix Table B1 for more details

youth population in terms of both gender and race (Modestino, 2019). As a result, for the remainder of the analysis, we focus exclusively on youth who have submitted at least one valid job application.

#### 5.1.2 Completed Applications

Table 2 provides some basic descriptive statistics for the 3,762 youth who successfully completed at least one application. Youth who apply to SuccessLink 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) had previously participated in the City's summer youth employment program.

Using the rich data collected by the online application 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 about 80 percent choose to respond to the open-ended question "Why do you want to participate in SuccessLink this summer?" Among those who answer the open-ended question, nearly half (46 percent) have a response that was written below the 8th grade level.[16]

Overall, roughly two-thirds of youth were selected for a job by an employer. Yet Table 2 shows that employers were nearly twice as likely to select white youth relative to the percentage of whites in the overall pool of applicants and less likely to select Black and Hispanic applicants. This disparity between the applicant and hiring pools was also observed for youth who were native English speakers and students from Boston's prestigious "exam" schools. We next examine whether other aspects of youth behavior might be contributing to this racial disparity.

[16] We use the Flesch Score to evaluate readaibility and categorize responses as below the 8th grade level, at the 8th/9th grade level, or above the 9th grade level. See https://readable.com/readability/flesch-reading-ease-flesch-kincaid-grade-level/ for more details

### 5.1.3 Number of Applications per Youth

It could be the case that Black and Hispanic youth submit fewer job applications which might account for their lower likelihood of being selected by an employer. Figure 2 shows that despite most positions being fairly competitive, over 50 percent of youth apply for only one position. However, interviews with OYEO staff and employer partners revealed that youth who apply to fewer jobs often have either a prior relationship with the employer (e.g., had worked there during a prior summer) or the employer strategically hand-picks the youth in advance and directs them to the online portal to get funding for that position through the City. Thus, having fewer applications does not necessarily correlate with lower odds of landing a job.

Given the potential mismatch between the distribution of youth versus job openings, we also explore how application behavior varies across different groups of youth to understand the equity implications of this heterogeneity. Table 4 estimates the relationship between the number of job applications submitted by youth and their basic demographic characteristics (age, race, gender, and our proxies for immigrant status) and timing of the youth's earliest application. We then sequentially add in our proxies for English language fluency, academic preparation, job experience, and socioeconomic status (residential ZIP code).

The results indicate that important differences exist regarding how many job applications youth complete based on their observable characteristics. In general, more advantaged demographic groups tend to apply to **fewer** jobs. For example, older youth submit fewer applications, likely because they have some job experience or more outside options compared to those aged 15 years and younger. Youth who have participated in a prior summer also submit fewer applications, probably because they have a pre-existing relationship with the employer. In general, youth who who have a resume to upload submit fewer applications, perhaps because they already have some prior job experience, although they also tend to have shorter resumes.

Yet applying to fewer jobs is not perfectly correlated with advantage. Non-native English speakers submit fewer applications, likely because of both language and perhaps documentation barriers Similarly, although most youth answer the "why work" question, those with below grade level writing quality also tend to apply to fewer jobs.

However, application behavior by marginalized youth suggests that the lower employer selection rate for non-white youth is not because these youth apply to fewer jobs. Female and non-white youth submit more applications than white males. In particular, Black and Hispanic youth submit one additional application (a 33 percent increase over the mean) yet we have seen that employers are twice as likely to select white youth for a job. Including our other observable indicators of candidate qualifications does little to reduce the racial gap in the number of applications. Even including youth residential zip code as a proxy for socioeconomic status 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.

#### 5.1.4 Distribution of Applications across Positions

How does the distribution of youth applications compare to the distribution of openings across employers? If many youth are chasing a handful 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 or as many as 40 applications per job opening. 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 SuccessLink 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[17]. 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

[17] Parents have indicated on open ended survey responses that the lack of search-ability is a problem for youth.

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." The concentration of applications among few employers also varies considerably by race, suggesting that youth may lack information on the wide variety of positions that are available beyond their neighborhood [18].

## 5.2 Employer Selection Behavior: Limiting Disproportionate Selections

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

### 5.2.1 The Selection Process

During the 2022 hiring cycle, we observed 5,488 valid youth applicants in our analytical dataset who had created a profile, of which 3,762 had applied to a job before June 15th. We categorize any youth selected for a job on or before the employer deadline as "selected by employer" based on the timestamp of when the youth's status changed[19]. Of these 3,762 youth, just over two-thirds (2,495) were selected by an employer. However, some employer partners failed to fill all of their openings by the deadline, either because they had staff capacity constraints or some youth declined their offer.

Thus, after the employer deadline, the remaining 33 percent of youth with valid applications who had not yet been selected by an employer (1,254) were eligible to be selected using the Northeastern University job matching algorithm. Although the job

[18] See Figure B2 in the Appendix for more details

[19] 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."

matching algorithm aimed to improve both efficiency and equity, it did so in a very simplistic way. Specifically, the algorithm filled under-subscribed jobs first, followed by lotteries run within employer applicant pools starting with employers that had the most openings. The algorithm was stratified by race so that the racial distribution of the youth hired through the program would match the racial distribution of the applicants. As such, the algorithm does not maximize youth-job matches in a sophisticated way like a Deferred Acceptance algorithm. This is because there are no rankings by either the applicant or the employer to work with since the program operates more like a real-world labor market. Using our algorithm, an additional 309 youth (8 percent) were selected and notified to start the hiring process.

However, even after the algorithm was run, there were still jobs that had not yet been filled. This is because of labor market frictions stemming from either labor market mismatch (e.g., some jobs were under-subscribed with too few applicants per opening) or administrative burdens related to the hiring process (e.g., youth failed to submit all the necessary documentation to get onto the payroll). Thus, a final wave of selections occurred at the SuccessLink 'We Hire' in-person event at the end of June that included the original pool of applicants as well as youth who had applied to the program very late as "walk-ins".

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

### 5.2.2 Employer Selections: Accounting for Differences in Youth Characteristics

During the 2022 hiring season, there were notable differences in the characteristics of youth who received job offers from employers. 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 D1).

There were also differences in terms of other demographic characteristics with employers more likely to select older youth or youth who had previously participated (both of which would likely more experienced) as well as youth who attended an exam school who might be more academically prepared. Similarly, youth application behaviors also affected whether or not they received a job offer, with youth that had completed more applications, applied for less competitive positions[20], and applied earlier (in March or April) being more likely to have been selected by an employer.

Table 5 tests whether the racial and ethnic disparity in employer selections might be driven by either youth demographic characteristics or applications behaviors that are observable by the employers observe. Controlling for just age and gender, employers were 13 percent less likely to select a Black applicant and 15 percent less likely to select Hispanic or Asian applicants relative to white applicants. These estimates change little in magnitude when we add in controls for school type, having previously participated, or even youth application behavior. Recall from our analysis of youth application behavior that non-white applicants were in fact more likely to apply to multiple jobs than white candidates, yet our estimates of employer behavior show that they are still less likely to be selected.

Perhaps non-white youth who are more likely to live in neighborhoods with fewer job opportunities are lacking job readiness skills to be able to navigate the selection process, even within a structured labor market such as the Boston SYEP. The last column of Table 5 adds in our proxies for job readiness such as whether the youth uploaded a resume and/or answered the open-ended question "Why do you want to participate in the SuccessLink program?", along with measures for the length and readability level of those responses.[21] Controlling for job readiness reduces the magnitude of the coefficients by race and ethnicity by about one-third, but does not diminish their significance. Overall, Black, Hispanic, and Asian youth had significantly **lower** rates of being selected by an employer compared to white youth, even when controlling for this rich set of observable demographic characteristics, application behaviors, and job readiness proxies.

Regardless, it is surprising that we observe a **negative** relationship between submitting a resume with an application and the probability of being selected by an employer.

[20] We measure competitiveness based on the average number of applications submitted for each position that the youth applied to.

[21] Because the unit of observation for the regression is the youth, we average resume text length and reading level across all of the youth's applications.

As discussed earlier, OYEO noted that some employers have pre-existing relationships with youth they want to hire (e.g., had hired them the previous summer) and will direct those youth to apply through SuccessLink to gain access to funding that will cover the youth's wages. Alternatively, employers might be basing their selections on factors other than those that are collected through the SuccessLink application portal. For example, employers may choose to interview youth applicants which may reveal additional information about soft skills or work habits that are not observable to the research team. Regardless, even when controlling for job readiness behaviors, non-white youth are selected 8 to 13 percent less often than white youth.

#### 5.2.3 Automated Selections: Northeastern Job Matching Algorithm

After the first round of selections was completed by employers in early June, OYEO implemented two mechanisms to match youth who had not yet received a job offer to those employers that still had job openings. There were two explicit goals for this matching process: (1) improve equity and, (2) minimize the number of jobs left unfilled. The first mechanism was to implement a job matching algorithm designed by the Northeastern University (NU) research team between June 2nd and June 21st. The second was the in-person 'We Hire' event that was held June 21st through June 24th and is discussed in greater detail in the next section when we explore hiring over multiple waves.

To implement the job matching algorithm, the NU research team received regular snapshots of the application portal data to determine which jobs still had openings and which youth had not yet been selected. [22]To maximize both efficiency and equity, the algorithm place youth into under-subscribed jobs first and then randomly assigned youth to the oversubscribed jobs, by running lotteries within each employers' applicant pool that were stratified by race and ethnicity. Upon receiving the list of suggested job matches, OYEO verified that the youth was not already selected by another employer and that the position was still available. If both were true, the youth was placed into hiring for the position.

To investigate whether the job matching algorithm improved the equity of youth selections, Table 6 compares the demographic characteristics of the application pool to

[22]A job could have openings for one of the following three reasons: the job was under-subscribed (e.g. their were fewer applicants than allotted positions), youth declined the position, or OYEO removed some youth who failed to submit all the necessary documentation to get onto the payroll.

those selected by an employer versus the job matching algorithm. 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 application portal closed to ensure that youth were able to have been selected by the employer prior to the deadline. In total, the Northeastern research team suggested placements for 420 youth. However, due to the timing of those placements, there were 111 youth who were inadvertantly selected by one of the employers for whom OYEO had extended the deadline through June 15th. To hold these employers harmless, we only count the 309 youth who were placed solely by the algorithm as part of the automated allocations pool.

