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AN EXAMINATION INTO TEACHER HIRING: PREFERNCES, EFFICIENCY, STABILITY, AND STUDENT OUTCOMES

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ABSTRACT

AN EXAMINATION INTO TEACHER HIRING: PREFERNCES, EFFICIENCY, STABILITY, AND STUDENT OUTCOMES

BY

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Committee Chair: Dr. Tim Sass
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This dissertation studies teacher hiring practices, an avenue to potentially raise teacher quality which has not been studied extensively. I analyze three aspects of the teacher hiring process, which, if improved, could promote education quality: the principal hiring decision, the teacher application decision, and the effects of information on teacher behavior and market outcomes in the teacher labor market. The first two are empirical studies utilizing administrative data from an urban school district, and the last is a laboratory experiment.

Education is a labor focused enterprise where outcomes are largely determined by teacher quality, so hiring the most productive teachers is paramount. Hiring is even more important given that teaching is a high-turnover profession, thus hiring occurs frequently. I first compare the elements of a teacher's application that predict principal hiring decisions to those predicting teacher performance and retention outcomes. Similar to other recent work, I find disparities between the two sets of predictors. I utilize additional methods to study the relation of the size and quality of the applicant pool, as well as how those factors relate to the quality of the selected candidate. The results indicate that the applicant pools do not systematically vary by school characteristics in an obvious manner. Also, while the quality of the candidate pool may influence principal hiring decisions, it is not the dominate factor.

Given that teaching sorting across schools occurs in the new-teacher labor market (Sass, et al. 2012) and in post-hire differential patterns of teacher mobility,[1] which in turn create disparities in access to effective teachers, it is important to understand the mechanisms that lead to teacher sorting across schools. In chapter 2, I study how teacher application behavior reveals teacher preferences over schools. The preferences can lead to differences in application pools, thereby affecting principals' ability to hire quality candidates. I find that the application decisions of new-to-the-district candidates may be affected by accountability pressures or the resource level in high-needs schools, but current teachers' revealed preferences agree with those previously found in the research literature.

It has also been found that a teacher's compatibility with a school can affect their ability to improve student outcomes and their own satisfaction (which decreases mobility, thereby increasing experience and decreasing turnover costs). In my third chapter, I use a laboratory experiment to examine teacher and school behavior and their effects on outcomes in a controlled setting while varying the preference structure of the market and the information agents have on competitors' actions. I find that information on competitor behavior affects signaling behavior and the market efficiency and payoffs, but that these effects are dependent on the preference structure. I also find that the preference structure affects the stability of the matches.

[1] Darling-Hammond, 2001; Viadero, 2002; Gordon & Maxey, 2000; Goldhaber et al., 2007; Feng & Sass, 2017

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KATHERINE ANN STEWART

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Dedication

I dedicate my dissertation to my family and friends. My parents, John and Gay Stewart, and sister, Bernadette Stewart, supported me emotionally and physically to complete the program with a wealth of humor and care. Many friends supported me to completing this dissertation and program, but a special thanks must be given to Alicia Plemmons who was ready to edit a paper if needed and always gave me an ear for my emotional wellbeing and research planning.

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Introduction

There are many possible avenues for improving teacher quality, including pre-service training, professional development, performance-based compensation, and selective retention. While these mechanisms have been studied extensively, until recently there has been little attention paid to another potentially efficient means of raising teacher quality: improving the system for selecting and hiring teachers. In this dissertation, I research three aspects of teacher hiring that could be adjusted to promote education quality, if they were better understood. The first chapter examines how principals make hiring decisions. The second chapter uses teacher job applications as a tool to understand teacher preferences over place of employment. These chapters are both empirical works applicant and employment data for an Atlanta metropolitan area school district. The third chapter utilizes a lab experiment designed to provide preliminary evidence regarding the effects of information on competitor behavior in a school district's hiring process on signaling investment and the match outcomes between schools and teachers.

In the first chapter, I investigate principals' decisions during the hiring process. Hiring the most productive workers is paramount in service sectors where human resources are the primary input. This is particularly true in education, where teachers are the most important factor in promoting student achievement and turnover is considerable, which in turn leads to substantial hiring on a persistent basis. I study the hiring decisions of principals using data on applicants for teaching positions in a mid-sized urban school district. I compare characteristics of teaching candidates that are associated with a higher likelihood of receiving a job offer with those that enhance productivity as a teacher. Similar to other recent work, I find multiple instances where the factors driving hiring decisions do not align with the factors associated with teacher productivity. Other studies infer this misalignment is due to a lack of information or incorrect choices on the part of principals and suggest an appropriate policy response would be to provide better information to principals or to reduce principal discretion and centralize hiring decisions. In contrast, I account for the fact that work environments differ across schools and thus different principals face de-facto different pools of teaching candidates. I find that the quality of the pool may affect principal decisions, but that the pool does not systematically vary by school characteristics within the system in an obvious manner.

In the second chapter, I study how differences in teacher preferences can affect the variation in makeup of the applicant pool across schools. Given the importance of teachers in determining student outcomes, policymakers are concerned that teacher sorting across schools may limit access to high-quality teachers for minority, impoverished, or low-performing students. Teacher sorting may occur in the new teacher labor market (Sass, et al. 2012) as well as through post-hire differential patterns of teacher mobility.[2] It is possible that disparities in access to high-quality teachers can be mitigated by targeted hiring and retention policies.[3] I restructure the data used in Chapter 1 to represent the choice set of the teachers. I implement a conditional logistic model to estimate the impacts of school characteristics on prospective and current teachers' application likelihoods. I find evidence that the applicants who are new to the district may be attracted to high-needs schools which may have greater resources. However, the application probabilities of current teachers coincide with the findings of prior research.

Outside of a teachers' baseline ability, their school compatibility (Jackson 2013) and experience[4] also affects their ability to improve student outcomes. Teacher satisfaction within a

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[2] Darling-Hammond 2001; Viadero 2002; Gordon and Maxey 2000; Goldhaber, Gross, and Player 2007; Feng and Sass 2017
[3] Adnot, Dee, Katz, and Wycoff 2017
[4] Chingos and Peterson 2011; Staiger and Rockoff 2010; Rivkin, Hanushek, and Kane 2005; Clotfelter, Ladd, and Vigdor 2006; Dobbie 2011; Wiswall 2013; Papay and Kraft 2015; Rockoff 2004

school leads to prolonged tenure, which naturally increases experience. Extending the length of time a teacher remains in a school also decreases the pecuniary and non-pecuniary turnover costs to schools.[5] Therefore, in attempting to provide quality education, it is imperative to understand how the hiring process affects teacher-school matches. My third chapter utilizes a laboratory experiment to examine teacher and school behavior. This is a simplified teacher labor market modeled through a two-sided matching markets framework. I introduce information asymmetry by making teacher quality unknown to employers. Teachers then signal their quality through a costly signal, either simultaneously or sequentially, where later applicants observe prior signaling investment amounts. In addition, I examine two preferences rankings to ensure the effects found are not driven by the enforced preferences. The matching procedure School Hiring (SH), designed by mimicking a current hiring policy of a metropolitan Atlanta school district hiring process, is very similar to the Priority (Boston) matching procedure. I find that the effects of participants having additional information on competitor investment amounts and participant payoffs are dependent on the structure of the preferences, In addition, the information treatment decreases the portion of the time that investments are type revealing. The market stability is unaffected by the information treatment, but is higher when the preferences of participating agents are homogenous.