Comparing columns (1) and (2) shows that the automated allocations were more likely to select youth who were Black and Hispanic, although this is perhaps not surprising given that the algorithm was stratified by race and ethnicity. Yet the algorithm was 10 percentage points more likely to select Black youth which was large enough to nudge the racial composition of total selections (column 3, Employer + NU selected) towards a more equitable distribution that was more representative of the applicant pool (column 4). The algorithm also selected a greater share of youth that were fluent in another language and enrolled in school comapared to the employer selections. The youth selected by the algorithm were also more likely to have applied during the middle of the hiring cycle (April/May) and to have applied to more competitive jobs, which perhaps had put them at a disadvantage compared to earlier applicants and those who had applied earlier or to under-subscribed jobs. However, the youth selected by the algorithm were also more likely to have uploaded a longer resume and completed the "Why Work" question–actions that would typically get an applicant noticed by an employer–which again makes the racial gaps among the employer selections all the more eye-opening.

Finally, although the job matching algorithm also aimed to improve efficiency, it did so in a very simplistic way. To test the degree to which the algorithm was efficient, we retroactively applied the Ford–Fulkerson algorithm and compared our results[23]. 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 E).

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

## 5.3 Hiring over Multiple Waves: Back-filling Positions

Across the Boston summer jobs ecosystem most intermediaries conduct hiring over multiple waves for several reasons. First, the market frictions discussed earlier prevent some youth from ever getting hired, which is unknown until just before the program starts.[24] This can result in a sizeable number of unexpected vacancies for employers with upwards of 15 percent of youth selected for a position never making it onto the payroll. Second, many youth do not start thinking about a summer job until the end of the school year. For example, only 28 percent of youth submit an application in March. Third, many youth need to align having a summer job with going to summer school or participating in extracurricular activities which is often not known until the week before the start of summer vacation, resulting in a surge of late applicants as shown in Figure 4.

In this section, we explore the characteristics of these late applicants to understand whether imposing stricter deadlines could improve efficiency without harming equity. If youth who apply late to the program have characteristics that put them at a disadvantage, then the timing of the hiring decisions will matter for achieving the City's goal of improving equity by providing access to these early employment experiences. This is especially important if these marginal applicants have more to gain from participating in the program compared to youth who apply earlier.

We explore both the equity and efficiency implications of conducting multiple waves of hiring leading up to and through the start of the program by assessing the effectiveness of OYEO's "We Hire" event and other outreach efforts to late applicants.[25] During the "We Hire" event, youth who had yet to be selected for a summer job were invited in person to the OYEO offices between June 21st to June 24th during which time they could be matched in real-time with any position that was still available. In addition, OYEO also conducted additional outreach to youth through the Boston Public Schools and community based organizations to provide access to very late applicants on a rolling basis as walk-ins through July 22nd.

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

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

### 5.3.1 Timing and Characteristics of Late Applicants

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 such that the timing of youth applications varied considerably. Figure 4 plots the number of youth by their first date of application during the 2022 hiring season. The number of first-time applicants is quite high when the SuccessLink portal first opens in March but then drifts down over time until May 29th when we see a spike as applicants respond to the deadline. We can see also spike in applicants during the "We Hire" event between June 21st and June 24th when OYEO placed youth applicants into any remaining job openings in real-time.

Although this late wave of applicants might seem inefficient, there are important equity implications associated with this program feature. This is because youth who submit applications later in the recruitment process differ in terms of key demographic traits. To explore this program feature, we categorize youth as being either an "early" applicant who submitted their first application well before employers made their selections (between March 18th and April 30th), a "late" applicant who submitted their first job application after the employer selection process was underway (between May 1st and June 15th), or a "very late" applicant who submitted their first application after all employers had finished selections (after June 15th). Table 7 reveals that "late" applicants are significantly more likely to be older, Black, female, and less likely to attend a prestigious exam school or have been a previous SuccessLink participant. "Very late" applicants are even more likely to be Black but also younger and much less likely to have previously participated.

Providing an opportunity for youth to apply later appears to be quite important for ensuring equity and open access among youth seeking employment. Of the total number of applicants, there are 737 youth who submitted their first application after the employer selection deadline. In the absence of a mechanism such as the "We Hire" event to help match these youth to jobs, these marginal applicants would miss out on the well-documented benefits of summer employment programs for academic, employment, and criminal justice outcomes (Modestino 2019, Kessler et al. 2016, Heller 2014, Modestino and Paulsen, 2023).

### 5.3.2 OYEO Selections: We Hire Event

We examined the effectiveness of backfilling open positions with late applicants on the efficiency and equity of youth selections. To do this, we identified youth who participated in the 'We Hire' event as those with an application status of 'Recruiter Submitted' in any daily snapshot that occurred after June 20th. Note that it is possible that a youth had already been selected by an employer, declined the position, and was subsequently placed during the 'We Hire' event into a different position. We code these observations as being selected by an employer and not by the 'We Hire' event to provide a more conservative assessment of the benefits of backfilling positions.

Table 8 compares the descriptive statistics of youth who were selected by an employer, and those who were selected by attending the 'We Hire' event. Youth selected during the event were 19 percentage points more likely to be Black compared to the youth selected by employers, producing an even larger impact on equity than the algorithm, largely due to the characteristics of the very late applicant pool. The WeHire event also favored younger youth, youth who did not attend one of the prestigious exam schools, and youth who had not previously participated in the program. Similar to those selected by the job matching algorithm, youth selected through the WeHire event had submitted more applications and applied to jobs that were more competitive. However, they were less likely to have uploaded a resume—most likely because a large share of youth attending the event were applying for the first time in-person and being rapidly placed into jobs.

### 5.3.3 Improving Equity and Efficiency

To assess whether the overall impact of both placement mechanisms implemented by OYEO (algorithm plus '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 youth selected using either of the two OYEO mechanisms were more racially diverse than those selected by an employer. Moreover, when used in combination, these two methods served to largely offset the racial disparities between the applicant and the selected pool. In addition to reducing the disparities in placements across race and ethnicity, the job matching algorithm, in combination with the "We Hire" event, also improved equity with regards to school type (see Table E2 in the Appendix).

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

### 5.4 Remaining Barriers to the Hiring Process

In this final section, we examine how youth complete the hiring process once being selected by either an employer, the job matching algorithm or through the We Hire Event. 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 is burdensome at best and at worst, presents a barrier for some youth.

To explore the equity implications of these remaining barriers, we document the number and characteristics of youth who fail to make it through the hiring process. Our analysis focuses on those who were selected for a position and then proceeded to the hiring stage, but ultimately did not get hired. Specifically, we code youth as entering the hiring stage if they are ever reached a status of "Onboarding" and then check if they ever reached a status of "Hired."[26] Youth took 25 days on average to complete onboarding with most taking upwards of 5-6 weeks, potentially delaying their start date.

[26] 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. Table 9 shows that controlling for other demographics (e.g., fluent in another language, attends an exam school), the number and timing of applications, and the method of selection (e.g., employer versus Northeastern algorithm versus OYEO) does not eliminate these racial and gender disparities. This suggests that programs need to consider how to reduce paperwork and administrative barriers to hiring even once youth are selected if equity is a primary goal.

# 6 Conclusion

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

However, the hiring platforms used by many programs are 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 application and selection process can become inefficient, serving to slow down or even derail the hiring process for some youth. Moreover, when the employer selection process is left unchecked, the programs run the risk of replicating 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 inner-city youth of color, City leaders sought to increase both the efficiency and equity of how jobs assignments are made. During the summer of 2022, Northeastern partnered with OYEO to perform an efficiency and equity audit of the SuccessLink application and hiring system. Overall, it appears that youth applicant behaviors 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 percent 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.

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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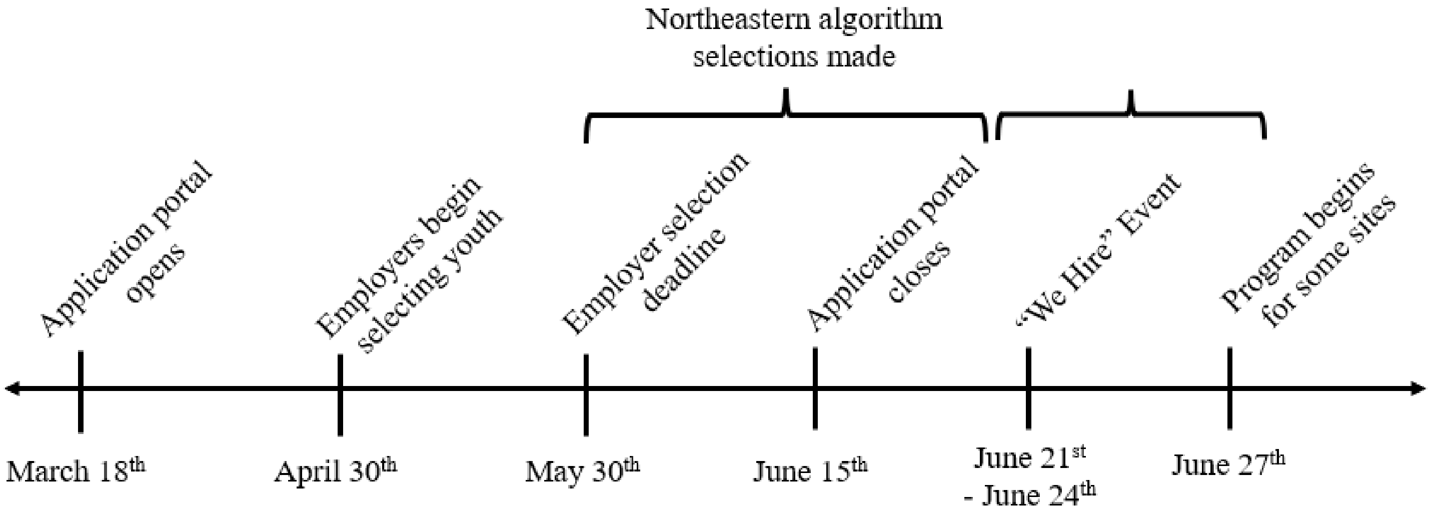
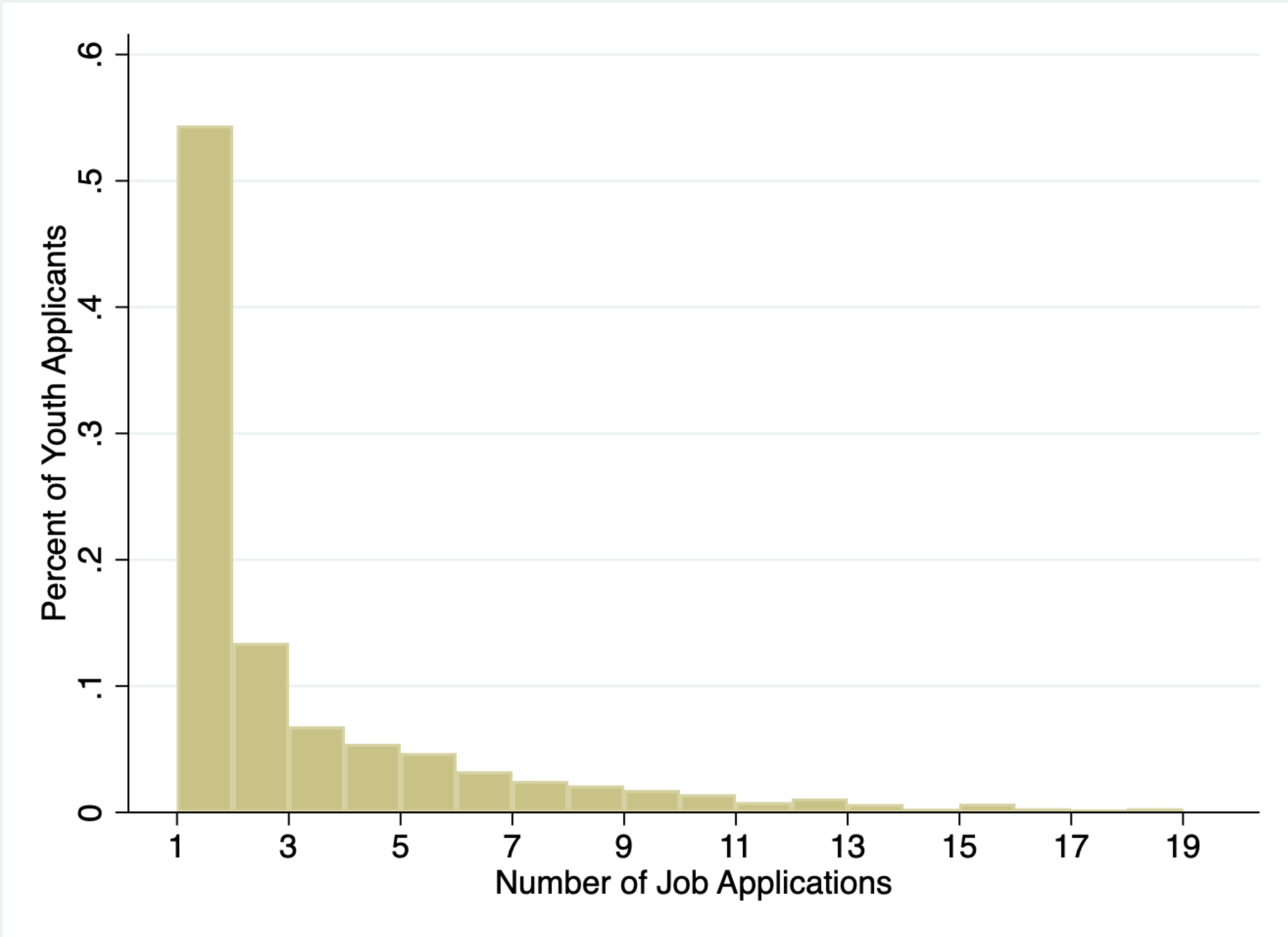
Figure 1: OYEO Job Application Timeline, Summer 2022