[5] Milanowski and Odden 2007; Guin 2004

1 Missed Opportunities or Making the Best of Bad Situations? Principal Selection of Teacher Applicants

1.1 Introduction

Creating the best match between employees and employers has long been shown to improve productivity, satisfaction, and employee tenure (Liu & Johnson, 2006; Koch & McGrath, 1996). To create successful matches, both job seekers and firms must gather information regarding their counterparts in order to choose an optimal employment match. However, existing research regarding employers' search for employees is somewhat limited, particularly regarding the reasons and beliefs informing hiring decisions in the public sector.

This paper examines employer search in the context of the public school teacher labor market in a mid-size urban school district. As the teaching profession is one wherein the quality of workers substantially affects the benefits accrued by their students, both short-run academic achievement and labor market outcomes as adults, the characteristics of the labor market are of considerable policy importance (Rivkin, Hanushek, & Kain, 2005; Aaronson, Barrow, & Sander, 2007; Kane, Rockoff, & Staiger, 2008; Chetty et al., 2011; Chetty, Friedman, & Rockoff, 2014). Given that researchers have demonstrated the ability of careful hiring to improve the average worker's productivity in several professions, and that teaching is a profession with substantial amounts of employee turnover (Darling-Hammond, 2001; Viadero, 2002) and, therefore, persistent hiring, improving the teacher-hiring process could significantly impact the quality of employees in this field. Compared to other school-based methods used to improve teacher performance (performance pay, selective retention, and professional development) employing hiring as a policy lever to promote performance has potential advantages, such as fewer implementation barriers or being more cost effective.

Furthermore, preventing sub-par teacher hires is crucial as there are significant barriers to removing low-performing teachers (Griffith & McDougald, 2016; Painter, 2000; Levin et al., Schunck, 2005), and those students taught by the low-performing teachers are permanently affected by their teachers' relative lack of performance quality. Studying the teacher labor market is also particularly advantageous for research on employer search, as schools collect productivity measures of those hired so that the quality of the employer's choice can be evaluated.

There are constraints on a principal's ability to hire the best teacher; these barriers, if acknowledged, could potentially be circumvented in order to ultimately improve hiring outcomes. For example, the hiring process may not provide enough information for principals to identify superior teachers (Liu & Johnson, 2006; Donaldson, 2013; Neild et al., 2003; DeArmond et al., 2010; Bruno & Strunk, 2019; Jacob et al., 2018), or the principals may not use the information they have (Jacob et al., 2018; Bruno & Strunk, 2019). A principal could be too inexperienced with the hiring process to successfully find and hire the best candidate (Loeb et al., 2012; Dipboy & Jackson, 1999). In addition, teacher salary schedules are often fixed, so superior teachers may seek higher paying employment in other fields or districts (Imazeki, 2005; Feng, 2014; Feng, 2009). Procedural barriers also exist that may inhibit a principal's ability to hire superior teacher candidates: late leave notices, insufficient human resources staff, and delays associated with collective bargaining and belated budgets (e.g. Levin & Quinn, 2003; Liu et al., 2008; Strunk et al., 2018; Levin et al., 2005; Odden & Kelley, 2008; Campbell et al., 2004; Bassi & McMurrer, 2007; Flandez, 2009; Grensing-Pophal, 2017; Ryan et al., 2000; Converse et al., 2004). In addition to these constraints, principals also work in a non-profit sector so they may make choices to maximize their own utility rather that to maximize educational output, such as selecting teachers with amenable personalities regardless of quality.

Jacob et al. (2018) and Bruno and Strunk (2019) study principal hiring choices in Washington, DC and Los Angeles, CA, respectively. The two papers employ a similar strategy; they use pooled district-wide data to estimate both the relationship between candidate characteristics and the likelihood of being hired and the relationship between candidate characteristics and subsequent teacher performance. They then compare the factors that are correlated with hiring and the factors that are associated with teacher performance. These two papers find that some candidate information and hiring procedures correlate with teacher performance; however, discrepancies between the predictors of principal hiring decisions and the predictors of teacher performance suggest that principals may not be making the best hiring decisions and thus there may be room for improvement in the teacher hiring process.

The use of pooled district-wide data in previous studies to compare the factors driving hiring decisions with those determining teacher performance appear to be a function of data availability. In the case of the District of Columbia Public Schools (DCPS), prospective teachers could apply for a recommendation through a centralized process called TeachDC, or they could apply directly to a school. During the period studied by Jacob, et al. (2011-2013), about half of new hires came from candidates in the TeachDC system. Jacob and co-authors only had access to applications submitted through TeachDC and could not observe candidates who applied directly to individual schools. They examined the relationship between scores on the components of the recommendation, as well as getting recommended, on the probability of being hired and eventual performance as a teacher. In the Los Angeles Unified School District (LAUSD), all applications for teaching were submitted through a centralized application system.

Neither Jacob et al. or Bruno and Strunk indicate that applicants to the centralized system could indicate preferences for a particular school or schools. Yet both papers make clear that no matter how applications were initially received, hiring decisions were decentralized. In both DCPS and LAUSD, principals or other site administrators decided which candidates would be offered a teaching position.

Pooling data across schools makes the implicit assumption that every principal within a given district has access to the same teacher applicant pool and that candidates have no outside options. Even though all teachers who meet the district standards might be in a single "available" pool (as in LAUSD), the de-facto applicant pool could be still vary widely between schools, based on teacher preferences and opportunity costs. In this paper I consider not only the district-wide pool of prospective teachers, but also the pool of candidates who apply for a position at a particular school.