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.

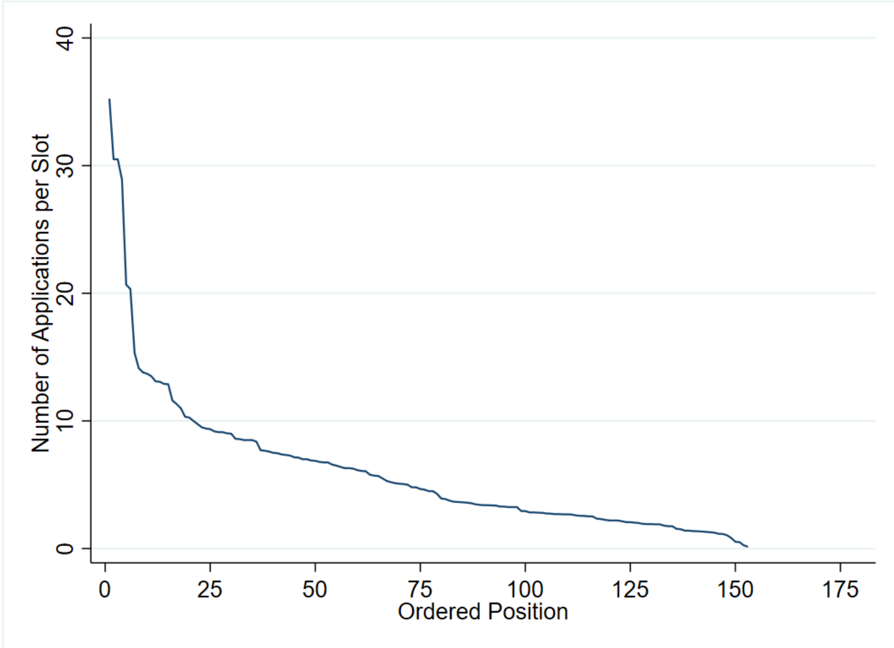
Note: Some employers made selections after May 30th deadline, as such we include application until June 15th in the analysis. These included STRIVE Madison, STRIVE Wentworth Training Program, BCYF - SOAR Boston, Hawthorne Youth and Community Center, WriteBoston, STRIVE: Document Imaging Service Center, and Boston Parks and Recreation.

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



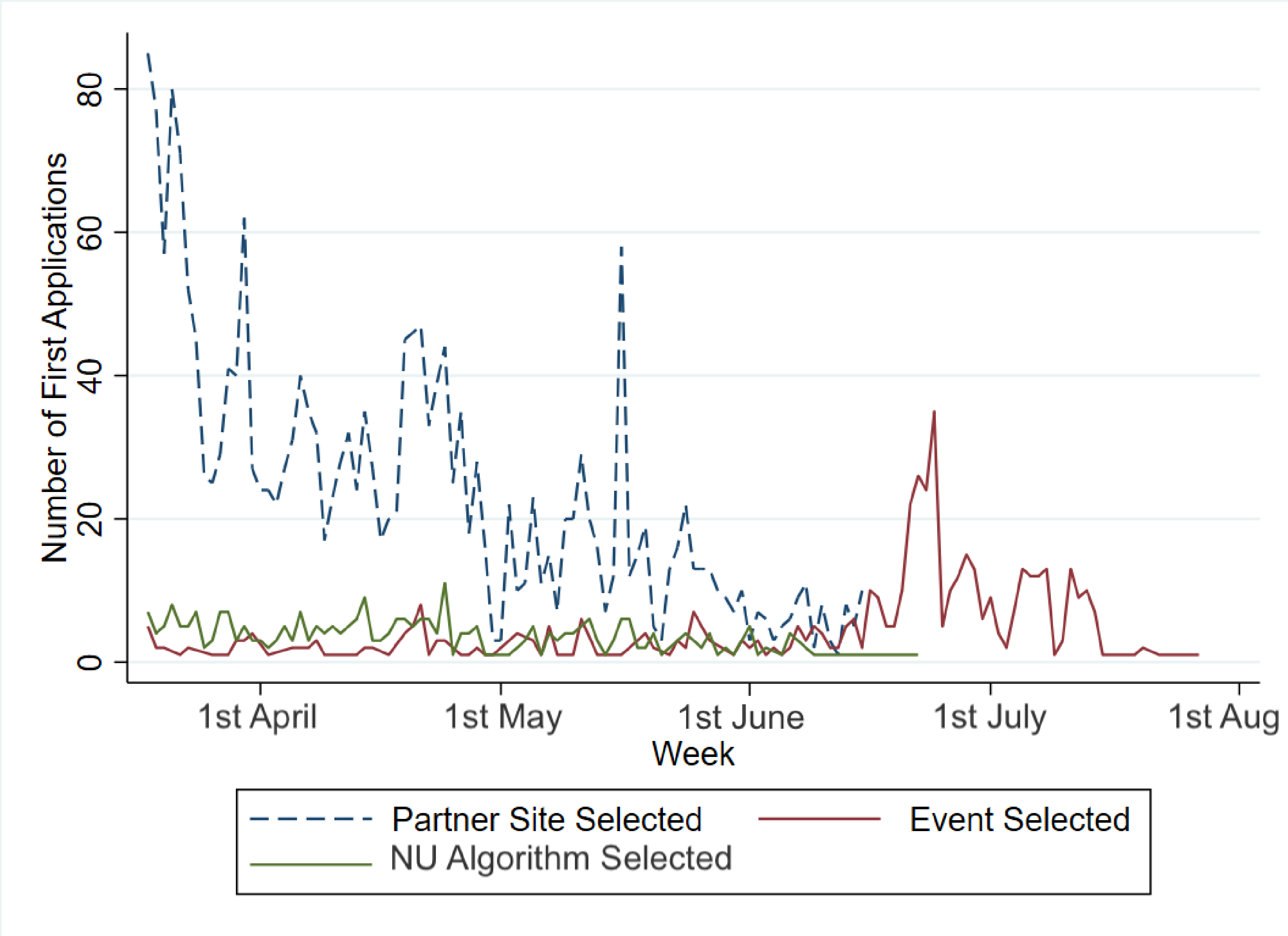

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: The histogram shows the distribution of youth by the number of job applications they submitted as of June 15th.