This research delves into factors that may lead an apparent discrepancy between the candidate who is expected to be the most effective teacher and the candidate actually selected by the principal, previously interpreted as principals making poor hiring decisions. Each possible factor has a significantly different policy implication, which will be included in the policy discussion section. Principals must compete against each other in order to hire quality candidates, which causes principals to be uncertain of being able to successfully hire a candidate. Aspects of this competition between principals, such as attractiveness of one's position and the loss of potential alternate candidates while waiting for the outcome of an extant offer, means principals may make strategic selections regarding which candidate to attempt to hire.

As this research seeks to go beyond prior district-wide analyses, I first establish that there are differences between the hiring and performance predictions for the studied school district as a whole, in similar manner as the prior work by Jacob et al. and Bruno and Strunk. In contrast to prior work, which measures actual hires, I consider the earlier decision of initiating a request to offer a position to a candidate. This change in approach allows the choices of the teacher and the district to be disentangled from the decisions of the principal. Jacob et al. also examined offer choices briefly, but found it had few differences from hires and thus did not examine the decision closely. In addition to disentangling the applicant choice like the offer does, the hiring request decision also precludes the district rejecting the principal's choice.

I also analyze the systemic variation in the applicant pool and how this variation may affect the relationship between characteristics of the candidate pool and the selected candidate, while controlling for position, school, and principal characteristics. Given that college GPA predicts multiple measures of teacher performance in my teacher quality estimations, I use it as my measure of candidate quality.[6] Then I directly estimate the relationship between pool characteristics and selected teacher candidate quality. Since the applicant pool may affect the principals' decisions, I then use conditional logistic specifications to estimate the principals' hiring decisions in the context of the pools of applicants available to them.

When I follow the approach of prior researchers and pool all candidates districtwide, I find that principals over-select transfer candidates as well as those candidates with education majors or teaching certification, while also under-selecting candidates with high college GPAs and those who on average apply quickly after the position is posted. As GPA is a non-malleable characteristic of job candidates that seems to be indicative of superior teacher performance on several measures, it is a good candidate for use in a screening policy based on these initial

[6] This is a strong assumption but characterizing teacher quality has always been difficult. In my analysis of the relationship between candidate characteristics and teacher performance, college GPA is the most consistent statistically significant predictor.

results. However, when examining how the characteristics contextualizing the hiring decision (the school, the principal, the subject, the applicant pool) relate to the college GPA of the selected, I find that schools with better and larger applicant pools select candidates with higher college GPAs. This result suggests that variation in principals' offer decisions could be driven in part by differences between applicant pools.

Furthermore, when controlling for different applicant pools using conditional logistic regression, I find that teaching certification, education majors (for only the new sample), and finding a job through another district employee, no longer affect hiring-request decisions, and thus no longer present a contradiction between their estimated impacts on hiring requests and performance indicators. This finding suggests that a portion of the apparent mismatch is due to assuming that all principals within a district face the same applicant pool. However, these results may be the result of statistical noise.

This research contributes to the employer search literature through additional empirical analysis of employer decision-making when applicant pools are endogenous and hiring managers compete for quality applicants. In addition, this research focuses on identifying why a principal might select candidates who do not appear to the best qualified, while previous research on principal hiring decisions implicitly assumes the selection and performance misalignment results entirely from the principal's lack of information or poor choices. Finally, rather than measure employment outcomes, which are a function of both employment offers and candidate acceptances, this research analyzes principals' hiring requests, data on which have not previously been available. The advantage of this approach is that it isolates employer decision making, whereas employment outcomes are a function of employer (principal), organization (district), and candidate decisions.

1.**2 Literature Review**

As this paper studies factors which can influence hiring decisions, the literature review discusses the existing relevant research regarding the decisions hiring managers make and various aspects of the hiring process. This includes a brief review of the employer search literature. Then the research on how hiring manager choices are affected by the uncertainty over a candidate's commitment to the firm (either prospective tenure or willingness to accept an offer) and competition over quality candidates. In addition, the research on how applicant pools can differ will be reviewed. This section will finish with a discussion of the existing research on the information that influences hiring managers' decisions and the prior findings on how principals use information, as well as my contributions to these research areas.

Most of the empirical employer search literature has focused on vacancy duration (e.g., Andrews et al., 2008; van Ours & Ridder. 1991; Barron et al., 1987; Gorter et al. 1996) or recruitment and screening methods (e.g. Murphy, 1986; Barron et al. 1985; Holzer, 1987; Russo et al., 2000; DeVaro, 2005; Hoffman, et al., 2018; Burks, et al. 2015; Barling et al. 2009). Much of the research on employer candidate selection has been theoretical or experimental, especially in situations where employers compete for high-quality candidates, and each firm has an endogenous sets of applicants (Spence 1973; Immorlica et al., 2006; Vanderbei 2012; Abdulkadiroğlu & Sönmez, 2003; Abdulkadiroğlu et al., 2005; Ergin & Sönmez, 2006; Chen & Sönmez, 2006; Galperin et al., 2019). Outside of studying employee referrals, there has been relatively little empirical analysis of the reasoning firms use to select a given candidate (Coles et al., 2010; Fahr & Sunde, 2001).

To understand how a hiring manager's perceptions of a candidate's commitment to a firm affect hiring decisions, Galperin et al. (2019) conducted an online experiment. They find that hiring managers trade some amount of candidate capability for perceived organizational commitment. Commitment takes the form of valuing the firm more or staying with the firm longer. They did not find evidence that the choice of candidate was affected by the manager's beliefs regarding offer acceptance.

Although a candidate's probability of accepting an offer had no effect on the hiring managers' decisions in Galperin et al. (2019), its affects have been shown in other hiring situations. In theoretical labor markets covered under the umbrella of "Secretary Games," employers compete against each other for high-quality candidates. The research in this area finds that competition results in earlier offers, and can also lead to the use of "exploding offers" (offers that candidates are given a short time frame to consider) in order to pressure better candidates to accept (Immorlica et al., 2006; Vanderbei 2012; Fahr & Sunde 2001).

The literature on how to match two pools of people, such as matching employers to employees, called the Matching Markets literature, shows several circumstances where a participant may not choose their top candidate as part of a strategic choice. In particular, hiring managers have a rank-ordered list of candidates regarding quality; however, each candidate also has an acceptance probability. Hiring managers may issue offers to candidates lower on the quality ranking who have higher acceptance probabilities to minimize the risk of losing certain employee candidates.

A set of studies that analyze how Boston public schools matched students to schools demonstrates strategic selection in a matching market. Students were assigned a school at which they had priority acceptance and were then asked to rank all the schools according to where they would most like to attend. Students who strategically ranked their schools (listed the best schools they could enter first) got into better schools compared to those who ranked schools strictly according to where they would prefer to attend (Abdulkadiroğlu & Sönmez, 2003; Abdulkadiroğlu et al., 2005; Ergin & Sönmez, 2006; Chen & Sönmez, 2006).

In the economics academic job market, a similar phenomenon happens. Employee candidates apply to a large number of positions, but universities have a limited number of interview slots. The universities could easily fill all their interview slots with top candidates, but these top candidates have low chances of accepting if they are eventually given an offer. So the universities act strategically and assign some of their interview spots to less appealing candidates who have a higher likelihood of later accepting an offer (Coles et al., 2010).

Employer search is partially a function of the pool of candidates who applied to the job. A firm cannot select the best candidate if the candidate never applies. However, applicant pools can endogenously vary between jobs and locations. For example, Manning (2000) found that pecuniary and non-pecuniary aspects of the job affect the number of applicants to a vacancy for low-wage jobs. For teachers trying to match to jobs, Boyd et al. (2013) finds teachers strongly prefer certain non-pecuniary aspects of schools, including location and student demographics. These teacher preferences can cause considerable variations among schools in the pools of applicants they select from. A great deal of additional research demonstrates that the preferences of already-employed teachers are consistent with the applicants' preferences found in Boyd et al. (2013) (e.g. Sass et al., 2012; Levin & Quinn, 2003; Liu et al., 2008; Hanushek & Rivkin, 2007; Boyd et al., 2011; Lankford et al., 2002; Imazeki, 2005; Scafidi et al., 2007).

In addition to the external factors in hiring, hiring managers must also be able to discern candidate quality using the information they gather. Hiring managers have access to candidate-supplied information from applications and resumes. The hiring managers may also gather information through their professional networks and by conducting candidate interviews. This private information is the most interesting and also the most troublesome. The sheer amount of research on the importance of the interview to information gathering and decision-making is staggering. This voluminous research points yields two broad conclusions. First, the interview is heavily relied on by hiring managers (e.g. Rutledge et al., 2008; Schmidt & Hunter, 1998). Second, hiring managers who ignore firm-based screens of candidates in favor of their interview results often hire lower performing candidates (Dipboye & Jackson, 1999; Hoffman et al., 2018). This reliance on interviews is often explained as the hiring manager being biased or mistaken in their information usage. Another source of private information is a hiring manger's professional network. This informal information gathering is hard to capture, so the research has mainly focused on employee referrals. Several studies find that hiring managers use referrals to decrease the uncertainty regarding the candidate's acceptance of a job offer and tenure with the firm (Dustmann et al., 2016; Burks et al., 2015).

Two papers have examined how principal information usage in the hiring decisions compares to the information related to teacher quality, Jacob et al. (2018) and Bruno and Strunk (2019). Jacob et al. (2018), studies the effects of Washington DC Public School's 2011 implementation of a recommendation process. Teacher candidates participated voluntarily, and those who took part completed several screens (e.g., interviews, sample lessons, and written assessments). Then a recommended list containing candidates who passed every screen was distributed to principals, as was all the information gathered during the process. The authors find that while principals use the recommendation in their hiring decisions, they do not use the component scores that determine recommendation status. They also find that the candidate characteristics that are correlated with teacher performance are not the same characteristics as those that are associated with principal hiring decisions. In some cases characteristics that are positively associated with better teacher performance (e.g. SAT scores and college GPAs) are actually negatively correlated with the probability of being hired. These results suggest that principals undervalue some attributes that are indicative of superior teacher performance. If true, this suggests that modifying the selection process could improve the average quality of hired teachers.

Bruno and Strunk (2019) analyzes the teacher hiring process in the Los Angeles Unified School District. The researchers find that the overall score on a multi-component screening system predicts principal hiring decisions, teacher attendance, teacher impact on student test scores, and teacher evaluation scores, but not teacher retention within the district. However, the way individual components of the screening system correlate with the teacher quality measures varies considerably, highlighting the potential multi-dimensionality of teacher quality. Bruno and Strunk find that the adoption of the screening system as a whole improves teacher quality in the district relative to the average quality of teachers in similar districts. They also find that while the scores on screens are predictive of some teacher outcomes, they are not strongly correlated with hiring decisions, echoing the findings in Jacob et al. (2018).

This paper expands on the extant hiring research in several ways. Few researchers have had access to all job applications, hiring requests, and performance outcomes of hired workers, particularly for public-sector occupations. This paper, using unique data, adds to the empirical research on employer search and decision making under competition with endogenous applicant pools. The previous principal hiring-decision research established that there is misalignment between statistical predictors of principal hiring choices and teacher performance at the district level (Jacob et al., 2018; Bruno & Strunk, 2019). The current paper seeks to understand why these misalignments may occur and determine if they are they are the result of poor decisions by principals. First, I will determine if the districtwide misalignments uncovered in Los Angeles and Washington, DC also occur in the district I study. Second, I will investigate whether there is significant variation in the pools of candidates that schools attract and whether the misalignment between candidate characteristics that are associated with teacher quality and the traits that predict whether a principal makes a request to hire a candidate continue to appear when comparisons are made at the school level rather than at the district level.

1.3 The Studied School District

1.3.1 The School District's Hiring Process

For the past several years, the studied school district, located in the Atlanta metropolitan-area, implemented a series of changes intended to improve the teacher hiring process. Before these changes, teacher candidates would apply online to the district for open positions, and then the district simply conducted a background and credential check before posting a candidate's information to a hiring portal that is accessible to principals. In December 2015, the district initiated the use of the GALLUP TeacherInsight exam, which was meant to check the candidate's compatibility with the school district. The Human Resources (HR) department set 70 out of 100 to be a passing score on the GALLUP assessment and encouraged principals to hire candidates with a passing score. Initially, however, candidates were not required to complete the test to be considered for a position, and principals did not have to limit their selection to candidates with a passing score. In January 2019, passing the test became a requirement to enter the teacher candidate pool.

In January 2017, following a pilot period, the district introduced a video interview tool, HireVue. Candidates were not required to submit a video, and completing a HireVue interview continues to be voluntary. Beginning the next year, in 2018, a group of 24 trained teacher-leaders started scoring the video interviews on a five-point scale, though the scoring was only for candidates applying before the end of May. The HR Department then posts both the video and the accompanying score to the hiring portal. Principals were encouraged to select candidates with a score of three or above. The present analysis does not include the HireVue scores due to the limited number currently available.