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



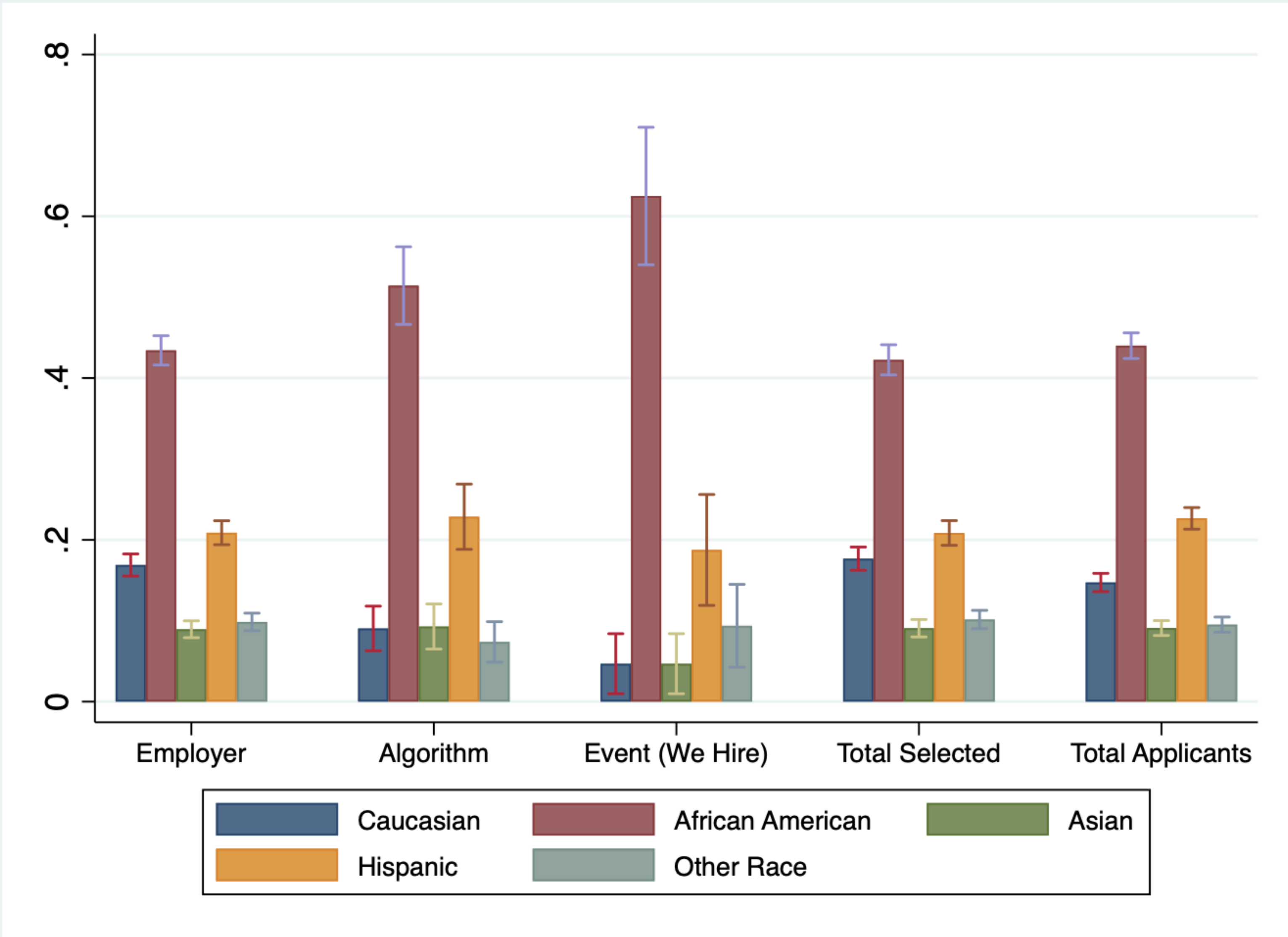

Source: Authors' calculations based on data from the City of Boston's Office of Youth Employment and Opportunity.
Note: As of June 15th, the top employer-partner sites who received the greatest number of applications per opening were YMCA Dorchester, YMCA Roxbury, Boy & Girls Clubs of Dorchester, YMCA Hyde Park, YMCA West Roxbury, and Zoo New England.

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




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

Figure 5: Racial Distribution of Selected Youth by Employer versus OYEO 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: Program Efficiency and Equity over Time

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

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

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

| | Mean | Std. Dev. | Count |
|---|---|---|---|
| Age | 16.7 | 1.37 | 3,727 |
| African American | 0.44 | 0.50 | 3,761 |
| White | 0.15 | 0.35 | 3,761 |
| Hispanic or Latino | 0.23 | 0.42 | 3,761 |
| Asian | 0.09 | 0.29 | 3,761 |
| Other Race | 0.10 | 0.29 | 3,761 |
| Female | 0.49 | 0.50 | 3,761 |
| Fluent in Another Language | 0.33 | 0.47 | 3,652 |
| First Language English | 0.84 | 0.36 | 3,652 |
| Attends Exam School | 0.23 | 0.42 | 3,418 |
| Enrolled in School | 0.99 | 0.08 | 3,652 |
| School Year Participant | 0.10 | 0.30 | 3,762 |
| Prior Summer Participant | 0.26 | 0.44 | 3,762 |
| Number of Applications | 3.04 | 3.74 | 3,762 |
| Avg. # of Applications per Slot | 8.92 | 12.3 | 3,762 |
| Earliest App Submitted in March | 0.28 | 0.45 | 3,762 |
| Earliest App Submitted in April | 0.36 | 0.48 | 3,762 |
| Earliest App Submitted in May | 0.23 | 0.42 | 3,762 |
| Earliest App Submitted in June | 0.14 | 0.35 | 3,762 |
| Uploaded Resume | 0.53 | 0.50 | 3,762 |
| Avg. Resume Character Length (in 100s) | 59.2 | 37.5 | 2,004 |
| Completed Work Question | 0.83 | 0.37 | 3,762 |
| Avg. Work Question Length (in 100s) | 3.08 | 2.80 | 3,143 |
| Avg. Work Question Flesh Score - below grade level | 0.46 | 0.50 | 3,134 |
| Avg. Work Question Flesh Score - at grade level | 0.27 | 0.45 | 3,134 |
| Avg. Work Question Flesh Score - above grade level | 0.24 | 0.43 | 3,134 |
| Employer Selected | 0.66 | 0.22 | 3,762 |
| Total Number of Observations | | | 3,762 |

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

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

| | Not Selected Mean/Std. Dev. | Selected Mean/Std. Dev. | Diff in Means/ Std.Err. in Diff |
|---|---|---|---|
| Age | 16.45 | 16.84 | -0.39*** |
| | (1.28) | (1.38) | (0.05) |
| African American | 0.49 | 0.42 | 0.070*** |
| | (0.50) | (0.49) | (0.02) |
| White | 0.08 | 0.18 | -0.10*** |
| | (0.26) | (0.38) | (0.01) |
| Hispanic or Latino | 0.27 | 0.21 | 0.06*** |
| | (0.45) | (0.41) | (0.014) |
| Asian | 0.09 | 0.09 | 0.00 |
| | (0.29) | (0.29) | (0.01) |
| Other Race | 0.07 | 0.11 | -0.03** |
| | (0.27) | (0.30) | (0.01) |
| Female | 0.49 | 0.48 | 0.01 |
| | (0.50) | (0.50) | (0.02) |
| Fluent in Another Language | 0.36 | 0.31 | 0.05** |
| | (0.48) | (0.46) | (0.02) |
| First Language English | 0.83 | 0.85 | -0.02 |
| | (0.38) | (0.36) | (0.01) |
| Attends Exam School | 0.17 | 0.26 | -0.09*** |
| | (0.37) | (0.44) | (0.02) |
| Prior Summer Participant | 0.18 | 0.31 | -0.13*** |
| | (0.37) | (0.46) | (0.02) |
| School Year Participant | 0.00 | 0.15 | -0.15*** |
| | (0.00) | (0.34) | (0.01) |
| Number of Applications | 2.46 | 3.34 | -0.88*** |
| | (2.38) | (4.11) | (0.13) |
| Avg. # of Other Apps Per Slot | 13.40 | 6.65 | 6.75*** |
| | (18.99) | (7.48) | (0.41) |
| Earliest App Submitted in March | 0.21 | 0.31 | -0.09*** |
| | (0.41) | (0.46) | (0.02) |
| Earliest App Submitted in April | 0.35 | 0.36 | -0.01 |
| | (0.48) | (0.48) | (0.02) |
| Earliest App Submitted in May | 0.30 | 0.19 | 0.10*** |
| | (0.46) | (0.40) | (0.01) |
| Earliest App Submitted in June | 0.13 | 0.14 | -0.01 |
| | (0.36) | (0.34) | (0.01) |
| Uploaded Resume | 0.58 | 0.51 | 0.07*** |
| | (0.50) | (0.50) | (0.02) |
| Avg. Resume Character Length | 6899.11 | 5493.35 | 1405.76*** |
| | (4318.97) | (3291.96) | (136.51) |
| Avg. Resume Flesch Score | -36.31 | -9.15 | -27.16*** |
| | (46.45) | (42.47) | (1.64) |
| Avg. Work Question Length | 262.46 | 333.67 | -71.21*** |
| | (237.95) | (292.80) | (10.38) |
| Avg. Work Question Flesch Score | 69.14 | 67.91 | 1.23 |
| | (24.97) | (28.58) | (1.03) |
| Observations | 1,267 | 2,495 | |

Note: Column 1 reports the averages for youth who were not selected for employment by at least one employer. Column 2 reports the average for youth who were selected by a employer. Column 3 reports the differences in the reported averages.Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: * p<0.1, ** p<0.05, *** p<0.01.

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

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Age | -0.31*** | -0.30*** | -0.27*** | -0.20*** | -0.21*** |
| | (-6.23) | (-6.16) | (-5.11) | (-3.85) | (-3.85) |
| African American | 1.17*** | 1.25*** | 1.22*** | 1.19*** | 1.16*** |
| | (6.38) | (6.62) | (6.44) | (6.43) | (5.51) |
| Hispanic or Latino | 1.02*** | 1.10*** | 1.06*** | 1.11*** | 1.08*** |
| | (4.68) | (4.94) | (4.74) | (5.13) | (4.62) |
| Asian | 0.80*** | 0.74*** | 0.71*** | 0.64** | 0.81*** |
| | (2.99) | (2.71) | (2.62) | (2.45) | (2.84) |
| Other Race | 1.44*** | 1.49*** | 1.48*** | 1.36*** | 1.36*** |
| | (5.73) | (5.90) | (5.81) | (5.52) | (5.22) |
| Female | 0.41*** | 0.39*** | 0.39*** | 0.37*** | 0.37*** |
| | (3.36) | (3.21) | (3.23) | (3.15) | (3.10) |
| Fluent in Another Language | 0.04 | 0.03 | 0.03 | 0.06 | 0.09 |
| | (0.26) | (0.18) | (0.18) | (0.43) | (0.61) |
| First Language English | 0.49*** | 0.47** | 0.49*** | 0.46** | 0.43** |
| | (2.66) | (2.53) | (2.64) | (2.58) | (2.38) |
| Enrolled in School | | 0.48 | 0.50 | 0.29 | 0.24 |
| | | (0.65) | (0.68) | (0.41) | (0.32) |
| Attends Exam School | | 0.28* | 0.28* | 0.24 | 0.20 |
| | | (1.68) | (1.69) | (1.49) | (1.19) |
| Prior Summer Participant | | | -0.32** | -0.37** | -0.36** |
| | | | (-2.10) | (-2.54) | (-2.44) |
| School Year Participant | | | 0.22 | 0.76** | 0.75** |
| | | | (0.71) | (2.56) | (2.51) |
| Uploaded Resume | | | | -1.37*** | -1.35*** |
| | | | | (-7.81) | (-7.60) |
| Avg. Resume Character Length (in 100s) | | | | -0.01*** | -0.01*** |
| | | | | (-3.96) | (-4.37) |
| Completed Work Question | | | | 0.24 | 0.24 |
| | | | | (1.22) | (1.20) |
| Avg. Work Question Length (in 100s) | | | | 0.05** | 0.04 |
| | | | | (2.02) | (1.63) |
| Avg. Work Question Flesh Score - at grade level | | | | 0.03 | 0.00 |
| | | | | (0.19) | (0.01) |
| Avg. Work Question Flesh Score - above grade level | | | | 0.29* | 0.28* |
| | | | | (1.80) | (1.71) |
| $R^2$ | 0.092 | 0.093 | 0.094 | 0.157 | 0.166 |
| Observations | 3762 | 3762 | 3762 | 3762 | 3762 |
| Zip Code Controls | No | No | No | No | Yes |