The principals may interview any qualified candidate once the applicant's information is posted to the hiring portal. They are able to view the candidate information for any applicant to the school system though they can also filter their views to only those candidates who applied to their school. However, before starting the process to hire a candidate, the principal must have the candidate submit a school-specific application if they had not already done so (candidates can initially apply to generic openings, like “middle school math teacher”). The vast majority of candidates did apply prior to their selection for a hiring request. Once the principal has selected a candidate, they then send an official request to HR to hire the candidate. If HR approves the request, they issue a formal offer to the applicant. The applicant is then free to accept or reject the offer. There is no official limit on the number of days a candidate can take to respond; however, principals can withdraw the offer.

In addition to the implementation of new screeners, the district also adjusted the requirements, the content, or both the content and requirements of several questions in the teacher candidate application in January 2019. These changes were done based on recommendations from the Metropolitan Atlanta Policy Lab for Education research team. All changes were designed to improve the information available to principals and improve the quality of data for future research.

1.3.2 Measures of Teacher Quality

Evaluating the efficacy of the principal's ability to identify and select quality teachers during the teacher hiring process requires a measure of teacher quality. Since there is no consensus on an ideal teacher quality metric, I utilize several measures, including official teacher evaluations scores, student growth percentiles (SGPs), a teacher's continued employment in their initial school or the district, and the percent of the year the teacher is present or in staff development. Because SGPs are only calculated for teachers in tested grades and subjects, the sample size for analyzing the relation between candidate characteristics and Mean Student Growth Percentile is relatively small; results should be considered in the context of this limitation. For simplicity, the phrase "teacher quality" refers to these measures as a whole.

The official teacher evaluation system in Georgia is the Teacher Keys Evaluation System (TKES). The TKES score is comprised of several components. The first component is the teacher's median SGP score, when available, and the mean SGP score for the school when a teacher's subject is not tested. SGPs measure the year-to-year growth in student achievement relative to that of students with similar prior test scores. The other two components are an evaluation of how the teacher followed their prescribed teacher growth plan and the teacher's score on a set of classroom observations from a credentialed evaluator, generally the principal.

The remaining measures have a less direct connection to student outcomes, and all represent a type of persistence in the school. A teacher staying in the school or district is beneficial as it prevents the costs of teacher departure (Milanowski & Odden, 2007) and mechanically increases teacher experience, which has been shown to improve student outcomes (Chingos & Peterson, 2011; Staiger & Rockoff, 2010; Rivkin, et al., 2005; Clotfelter, Ladd, & Vigdor, 2006; Dobbie, 2001; Wiswall, 2013; Papay & Kraft, 2015; Rockoff, 2004). All else equal among candidates, teachers with high rates of absenteeism are less desirable. This is because teacher absences are disruptive to student learning and require that the absent teacher is temporarily replaced with an often-less-effective substitute teacher, which can be a time consuming and costly process. The negative effect of teacher absenteeism on students has been documented in Miller et al. (2008), Coltfelter et al. (2009), and Gershenson (2016), and been shown to particularly affect schools serving primarily disadvantaged students. For this research, teacher attendance is defined as the portion of contractual employment days a teacher is present or in staff development.

1.3.3 The Data

The Metropolitan Atlanta Policy Lab for Education (MAPLE) provided the data for this research. MAPLE has a data-sharing agreement in place with five partner school districts in the Atlanta Metro Area. For this project, the researcher was allowed access to student performance, demographics, attendance, and discipline records, teacher attendance, employment, and evaluation records, and principal employment and evaluation records for school years 2015/16, 2016/17, and 2017/18. In addition, the studied district provided rich application and hiring decision data for the period between December 2015 and May 2018, which includes the bulk of hiring for school years 2016/17 through 2018/19. All applications were shared with the researcher, not just those selected for a hiring request or subsequent hires. The candidate information recorded in the applications includes their education, work history, student teaching experience, certification status, address, and scores on the district screening tools. Also, I further confirmed previous work experience within the district using the basic personnel files of the studied district for school years 1999-2000 through 2017-2018.

1.3.4 The Analysis Sample

The underlying supply and demand for teachers can vary across subject areas. For example, special education, secondary math and science, and foreign languages are typically considered “hard-to-staff” areas (Feng & Sass, 2017). Also, teachers may be hired for their ability to coach a sports team, rather than for their instructional skills in academic subjects. To minimize issues related to specialized positions while maintaining statistical power, the research removes any candidates who only applied to physical education, career, technical, and agricultural education, gifted education, foreign languages, special education, art, or remediation positions from the sample.

In each year, the district employs close to 4000 teachers and must fill approximately 600 open teaching positions, including roughly 150 that are filled by internal hires. These openings together attract approximately 7000 unique candidates. This number includes many candidates who do not complete their applications and many who submit multiple applications. For the analysis of hiring decision misalignment with teacher performance, following Bruno and Strunk (2019) and Jacob et al. (2018), each applicant has one observation per year they applied. Each observation consists of the candidate’s characteristics, the subjects,[7] and school levels the candidate applied to, their number of applications, and whether they were requested for hire. Then for all those hired, the observation also includes the candidate’s performance data, the characteristics of the principal who oversaw the candidate during their school year of employment, and some attributes of the school at which the candidate taught. These elements are also included when examining other factors that lead to the observed differences between the hiring and performance predictions. The sample consists of observations at the

[7] General Elementary, Math, Science, ELA, and Social Studies

applicant/school/subject level/year level (e.g. a person who applies to middle-school math positions in schools A and B and to middle-school science positions at schools B and C in March 2016 would have generate four observations.) For this purposes of this paper, general elementary teachers are being categorized as a subject. This is meant to mimic application-level observations, but in a manner that permits merging the application and hiring request data. Often the job titles specified in the application and the hiring request do not perfectly match. This is especially true at the elementary level where a teacher may apply to teach fourth grade, but only a hire for third grade occurs. The information in every observation includes the applicant, position, and school characteristics, as well as the following outcomes: (i) whether the school submitted a request to hire that applicant in the specified subject, (ii) if the request succeeded, and (iii) the performance of the teacher candidate during their first year if they were hired.

When comparing the hired candidates' characteristics with those of the entire candidate pool, a greater portion of those hired are certified, did their student-teaching in the district, or were previously district employees. Those hired were also more likely to have found the job through a district employee, possess an advanced degree, possess an education major, or applied to a non-core academic position. Those hired also had higher college grade point averages, higher GALLUP scores, and applied to more jobs. The characteristics of the applicants and hired candidates are reported in Table 1.1. In the performance regressions the attributes of the school and the principal at which the teacher taught are also taken into account, these characteristics are summarized in Table 1.2.

Not all of the 1443 hiring requests led to a candidate being hired, many are rejected by the by the requested candidate or the district. Of the 1,128 hired candidates, 743 were officially evaluated according to the Georgia Teacher Keys of Effectiveness System.[8] The official evaluation is scored on a scale of zero to thirty and hired candidates averaged a score of 19.9 points. Mean Student Growth Percentile is only available for a much smaller sample number of teachers (245), since not all subjects and grades are tested. The candidates received an average SGP score of 47.7. A total of 803 hired candidates are observed entering a district school,[9] 63.5 percent of whom remain in their school for a second year of employment. The district as a whole retained 69.0 percent of the 922 candidates who entered employment somewhere in the district.[10] For the 884 hired teacher candidates with attendance data, were present for work for 96.1 percent of their contractual employment days on average. More details regarding the hiring and performance outcomes of the candidates are reported in Table 1.3. For all other teachers in the district, their average official evaluation score was slightly higher at 21.1 points, as were there SGP scores at 49.7, a school retention rate of 68.9 percent, a district retention rate of 75.6 percent. The other teachers in the district did have slightly lower attendance of 95.3 percent of their contractual employment days.

1.4 Methods

1.4.1 Poor Decision Making?

For the first portion of the analysis, I follow the approach employed in previous research and focus on the principals' use of available information on the prospective teachers in the hiring decision. I determine which candidate characteristics are correlated with the teacher performance measures discussed previously. Similarly, I estimate the correlation between the same candidate

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[8] Not all teachers appear in the evaluation data.

[9] Hired in this paper are those marked as hired in the HR data, but there is melt between that confirmation and starting at the school. This is why there is a difference between the number of teachers entering a school and number hired.

[10] Teachers in this data set are structured as hired to a specific school but some teachers are hired but enter a different school in the district that the one they are reported as hired to.

characteristics and the likelihood of being selected for a hiring request by a principal. I then compare the extent to which the factors influencing hiring requests align with the characteristics correlated with teacher quality. If there are observable candidate characteristics that predict later performance but do not influence hiring requests, it suggests that principals may not be fully utilizing available information and thus making “poor decisions.” Principals could also be making poor choices if they base their hiring decisions on candidate characteristics which are unrelated to future teacher performance.

1.4.1.1 Identifying Quality Teachers

To give context to a principal’s decision, the predictors of teacher quality must be identified first. To do this, I estimate a multivariate regression model of teacher quality. In the model, teacher quality is a function of the teacher’s observable characteristics and other possible factors. The estimation takes the following form:

$$Pr(y_{ijt}|Hired_{it}) = \beta_0 + \beta_1 X_{it} + \beta_2 S_{jt} + \beta_3 \varphi_{tj} + \varepsilon_{itj} \quad (1)$$

where subscript *i* denotes the teacher, subscript *j* denotes the school, and subscript *t* denotes the year. y_{ijt} is the teacher quality measure and, depending on the measure in question, can either be continuous, binary, or a fraction. The form of the outcome variable dictates the exact regression functional form used, either linear, probit, or fractional probit. $Hired_{it}$ is an indicator of whether the candidate was hired or not. Since the teacher quality measures can only be observed for the hired candidates, the estimations only include the sample of candidates who are hired. X_{it} is the set of candidate characteristics that the principal can see during the hiring process such as highest degree attained, district screening scores, college grade point average, certifications held, student teaching assignments, and previous work experience. The model also controls for the number of application submissions, average speed of application, and whether a candidate applied to any positions in non-core subjects. S_{jt} is the set of school attributes, such as the percentage of students directly certified (a measure of the proportion of students who are economically disadvantaged in the school), the percentage of students of a given race or gender, the school's college and career readiness index, or the Georgia Department of Education assigned school report card grade indicators. φ_{tj} is the set of characteristics of the principal overseeing the teacher during the evaluation period. The principal characteristics include the principal's official state evaluation score, experience, and race and gender interacted with the teacher's race and gender. The characteristics of the principal are included in the model due to the extensive research on the effects of the presiding principal on the various measures of quality being used in the analysis. Specifically, a teacher's decision to remain in a school (teacher retention), their satisfaction with their school, and their performance. As there is evidence of principal's effects on teachers, not including their characteristics would allow additional possibilities of omitted variable bias (assuming that teachers sort into schools in part based on perceptions of the quality of school principals). The parameters of interest are the vector of coefficients β_1, which provide the partial correlations between the candidate characteristics and teacher quality. This estimation does not control for selection into being hired for two reasons. First, there was no sufficiently exogenous instrumental variable to use in a Heckman selection model. Second, prior work (Jacob et al., 2018 and Goldhaber et al., 2017) found little difference in estimates in the models with and without corrections for selection.

1.4.1.2 Identifying Principal Hiring Decisions

The principal's hiring request decision is estimated using a probit regression due to the binary nature of the decision. The decision to place a hiring request is modeled as the function of the candidate's observable characteristics, and takes the following form:

$$Pr(hire\ request_{it}) = \varphi(\beta_0 + \beta_1 X_{it}) \quad (2)$$

where $hire\ request_{it}$ is an indicator of whether the candidate was the subject of any principal's hiring request. X_{it} includes the same set of observable candidate characteristics used in the teacher quality estimations. β_1 are the parameters of interest, as they provide the partial correlations between teacher candidate characteristics and the principals' hiring decisions. The estimation is also completed with the outcome of hired for the full sample.

1.4.2 Or Making the Best of Bad Situations?

While a district-level misalignment between the candidate characteristics affecting hiring decisions and those associated with later teacher performance could be indicative of poor decision making by principals, I argue that mis-alignment at the district level could also reflect differences in the pool of candidates that principals can choose from and the likelihood a candidate will accept an offer of employment from a particular school. This section addresses the estimation methods employed to account for variation in the applicant pools. Due to identification difficulties,[11] there are no models specifically identifying the effects of applicant acceptance probabilities on the hiring decisions.

1.4.2.1 Demonstrating the Differences in Candidate Pools across Schools

In this paper, I demonstrate that principals face considerable variation in the applicant pool for an open teaching position. I first examine the mean and variation of the number of candidates and the portion of candidates in the top quintile of GPA for all applicants within and between key aspects of the school and job. These aspects are the school's state-issued grade, number of students, grade level (elementary/middle/high), incidence of students from low-

[11] I could determine no reliable way to estimate acceptance probabilities, and thus account for their effects of principal decision making. At most, I could make a strong assumption that more talented teachers are less likely to accept at qualitatively more difficult schools. But this was determined to strong and too noisy.

income households, and the academic subject of the position. The continuous variables are binned to create categories. Then, I determine if both the size and quality of the candidate pool are systematically related to school quality. To do this, I estimate linear regressions where the dependent variable is either the size of the applicant pool for a position (measured by the number of applicants) or the quality of the pool (measured by the proportion of applicants with college GPAs in the top quintile of the districtwide distribution of candidates).[12] Explanatory variables include a subset of school, subject, and principal characteristics used in equation (1). This takes the following form:

$$\text{Outcome}_i = \beta_i \text{ School Level} + \alpha_i \text{ School Characteristics} + \gamma_i \text{ Subject} + \psi_i \text{ School*Subject} + \lambda_i \text{ Principal Characteristics} + \epsilon_i \tag{3}$$

1.4.2.2 Relation of the Applicant Pool to Selected Candidate Quality

After estimating whether that candidate pools vary systematically across school-subjects, I study if the differences in available prospective teachers influence principal hiring request decisions. To do this, I regress the college GPA of selected applicants (a measure of candidate quality) on aspects of the applicant pool. Then I add further controls for a collection of job, school, and principal characteristics which may also affect the ways principals perceive acceptance probabilities and thereby influence the minimum acceptable candidate quality. In the estimations, I analyze both the sample of first-selected candidates and the full set of selected candidates with an additional control for request order.