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

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

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Age | 0.02*** | 0.01*** | 0.00 | 0.01** | 0.01** | 0.01** |
| | (4.58) | (3.89) | (1.26) | (2.15) | (2.07) | (2.13) |
| African American | -0.16*** | -0.15*** | -0.14*** | -0.13*** | -0.12*** | -0.11*** |
| | (-7.20) | (-6.21) | (-5.85) | (-5.67) | (-5.15) | (-4.23) |
| Hispanic or Latino | -0.19*** | -0.18*** | -0.16*** | -0.14*** | -0.13*** | -0.12*** |
| | (-6.95) | (-6.35) | (-5.81) | (-5.39) | (-4.77) | (-4.18) |
| Asian | -0.16*** | -0.18*** | -0.17*** | -0.16*** | -0.16*** | -0.19*** |
| | (-4.73) | (-5.19) | (-5.05) | (-4.85) | (-5.05) | (-5.46) |
| Other Race | -0.07** | -0.06* | -0.10*** | -0.10*** | -0.09*** | -0.08*** |
| | (-2.32) | (-1.77) | (-3.09) | (-3.28) | (-3.12) | (-2.69) |
| Female | -0.00 | -0.00 | -0.01 | -0.01 | -0.01 | -0.01 |
| | (-0.10) | (-0.12) | (-0.82) | (-0.56) | (-0.73) | (-0.94) |
| Fluent in Another Language | -0.02 | 0.00 | -0.01 | -0.01 | -0.01 | -0.01 |
| | (-0.96) | (0.03) | (-0.27) | (-0.59) | (-0.55) | (-0.51) |
| First Language English | -0.05** | -0.01 | -0.01 | -0.02 | -0.03 | -0.02 |
| | (-2.15) | (-0.48) | (-0.63) | (-1.13) | (-1.17) | (-0.95) |
| Enrolled in School | | 0.19** | 0.14 | 0.08 | 0.08 | 0.08 |
| | | (2.09) | (1.54) | (0.94) | (0.98) | (0.89) |
| Attends Exam School | | 0.07*** | 0.07*** | 0.07*** | 0.06*** | 0.07*** |
| | | (3.32) | (3.37) | (3.53) | (3.34) | (3.54) |
| Prior Summer Participant | | | 0.08*** | 0.09*** | 0.07*** | 0.07*** |
| | | | (4.70) | (5.08) | (4.24) | (3.97) |
| School Year Participants | | | 0.38*** | 0.35*** | 0.37*** | 0.36*** |
| | | | (10.26) | (9.97) | (10.28) | (10.11) |
| Number of Applications | | | | 0.02*** | 0.02*** | 0.02*** |
| | | | | (10.22) | (8.42) | (8.57) |
| Avg. # of Applications per Slot | | | | -0.01*** | -0.01*** | -0.01*** |
| | | | | (-13.88) | (-14.06) | (-13.66) |
| Uploaded Resume | | | | | 0.05** | 0.05** |
| | | | | | (2.45) | (2.47) |
| Avg. Resume Character Length (in 100s) | | | | | -0.00*** | -0.00*** |
| | | | | | (-7.44) | (-7.23) |
| Completed Work Question | | | | | -0.02 | -0.02 |
| | | | | | (-1.03) | (-0.67) |
| Avg. Work Question Length (in 100s) | | | | | 0.01*** | 0.01*** |
| | | | | | (2.61) | (2.78) |
| Avg. Work Question Flesh Score - at grade level | | | | | -0.03 | -0.03* |
| | | | | | (-1.61) | (-1.67) |
| Avg. Work Question Flesh Score - above grade level | | | | | 0.01 | 0.01 |
| $R^2$ | 0.110 | 0.119 | 0.151 | 0.221 | 0.227 | 0.245 |
| Observations | 3762 | 3762 | 3762 | 3762 | 3762 | 3762 |
| Zip Code Controls | No | No | No | 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 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 white, male, and and below grade level work question Flesch Score. The 'Other race' category includes American Indian or Alaska Native, Native Hawaiian or Pacific Islander, two or more races, or opt out of reporting race. Although not reported here, we also include controls a set of dummy variables for earliest application month (columns 1-5) as well as for missing data on the application for each of the demographic characteristics (columns 1-5), school enrollment status and school name (columns 2-5), and previous SYEP participation (columns 3-5). Column (5) also includes a set of dummy variables for youth ZIP code. Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: * p<0.1, ** p<0.05, *** p<0.01.

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

| | (1)<br>Employer Selected | (2)<br>Algorithm Selected | (3)<br>Employer or Algorithm Selected | (4)<br>Youth Applicants | (5)<br>Difference: (1)–(2) | (6)<br>Difference: (3) – (4) |
|---|---|---|---|---|---|---|
| Age | 16.73 | 16.66 | 16.71 | 16.56 | 0.072 | 0.16** |
| | (1.96) | (1.84) | (1.97) | (2.10) | (0.10) | (0.05) |
| White | 0.18 | 0.09 | 0.17 | 0.15 | 0.09*** | 0.03** |
| | (0.39) | (0.29) | (0.38) | (0.36) | (0.02) | (0.01) |
| African American | 0.42 | 0.51 | 0.43 | 0.44*** | −0.10*** | -0.01 |
| | (0.49) | (0.50) | (0.50) | (0.50) | (0.03) | (0.01) |
| Asian | 0.09 | 0.09 | 0.09 | 0.09 | 0.00 | 0.00 |
| | (0.29) | (0.29) | (0.29) | (0.29) | (0.02) | (0.01) |
| Hispanic or Latino | 0.21 | 0.23 | 0.21 | 0.23 | -0.02 | -0.02 |
| | (0.40) | (0.42) | (0.41) | (0.42) | (0.02) | (0.01) |
| Other Race | 0.11 | 0.071 | 0.10 | 0.09 | 0.03** | 0.01 |
| | (0.31) | (0.26) | (0.29) | (0.29) | (0.02) | (0.01) |
| Female | 0.48 | 0.49 | 0.48 | 0.49 | -0.009 | -0.01 |
| | (0.50) | (0.50) | (0.50) | (0.50) | (0.03) | (0.01) |
| Enrolled in School | 0.95 | 0.99 | 0.96 | 0.96 | −0.044*** | -0.01 |
| | (0.21) | (0.05) | (0.20) | (0.18) | (0.01) | (0.01) |
| Attends Exam School | 0.23 | 0.21 | 0.23 | 0.21 | 0.024 | 0.022** |
| | (0.42) | (0.41) | (0.42) | (0.41) | (0.02) | (0.01) |
| First Language English | 0.81 | 0.85 | 0.82 | 0.82 | -0.03 | 0.00 |
| | (0.39) | (0.36) | (0.39) | (0.39) | (0.02) | (0.01) |
| Fluent in Another Language | 0.30 | 0.34 | 0.30 | 0.32 | −0.04* | -0.02 |
| | (0.46) | (0.47) | (0.46) | (0.47) | (0.02) | (0.01) |
| Number of Applications | 3.33 | 4.33 | 3.37 | 3.04 | −0.99*** | 0.33*** |
| | (4.19) | (3.60) | (4.08) | (3.74) | (0.22) | (0.10) |
| Avg. # of Applications per Slot | 6.65 | 9.54 | 6.99 | 8.92 | −2.88*** | −1.92*** |
| | (7.17) | (8.99) | (7.54) | (12.32) | (0.39) | (0.26) |
| Earliest App Submitted in March | 0.31 | 0.28 | 0.30 | 0.28 | 0.03 | 0.02** |
| | (0.46) | (0.45) | (0.46) | (0.45) | (0.02) | (0.01) |
| Earliest App Submitted in April | 0.36 | 0.41 | 0.37 | 0.36 | −0.06** | 0.01 |
| | (0.48) | (0.49) | (0.48) | (0.48) | (0.03) | (0.01) |
| Earliest App Submitted in May | 0.19 | 0.26 | 0.20 | 0.23 | −0.07** | −0.03* |
| | (0.40) | (0.44) | (0.40) | (0.42) | (0.02) | (0.01) |
| Earliest App Submitted in June | 0.14 | 0.048 | 0.13 | 0.14 | 0.09*** | -0.01 |
| | (0.35) | (0.21) | (0.34) | (0.35) | (0.02) | (0.01) |
| Uploaded Resume | 0.51 | 0.55 | 0.52 | 0.53 | -0.04 | -0.01 |
| | (0.50) | (0.50) | (0.50) | (0.50) | (0.03) | (0.01) |
| Avg. Resume Character Length (in 100s) | 27.84 | 37.48 | 29.43 | 31.53 | −9.64*** | −2.10** |
| | (35.0) | (46.52) | (37.18) | (40.27) | (1.95) | (0.97) |
| Completed Work Question | 0.81 | 0.86 | 0.82 | 0.83 | −0.05* | −0.02** |
| | (0.39) | (0.35) | (0.39) | (0.37) | (0.02) | (0.01) |
| Avg. Work Question Length (in 100s) | 2.70 | 2.82 | 2.70 | 2.57 | -0.12 | −2.10** |
| | (2.92) | (3.12) | (2.94) | (2.81) | (0.16) | (0.97) |
| Avg. Work Question Flesh Score - at grade level | 0.22 | 0.25 | 0.22 | 0.23 | -0.03 | -0.01 |
| | (0.41) | (0.43) | (0.41) | (0.42) | (0.02) | (0.01) |
| Avg. Work Question Flesh Score - above grade level | 0.20 | 0.22 | 0.20 | 0.20 | -0.03 | 0.002 |
| | (0.40) | (0.42) | (0.40) | (0.40) | (0.02) | (0.01) |
| Observations | 2495 | 309 | 2804 | 3762 | | |