[12] GPA was selected because it is a readily observable characteristic of prospective teachers that has been shown to be predictive of teacher performance (Jacob et al., 2018).

1.4.2.3 Contextual Effects of the Applicant Pool on Selection

The analyses described in the two previous sub-sections are intended to determine if there are differences in the candidate pools and if these differences affect who is selected for a hiring request. The analysis in this section is intended to determine estimating the decision within the principals' specific for the hiring pool affects estimates of the weight that principals place on various candidate characteristics.

I compare the estimates of the hiring-request decision from the initial probit specification, which assumes all principals face the same pool, to estimates from a conditional logit model, which accounts for each principal facing different candidate pools. Conditional logit is a particular form of general discrete choice models where an individual is faced with J options to choose from, with each option yielding a particular level of utility. Individuals are assumed to choose the option that maximizes their utility. In the typical multinomial logit model approach, the expected utilities of the options are modeled as a function of the characteristics of the individuals making the choice. In the conditional logit approach, first introduced by McFadden (1973), the expected utilities are modeled as a function of the characteristics of the alternatives rather than attributes of the individuals. This model, like most logistic choice models, assumes that the error term follows an extreme value distribution and is independent across alternatives. In the present context, a principal is choosing among J candidates for a position, with candidates varying in the levels of a set of characteristics they possess. I use observations at the application level to construct each principal's choice sets, allowing the set of options to vary between each school and subject. As this specification only allows for one positive outcome. The choice set is all individuals applying to the position before the first request. Conditional logit takes the following form:

$$\Pr\left(Y_j \middle| Y_j \epsilon \{Applicant\ Set\}\right) = \frac{\exp(x'_{ij}\beta)}{\exp\left(x'_{ij}\beta\right) + \sum_{i'\epsilon I^\wedge j} \exp(x'_{i'j}\beta)} \qquad (4)$$

Where i is the set of applicants, and j is the set of open positions.

In addition, I estimate an alternative-specific conditional logistic regression to account for variation in the applicant pools for different positions while also controlling for interactions with characteristics of the principals making the hiring request decision. Traditional conditional logit assumes the property of Independence of Irrelevant Alternatives, that is, the odds of choosing alternative j over alternative k should be independent of the choice set for all pairs j,k. The classic example of a situation where this assumption does not hold is commuters choosing between three transportation alternatives, a train, a red bus and a blue bus. If consumers do not care about bus color, the choice between a train and a red bus will vary with the availability of blue buses, violating the assumption, which is resolved by using the alternative-specific conditional estimation model, which takes the following form:

$$\Pr\left(Y_j \middle| Y_j \epsilon \{Applicant\ Set\}, \lambda_i\right) = \frac{\exp(x'_{ij}\beta + \lambda_i)}{\exp\left(x'_{ij}\beta + \lambda_i\right) + \sum_{i'\epsilon I^\wedge j} \exp(x'_{i'j}\beta + \lambda_i)} \qquad (5)$$

Where all main difference is now that principal-subject specific variables (λ_i) are allowed to affect the choices over alternatives.

1.5 Findings

1.5.1 Evidence of Poor Decision Making

The main results evaluating the principals' choices in the context of later teacher performance use the sample of all applicants who applied to at least one core academic position: Elementary general education, Math, Science, English, or Social Science. Table 1.4 reports the marginal effects of the of candidate characteristics on the probability of being selected for a hiring request and (for those that are hired) on various teacher performance measures. Table 1.5

presents the estimates for the sub-sample of candidates who could not be identified as having previously worked in the district and are denoted as “New.” This second sample is meaningful as the application requirements differed between new and internal hires (internal hires can only be hired during April and are not required to complete the screening tools), and principals may evaluate internal hires differently. In addition, in Table A1.1 it can be seen for the full sample that the following results would not change much if the hired outcomes was used instead of the hiring request outcome.

The estimates show that in both the full and new-applicant samples, teaching certification, student teaching in the district, employee referral, advanced degrees and education majors are associated with a greater likelihood of being selected for a hiring offer. Advanced degrees are positively related with state evaluation and negatively related with attendance for the full sample only, as well as negatively related with both retention measures for both samples. Student teaching in the district is positively related with attendance for both samples. The marginal effect of teaching experience is negative for state evaluation scores and retention in the school for the full sample. Certifications were rarely related to positive performance outcomes in the two analysis samples. College GPA is positively related with the state teacher observation measure and one retention measure in both analysis samples. Referrals are negatively correlated with attendance in the new-teacher sample and are not significantly related to any other teacher performance measure. Possessing an Education degree is not significantly correlated with any performance measure.

Despite using different application information than what is employed in prior studies, the results are consistent with the findings on college GPA in Jacob et al. (2018) and Bruno and Strunk, 2019. However, possibly due to a noisy measure of teacher experience and different measures of being a local applicant, my results differ from those of Jacob et al. on those characteristics of candidates.

If one were to rely on district wide comparisons, the policy implications (if teacher quality is the only factor in the hiring decision) are those where the direction of the predictors of the principal hiring decision and teacher quality do not match. The most important mismatches are those where candidate characteristics associated with improved classroom performance or persistence are uncorrelated or negatively correlated with principal hiring decisions. My estimates yield two such mismatches, college GPA and submitting an application close to the posting date. College GPA is positively correlated with official evaluation scores and the persistence of a teacher in their initial placement school, with no discernable effect on the principal hiring decision. Submitting an application soon after a job is posted has a small, positive effect on hiring decisions, but is negatively correlated with official evaluation scores and persistence in the initial school and district.