Source: Authors' calculations based on data from the Boston Office of Youth Employment and Opportunity. Note: This sample includes youth who applied before the deadline of June 15th. Column 1 reports the averages for youth who were selected for employment by at least one employer. Column 2 reports the averages for youth who were selected by the NU job matching algorithm and were not selected by an employer partner.. Column 3 reports the averages of youth selected either by an employer partner or by the NU job matching algorithm. Column 4 contains the averages of all youth who applied before the deadline of June 15th. Column 5 reports the differences in averages between employer selected youth and the NU job matching algorithm selected youth. Column 6 contains the differences in averages between column 3 (employer partner and NU selected youth) and column 4 (all applicants). Standard errors are reported in parentheses. Statistical significance is indicated at the following levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 7: Characteristics of Youth by Timing of Job Application

| | (1) Early Applicants | (2) Late Applicants | (3) Very Late Applicants | (4) Difference: (1)-(2) | (5) Difference: (2)-(3) |
|---|---|---|---|---|---|
| Age | 16.51 | 16.62 | 15.7 | -0.11 | 0.88*** |
| | (1.75) | (2.59) | (3.07) | (0.07) | (0.13) |
| African American | 0.43 | 0.47 | 0.57 | -0.04* | -0.11*** |
| | (0.49) | (0.50) | (0.50) | (0.01) | (0.02) |
| White | 0.17 | 0.11 | 0.09 | 0.07*** | 0.02 |
| | (0.38) | (0.31) | (0.28) | (0.01) | (0.01) |
| Hispanic or Latino | 0.22 | 0.24 | 0.22 | -0.03 | 0.03 |
| | (0.41) | (0.43) | (0.41) | (0.01) | (0.02) |
| Asian | 0.10 | 0.08 | 0.036 | 0.020* | 0.04*** |
| | (0.30) | (0.27) | (0.19) | (0.01) | (0.01) |
| Other Race | 0.09 | 0.11 | 0.09 | -0.02* | 0.02 |
| | (0.28) | (0.31) | (0.29) | (0.01) | (0.01) |
| Female | 0.47 | 0.52 | 0.45 | -0.05** | 0.07*** |
| | (0.50) | (0.50) | (0.50) | (0.02) | (0.02) |
| Fluent in Another Language | 0.32 | 0.32 | 0.29 | -0.001 | 0.03 |
| | (0.47) | (0.47) | (0.45) | (0.02) | (0.02) |
| First Language English | 0.85 | 0.76 | 0.82 | 0.09*** | -0.06** |
| | (0.36) | (0.43) | (0.38) | (0.01) | (0.02) |
| Enrolled in School | 0.99 | 0.91 | 0.96 | 0.08*** | -0.05*** |
| | (0.05) | (0.81) | (0.20) | (0.01) | (0.01) |
| Attends Exam School | 0.25 | 0.19 | 0.15 | 0.06*** | 0.03 |
| | (0.43) | (0.37) | (0.36) | (0.01) | (0.02) |
| Prior Summer Participant | 0.29 | 0.21 | 0.12 | 0.09*** | 0.08*** |
| | (0.46) | (0.41) | (0.33) | (0.02) | (0.02) |
| Number of Applications | 3.55 | 2.71 | 2.81 | 0.85*** | -0.10 |
| | (4.12) | (3.34) | (4.76) | (0.13) | (0.18) |
| Avg. # of Applications per Slot | 8.38 | 9.95 | 8.35 | -1.57*** | 1.61* |
| | (8.07) | (17.14) | (11.73) | (0.41) | (0.70) |
| Uploaded Resume | 0.46 | 0.60 | 0.47 | -0.14*** | 0.13*** |
| | (0.50) | (0.49) | (0.50) | (0.02) | (0.02) |
| Avg. Resume Character Length (in 100s) | 57.09 | 68.20 | 68.35 | -4.11*** | -7.15*** |
| | (38.17) | (35.15) | (45.95) | (1.69) | (2.45) |
| Completed work Question | 0.87 | 0.77 | 0.71 | 0.10*** | 0.06*** |
| | (0.34) | (0.42) | (0.45) | (0.01) | (0.02) |
| Avg. Work Question Length (in 100s) | 2.76 | 2.21 | 1.75 | 0.56*** | 0.46*** |
| | (2.87) | (2.64) | (2.42) | (0.09) | (-0.12) |
| Avg. Work Question Flesch Score - at grade level | 0.28 | 0.26 | 0.25 | 0.03 | 0.01 |
| | (0.45) | (0.44) | (0.43) | (0.02) | (0.02) |
| Avg. Work Question Flesch Score - above grade level | 0.24 | 0.24 | 0.25 | -0.01 | 0.00 |
| | (0.42) | (0.43) | (0.43) | (0.02) | (0.02) |
| Selected by Employer | 0.69 | 0.60 | 0.00 | 0.09*** | 0.69*** |
| | (0.46) | (0.49) | (0.00) | (0.02) | (0.02) |
| Selected by Algorithm | 0.12 | 0.09 | 0.01 | 0.029** | 0.08*** |
| | (0.33) | (0.29) | (0.11) | (0.011) | (0.01) |
| We Hire Event Selected | 0.05 | 0.09 | 0.44 | -0.03*** | -0.35*** |
| | (0.23) | (0.28) | (0.50) | (0.01) | (0.02) |
| Observations | 2,380 | 1,382 | 737 | | |

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

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

| | (1)<br>Event Selected | (2)<br>Employer Selected | (3)<br>Difference:<br>Event - Employer Selected |
|---|---|---|---|
| Age | 16.04 | 16.73 | -0.69*** |
| | (2.21) | (1.96) | (0.09) |
| African American | 0.60 | 0.42 | 0.19*** |
| | (0.49) | (0.49) | (0.02) |
| White | 0.06 | 0.18 | -0.13*** |
| | (0.23) | (0.39) | (0.02) |
| Hispanic or Latino | 0.20 | 0.21 | -0.01 |
| | (0.40) | (0.40) | (0.02) |
| Asian | 0.03 | 0.09 | -0.06*** |
| | (0.17) | (0.29) | (0.01) |
| Other Race | 0.11 | 0.11 | 0.01 |
| | (0.32) | (0.31) | (0.014) |
| Female | 0.46 | 0.48 | -0.03 |
| | (0.50) | (0.50) | (0.02) |
| Fluent in Another Language | 0.26 | 0.30 | -0.04 |
| | (0.44) | (0.46) | (0.021) |
| First Language English | 0.88 | 0.81 | 0.06*** |
| | (0.33) | (0.39) | (0.02) |
| Enrolled in School | 0.97 | 0.95 | 0.02 |
| | (0.18) | (0.21) | (0.01) |
| Attends Exam School | 0.14 | 0.26 | -0.12*** |
| | (0.33) | (0.44) | (0.02) |
| Prior Summer Participant | 0.20 | 0.31 | -0.11*** |
| | (0.40) | (0.46) | (0.02) |
| Number of Applications | 4.13 | 3.42 | 0.71*** |
| | (6.06) | (4.27) | (0.22) |
| Avg. # of Applications per Slot | 7.53 | 6.75 | 0.78* |
| | (6.82) | (7.42) | (0.34) |
| Uploaded Resume | 0.41 | 0.50 | -0.09*** |
| | (0.49) | (0.50) | (0.02) |
| Avg. Resume Character Length (in 100s) | 71.09 | 54.47 | 16.61*** |
| | (46.10) | (30.60) | (2.37) |
| Completed Work Question | 0.85 | 0.81 | 0.04* |
| | (0.36) | (0.39) | (0.02) |
| Avg. Work Question Length (in 100s) | 2.05 | 2.70 | -0.65*** |
| | (2.26) | (2.92) | (0.13) |
| Avg. Work Question Flesch Score - at grade level | 0.25 | 0.27 | -0.01 |
| | (0.43) | (0.44) | (0.02) |
| Avg. Work Question Flesch Score - above grade level | 0.24 | 0.24 | 0.00 |
| | (0.43) | (0.43) | (0.02) |
| Late Applicant | 0.21 | 0.33 | -0.12*** |
| | (0.41) | (0.47) | (0.02) |
| Very Late Applicant | 0.56 | 0.00 | 0.56*** |
| | (0.50) | (0) | (0.01) |
| Observations | 572 | 2495 | |

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

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

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Age | 0.00 | 0.00 | 0.00 | -0.03*** | -0.02*** |
| | (0.42) | (0.40) | (0.49) | (-3.61) | (-2.61) |
| African American | -0.18*** | -0.14*** | -0.13*** | -0.12*** | -0.11*** |
| | (-6.36) | (-5.11) | (-4.71) | (-4.40) | (-4.46) |
| Hispanic or Latino | -0.21*** | -0.17*** | -0.17*** | -0.15*** | -0.14*** |
| | (-6.72) | (-5.79) | (-5.51) | (-5.03) | (-4.86) |
| Asian | -0.07* | -0.04 | -0.05 | -0.05 | -0.07** |
| | (-1.82) | (-1.02) | (-1.32) | (-1.36) | (-2.06) |
| Other Race | -0.05 | -0.05 | -0.05 | -0.09*** | -0.10*** |
| | (-1.48) | (-1.48) | (-1.36) | (-2.60) | (-3.21) |
| Female | -0.15* | -0.17** | -0.17** | -0.23*** | -0.22*** |
| | (-1.75) | (-2.15) | (-2.11) | (-2.85) | (-3.05) |
| Fluent in Another Language | -0.03 | -0.03* | -0.03 | -0.04* | -0.03* |
| | (-1.50) | (-1.65) | (-1.62) | (-1.83) | (-1.69) |
| First Language English | 0.06** | 0.07*** | 0.07*** | 0.06** | 0.05** |
| | (2.36) | (2.78) | (2.66) | (2.40) | (2.20) |
| Employer partner selected after May 30th | | 0.08*** | 0.08*** | -0.00 | 0.05** |
| | | (3.78) | (3.78) | (-0.02) | (2.30) |
| Selected by Northeastern University List | | -0.40*** | -0.40*** | -0.34*** | -0.32*** |
| | | (-16.61) | (-16.57) | (-14.24) | (-14.14) |
| We Hire Event Selected | | -0.04 | -0.03 | -0.03 | -0.02 |
| | | (-1.01) | (-0.90) | (-0.80) | (-0.53) |
| Late Applicant | | 0.03 | 0.03* | 0.03 | 0.06*** |
| | | (1.53) | (1.70) | (1.31) | (3.14) |
| Enrolled in School | | | 0.30*** | 0.23** | 0.19* |
| | | | (2.58) | (2.04) | (1.80) |
| Attends Exam School | | | 0.03 | 0.03 | 0.02 |
| | | | (1.45) | (1.47) | (1.28) |
| Prior Summer Participant | | | | 0.10*** | 0.09*** |
| | | | | (5.58) | (5.15) |
| Reported Previous Participation | | | | -0.10 | -0.08 |
| | | | | (-0.44) | (-0.36) |
| School Year Participants | | | | 0.26*** | 0.32*** |
| | | | | (8.78) | (11.34) |
| Uploaded Resume | | | | | 0.07*** |
| | | | | | (2.99) |
| Completed Work Question | | | | | -0.02 |
| | | | | | (-0.70) |
| Avg. Resume Character Length (in 100s) | | | | | -0.00*** |
| | | | | | (-16.29) |
| Avg. Work Question Length (in 100s) | | | | | 0.00 |
| | | | | | (0.28) |
| Avg. Work Question Flesh Score - at grade level | | | | | -0.01 |
| | | | | | (-0.39) |
| Avg. Work Question Flesh Score - above grade level | | | | | 0.05** |
| | | | | | (2.47) |
| Observations | 2884 | 2884 | 2884 | 2884 | 2884 |
| Application Controls | No | No | No | No | Yes |

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

# Appendix A Data Appendix

The analytical data set was created by appending daily reports provided by OYEO 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 "School Year Participant" 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 "School Year Participant" 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 "School Year Participant" 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 OYEO determined that this job posting was created as a means to onboard youth who were continuing employment with a year-round employer partner. We refer to these youth as School Year Participants and 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.

# Appendix B Application Behavior

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. OYEO staff have the ability to move youth applications out of this bin after the applicant change their answers and alert OYEO 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 OYEO 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 in 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 |
|---|---|---|---|---|
| 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) | |
| 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) | |
| 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 | | | |

Note: 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

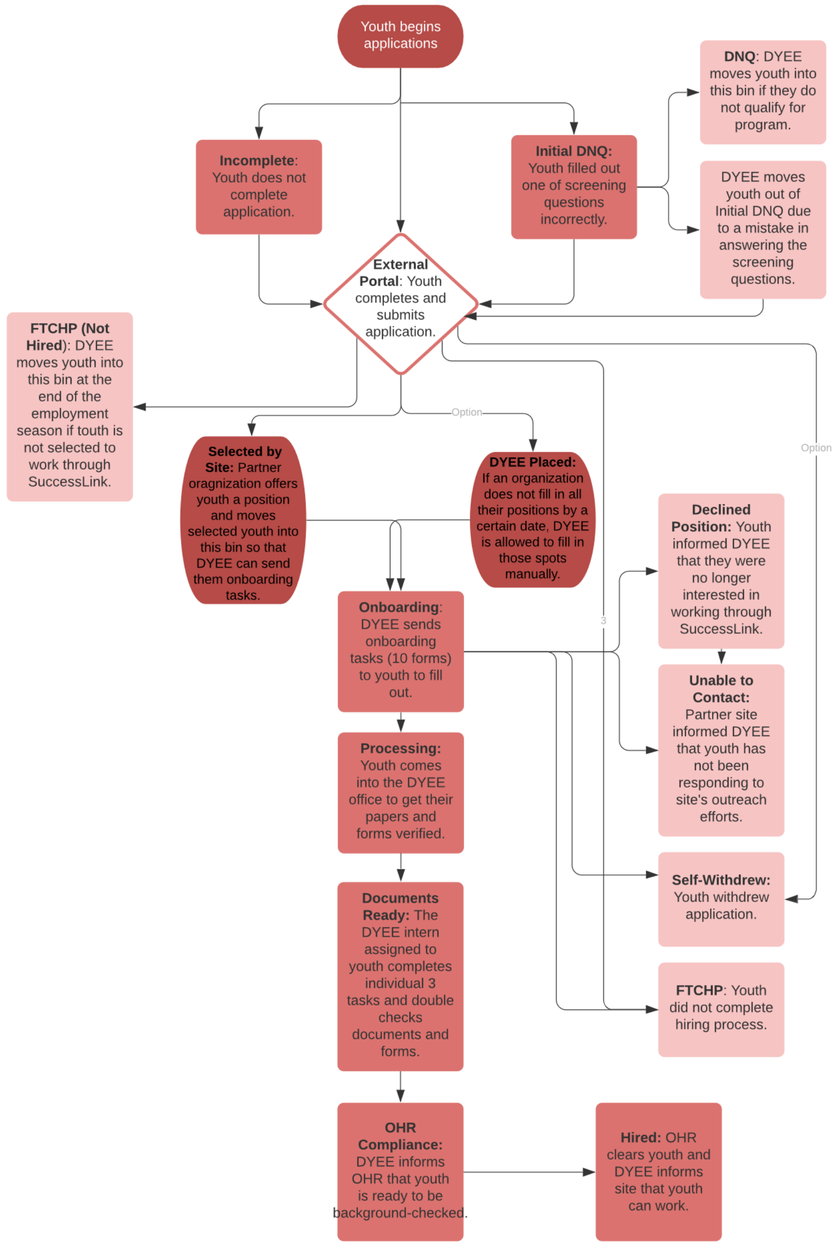
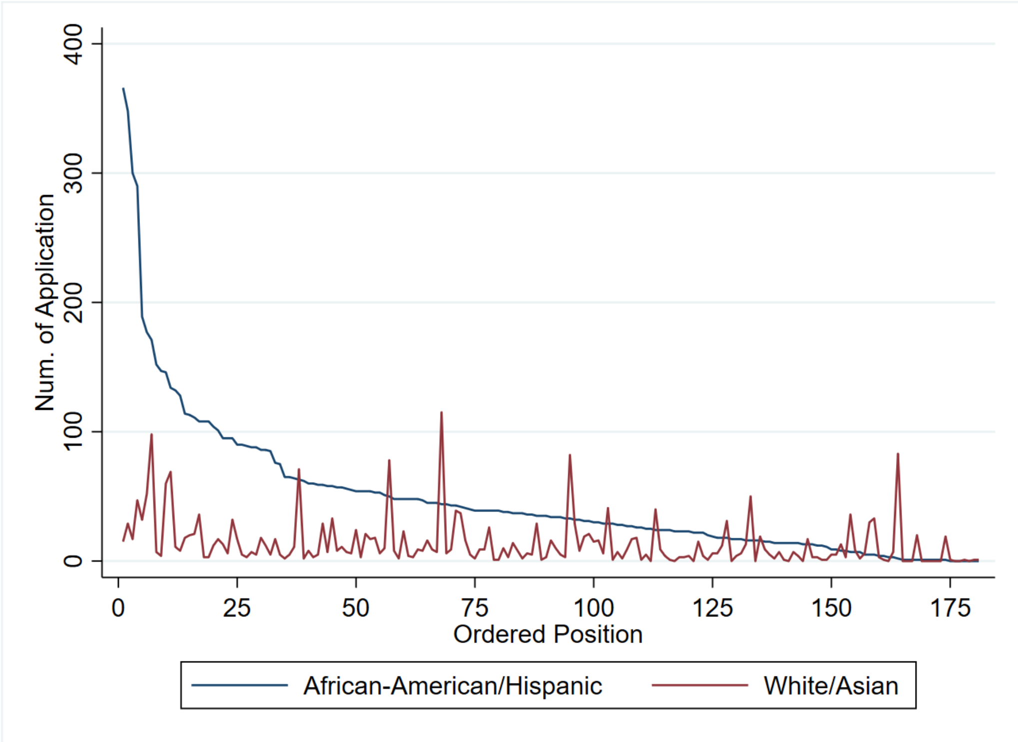


Figure B2: Distribution of Applications by Race




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

# Appendix C Timing of Applications

Table C1: Descriptive Statistics for Youth who Applied in March 2022

| | 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 |
| Prior Summer Participant | 0.33 | 0.471 | 1,038 |
| Number of Applications | 3.67 | 4.482 | 1,038 |
| Avg. # of Other Applications Per Slot | 6.82 | 4.570 | 1,038 |
| Uploaded Resume | 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 OYEO | 0.16 | 0.363 | 1,038 |

Table C2: Descriptive Statistics for Youth who Applied in April 2022

| | 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 |
| Previous Summer Participant | 0.26 | 0.441 | 1,351 |
| Number of Applications | 3.03 | 3.504 | 1,351 |
| Avg. # of Other Applications Per Slot | 6.51 | 3.762 | 1,351 |
| Uploaded Resume | 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 OYEO | 0.17 | 0.379 | 1,351 |

Table C3: Descriptive Statistics for Youth who Applied in May 2022

| | 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 |
| Prior Summer Participant | 0.19 | 0.392 | 867 |
| Number of Applications | 2.73 | 3.397 | 867 |
| Avg. # of Other Applications Per Slot | 5.94 | 3.742 | 867 |
| Uploaded Resume | 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 OYEO | 0.19 | 0.391 | 867 |

Table C4: Descriptive Statistics for Youth who Applied in June 2022

| | 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 |
| Prior Summer Participant | 0.14 | 0.352 | 623 |
| Number of Applications | 0.11 | 0.718 | 623 |
| Avg. # of Other Applications Per Slot | 5.69 | 3.722 | 623 |
| Uploaded Resume | 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 OYEO | 0.31 | 0.463 | 623 |

Table C5: Descriptive Statistics for Youth who Applied in July 2022

| | 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 |
| Prior Summer Participant | 0.13 | 0.334 | 282 |
| Number of Applications | 0 | 0 | 282 |
| Avg. # of Other Applications Per Slot | 4.91 | 3.432 | 282 |
| Uploaded Resume | 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 OYEO | 0.21 | 0.405 | 282 |

# Appendix D Employer Site Selection

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

Table D1 compares the descriptive statistics for youth who were selected versus not selected by an employer. In terms of demographic characteristics, youth who were selected by an employer were on average older, white, male, attended an exam school, and also indicated that they had previously participated in the OYEO program. In contrast, youth who were Black, Hispanic, or fluent in another language and/or did not have English as their first language were less likely to be selected by an employer.

In terms of labor market dynamics, youth who 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. Although youth selected by an employer were less likely to have uploaded resume or answered the open-ended "Why Work" text question, this is likely due to applicants who had a pre-existing relationship with the employer. Howvere, youth with longer text responses to the open-ended question were more likely to get selected by an employer.

Table D1: Descriptive Statistics for Youth Selected versus Not Selected by an Employer

| | Not Selected Mean/Std. Dev. | Selected Mean/Std. Dev. | Diff in Means/ Std.Err. in Diff |
|---|---|---|---|
| Age | 16.45 | 16.84 | -0.39*** |
| | (1.28) | (1.38) | (0.05) |
| African American | 0.49 | 0.42 | 0.070*** |
| | (0.50) | (0.49) | (0.02) |
| White | 0.08 | 0.18 | -0.10*** |
| | (0.26) | (0.38) | (0.01) |
| Hispanic or Latino | 0.27 | 0.21 | 0.06*** |
| | (0.45) | (0.41) | (0.014) |
| Asian | 0.09 | 0.09 | 0.00 |
| | (0.29) | (0.29) | (0.01) |
| Other Race | 0.07 | 0.11 | -0.03** |
| | (0.27) | (0.30) | (0.01) |
| Female | 0.49 | 0.48 | 0.01 |
| | (0.50) | (0.50) | (0.02) |
| Fluent in Another Language | 0.36 | 0.31 | 0.05** |
| | (0.48) | (0.46) | (0.02) |
| First Language English | 0.83 | 0.85 | -0.02 |
| | (0.38) | (0.36) | (0.01) |
| Attends Exam School | 0.17 | 0.26 | -0.09*** |
| | (0.37) | (0.44) | (0.02) |
| Prior Summer Participant | 0.18 | 0.31 | -0.13*** |
| | (0.37) | (0.46) | (0.02) |
| School Year Participant | 0.00 | 0.15 | -0.15*** |
| | (0.00) | (0.34) | (0.01) |
| Number of Applications | 2.46 | 3.34 | -0.88*** |
| | (2.38) | (4.11) | (0.13) |
| Avg. # of Other Apps Per Slot | 13.40 | 6.65 | 6.75*** |
| | (18.99) | (7.48) | (0.41) |
| Earliest App Submitted in March | 0.21 | 0.31 | -0.09*** |
| | (0.41) | (0.46) | (0.02) |
| Earliest App Submitted in April | 0.35 | 0.36 | -0.01 |
| | (0.48) | (0.48) | (0.02) |
| Earliest App Submitted in May | 0.30 | 0.19 | 0.10*** |
| | (0.46) | (0.40) | (0.01) |
| Earliest App Submitted in June | 0.13 | 0.14 | -0.01 |
| | (0.36) | (0.34) | (0.01) |
| Uploaded Resume | 0.58 | 0.51 | 0.07*** |
| | (0.50) | (0.50) | (0.02) |
| Avg. Resume Character Length | 6899.11 | 5493.35 | 1405.76*** |
| | (4318.97) | (3291.96) | (136.51) |
| Avg. Resume Flesch Score | -36.31 | -9.15 | -27.16*** |
| | (46.45) | (42.47) | (1.64) |
| Avg. Work Question Length | 262.46 | 333.67 | -71.21*** |
| | (237.95) | (292.80) | (10.38) |
| Avg. Work Question Flesch Score | 69.14 | 67.91 | 1.23 |
| | (24.97) | (28.58) | (1.03) |
| Observations | 1,267 | 2,495 | |

Note: Column 1 reports the averages for youth who were not selected for employment by at least one employer. Column 2 reports the average for youth who were selected by a employer. Column 3 reports the differences in the reported averages. Column 4 contains the p-value from a two-sampled t-test.

Table D2: 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) |
| Prior Summer Participant | | | | 0.56*** | 0.57*** | 0.42*** |
| | | | | (5.56) | (5.33) | (3.75) |
| Number of Applications | | | | | 0.16*** | 0.16*** |
| | | | | | (10.59) | (10.26) |
| Avg. # of Other Applications Per Slot | | | | | -0.08*** | -0.07*** |
| | | | | | (-11.88) | (-10.99) |
| Uploaded Resume | | | | | | -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 D3: 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) |
| Prior Summer Participant | | | | 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) |
| Uploaded Resume | | | | | | -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.

# Appendix E 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 E1: T-test Between Ford–Fulkerson and Pilot Job Matching Algorithm

| | F F Algorithm Selected Mean | Pilot Algorithm Mean | Difference | p value |
|---|---|---|---|---|
| African American | 0.44 | 0.60 | 0.162 | 0.000 |
| Hispanic or Latino | 0.28 | 0.24 | 0.039 | 0.304 |
| White | 0.09 | 0.02 | 0.069 | 0.001 |
| Asian | 0.09 | 0.07 | 0.012 | 0.600 |
| Other Race | 0.10 | 0.06 | 0.042 | 0.072 |
| Age | 16.52 | 16.84 | 0.315 | 0.003 |
| Female | 0.55 | 0.52 | 0.024 | 0.576 |
| Fluent in Another Language | 0.34 | 0.44 | 0.102 | 0.015 |
| First Language English | 0.83 | 0.85 | 0.025 | 0.437 |
| Attends Exam School | 0.20 | 0.19 | 0.009 | 0.792 |
| Missing School Name | 0.07 | 0.09 | 0.017 | 0.475 |
| Prior Summer Participant | 0.22 | 0.28 | 0.058 | 0.117 |
| Number of Applications | 4.19 | 4.44 | 0.255 | 0.458 |
| Avg Num of Other Apps Per Slot | 10.17 | 9.84 | 0.330 | 0.667 |
| Earliest App Submitted in March | 0.25 | 0.25 | 0.001 | 0.973 |
| Earliest App Submitted in April | 0.38 | 0.40 | 0.021 | 0.616 |
| Earliest App Submitted in May | 0.34 | 0.31 | 0.028 | 0.495 |
| Earliest App Submitted in June | 0.03 | 0.03 | 0.001 | 0.959 |
| Uploaded Resume | 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 selected by the job matching pilot algorithm. Nore than since a youth could have been selected by both algorithms, a subset of youth appears in both samples (119 youth in total).

Table E2: 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 - OYEO | (8) *p-value* |
|---|---|---|---|---|---|---|---|---|
| African American | 0.42 | 0.51 | 0.63 | 0.54 | 0.43 | 0.44 | -0.121 | 0.0000 |
| | (0.493) | (0.500) | (0.486) | (0.499) | (0.496) | (0.496) | (0.023) | |
| Hispanic or Latino | 0.21 | 0.23 | 0.19 | 0.22 | 0.21 | 0.23 | -0.013 | 0.4895 |
| | (0.404) | (0.420) | (0.392) | (0.414) | (0.407) | (0.419) | (0.019) | |
| White | 0.18 | 0.093 | 0.047 | 0.083 | 0.17 | 0.15 | 0.099 | 0.0000 |
| | (0.386) | (0.291) | (0.212) | (0.277) | (0.375) | (0.355) | (0.018) | |
| Asian | 0.091 | 0.093 | 0.047 | 0.083 | 0.089 | 0.091 | 0.007 | 0.5924 |
| | (0.287) | (0.291) | (0.212) | (0.277) | (0.285) | (0.288) | (0.014) | |
| Other Race | 0.11 | 0.071 | 0.094 | 0.078 | 0.098 | 0.095 | 0.028 | 0.0498 |
| | (0.308) | (0.258) | (0.293) | (0.268) | (0.298) | (0.293) | (0.014) | |
| Age | 16.8 | 16.8 | 16.3 | 16.7 | 16.8 | 16.7 | 0.176 | 0.0068 |
| | (1.392) | (1.185) | (1.228) | (1.210) | (1.372) | (1.366) | (0.065) | |
| Female | 0.48 | 0.49 | 0.47 | 0.49 | 0.48 | 0.49 | -0.006 | 0.8110 |
| | (0.500) | (0.501) | (0.501) | (0.500) | (0.500) | (0.500) | (0.024) | |
| Attends Exam School | 0.26 | 0.23 | 0.20 | 0.23 | 0.25 | 0.23 | 0.030 | 0.1656 |
| | (0.437) | (0.422) | (0.402) | (0.420) | (0.434) | (0.420) | (0.022) | |
| Fluent in Another Language | 0.31 | 0.34 | 0.30 | 0.33 | 0.31 | 0.33 | -0.019 | 0.3932 |
| | (0.462) | (0.474) | (0.459) | (0.470) | (0.464) | (0.469) | (0.022) | |
| Number of Applications | 3.34 | 4.33 | 5.65 | 4.62 | 3.37 | 3.04 | -1.278 | 0.0000 |
| | (4.191) | (3.604) | (6.364) | (4.442) | (4.101) | (3.744) | (0.201) | |
| Avg Num. of Other Apps Per Slot | 6.65 | 9.54 | 9.66 | 9.55 | 7.07 | 8.92 | -2.899 | 0.0000 |
| | (7.163) | (8.999) | (7.307) | (8.678) | (7.565) | (12.32) | (0.354) | |
| Earliest App Submitted in March | 0.31 | 0.28 | 0.25 | 0.27 | 0.29 | 0.28 | 0.036 | 0.0972 |
| | (0.462) | (0.449) | (0.434) | (0.445) | (0.455) | (0.447) | (0.022) | |
| Earliest App Submitted in April | 0.36 | 0.41 | 0.32 | 0.39 | 0.36 | 0.36 | -0.034 | 0.1369 |
| | (0.479) | (0.493) | (0.467) | (0.489) | (0.481) | (0.479) | (0.023) | |
| Earliest App Submitted in May | 0.19 | 0.26 | 0.24 | 0.25 | 0.21 | 0.23 | -0.060 | 0.0018 |
| | (0.395) | (0.439) | (0.429) | (0.435) | (0.405) | (0.420) | (0.019) | |
| Earliest App Submitted in June | 0.14 | 0.048 | 0.19 | 0.083 | 0.14 | 0.14 | 0.058 | 0.0003 |
| | (0.348) | (0.213) | (0.397) | (0.276) | (0.342) | (0.346) | (0.016) | |
| Uploaded Resume | 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 | | |

# Appendix F 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 F1 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 F1: 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 |
|---|---|---|---|---|
| African American | 0.49 | 0.41 | 0.080 | 0.0001 |
| | 812 | 2,071 | (0.020) | |
| Hispanic or Latino | 0.29 | 0.18 | 0.107 | 0.0000 |
| | 812 | 2,071 | (0.017) | |
| White | 0.08 | 0.20 | -0.122 | 0.0000 |
| | 812 | 2,071 | (0.015) | |
| 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) | |
| Age | 16.68 | 16.87 | -0.192 | 0.0008 |
| | 801 | 2,062 | (0.057) | |
| 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) | |
| Prior Summer Participant | 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) | |
| Uploaded Resume | 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 | | |

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.