However, as the sample sizes of hired candidates are relatively small, the estimated models exhibit only modest explanatory power. As such, the mismatches between indicators of teacher quality and hiring decisions are based on the comparison of two relatively imprecise relationships. However, the relationships being noisy is in line with prior research, which has long found that identifying superior teachers from observable characteristics is difficult.

1.5.2 Evidence of Making the Best of Bad Situations

Beyond statistical issues, there are more fundamental reasons to caution against drawing firm conclusions from the previous principal decision analysis. Like other recent quantitative studies of the principal hiring decisions, the analysis implicitly assumes that, in an optimal situation, principals should select the best teacher candidate among all applicants to the district.

Thus, the observable characteristics associated with selection for a hiring request differing from those associated with superior teacher performance implies that principals are making poor choices. Therefore, a policy altering principal decisions would improve hiring outcomes.

However, this inference that the disparities stem entirely from the principals' decisions might be incorrect for several reasons. One reason is that principals could obtain valuable information about candidates from sources other than the application, either through professional networks or during the interview process, and then use this private information to make their decisions. In this case, it may appear that principals are ignoring information which predicts teacher performance, when they are instead relying on other candidate-specific information that may better predict later teaching performance. However, since there is no recorded information about what information is obtained in interviews, I cannot examine principal usage of private information.

Second, the pool of candidates for a given position may differ from the total set of applicants for the district. For example, many studies have shown that given the fixed salary schedules for teachers, schools with low-performing, disruptive, or disadvantaged students have greater difficulty in attracting and retaining teachers (e.g. Sass et al., 2012; Levin & Quinn, 2003; Liu et al., 2008; Hanushek & Rivkin, 2007; Boyd et al., 2011; Lankford et al., 2002; Imazeki, 2005; Scafidi et al. 2007). Therefore, what appears to be a sub-optimal selection in the aggregate estimation, may be the best choice among the candidates willing to work at the school.

To provide context, Tables 1.6 provides descriptive evidence on variation in the size and quality of the applicant pool across schools and subjects. The statistics reported in Table 1.6 show that smaller schools receive more applications per position and greater portions of those applicants have relatively high GPAs. English and Social sciences have the greatest number of applicants of the 6-12 subjects, but math has the highest portion of high-GPA candidates. Elementary has a much higher number of applicants, but this is most likely an artifact of how every elementary hire at a school has to be aggregated into one “position” based on how the data set was constructed at the subject-school-year level and there are no consistent subject designations for elementary positions. Interestingly, however, even with these larger-pool elementary positions had a higher mean portion of candidates with high GPAs and a lower standard deviation. There is little relation between the portion of students who are economically disadvantaged at a school and the number of applicants, but a greater share of the applicants to low poverty schools had higher GPAs. Without adjusting for the school level or subject area, schools that received a grade of A have more applicants than F schools, but there is no clear overall relation between school grade and number of applicants.

Table 1.7 presents estimates of the coefficients from multivariate regressions predicting candidate pool size and quality. In this way, both the school level and subject area, as well as characteristics of interest can be controlled for simultaneously. In this estimation, there are no systematic differences in pool size or pool quality (as measured by the portion of candidates with a high GPA) across school grades or student body characteristics. The sample size for this regression may seem small in comparison to the number of hires, but this is due to the sample being at most four positions per year per middle and high school, and one per elementary school, as well as all hires for a non-core positions being removed from the sample. For the applicant pool size, there is no significant relationship outside of the other subjects and school levels having fewer applicants than elementary school positions, but this is probably due to the way the data set was constructed as discussed earlier.

Table 1.8 presents the estimated relationship between the GPA of the selected candidates and the pool of candidates for the position while controlling for other aspects of the position. With controls, the average GPA of the first selected candidate is unrelated to pool size, but does increase with the proportion of the pool with high GPAs, though this relation may be purely mechanical. With a greater proportion of high-GPA candidates in the pool, it is more likely that a high-GPA candidate is selected, even if principals are choosing randomly. However, these results are consistent with the notion that the apparent principal selection misalignment could partially stem from differences in the applicant pool. The results are very similar when all principal selections (not just the first choice) are included in the estimation; these results are in appendix Table A1.1. The relationship between the GPA of the selected candidate and pool characteristics is illustrated in the scatter plots in presented in Figures A1.1 and A1.2 in the appendix. These plots show that among similar applicants pools there is dramatic variation in selected the candidates' GPA, which does not support the hypothesis that the mismatches in Tables 1.4 and 1.5 are driven by applicant pool differences.

Using the conditional logistic regression model as a method to statistically control for the applicant pool when estimating principal choices, the discrepancies between the significant determinants of hiring offers and teacher productivity largely vanish, though this could likely be an artifact of decreased sample size and increased standard errors. In most instances the point estimates are roughly comparable across models, but the standard errors are generally considerably higher for the estimates from the conditional logit model, which reduces statistical significance. With the reduction in statistical significance there are no longer statistically significant mismatches between influence on hiring offers and teacher productivity for how the candidate learned about the job, having an advanced degree, being teaching certified, and the application timing. However, allowing for the differences in candidate pools using the conditional logistic model does not alter the basic finding that candidate GPA is unrelated to the probability of a request to hire. The comparisons of conditional logistic results and probit results are reported in Tables 1.9 (for all applicants) and 1.10 (for new hires only).

The estimates from the alternative specific conditional logit, which are presented in Table 1.11, are rather noisy, and as there is no consistent relation between principal characteristics and choices; the results do not support the hypothesis that the principal's experience or evaluation scores are related to the quality of candidate they selected. The few significant relationships may suggest that principals with higher evaluation scores are less likely to choose worse candidates when controlling for their applicant pool. Specifically, principals with experience are less likely to pick candidates with top attributes who are inexperienced, are also more likely to pick a teacher with all other top candidate characteristics that applied later, and less likely to choose a candidate without any top candidate characteristics. Higher rated pricnipals are more willing to select a top GPA candidate with no other top characteristics, and less likely to select a candidate with only experience.

A third possible reason for the apparent misalignment between candidate selection and candidate quality is that principals may recognize that they compete with other schools for candidates, and strategically choose potentially lower-quality candidates who have a higher probability of acceptance. (Murphy, 1986; Abdulkadiroğlu & Sönmez, 2003; Abdulkadiroğlu et al., 2005; Ergin & Sönmez, 2006; Chen & Sönmez, 2006). Partial evidence of this can be seen in Table A1.2 where the candidates requested later by the school have slightly lower college GPAs. During the time between an offer being made and its rejection by a candidate, the quantity and most likely the quality of remaining candidates may decline as they accept other offers (Ryan et al., 2000, Bruno & Strunk, 2019). In the district I study, the time frame for a request to be settled, whether accepted or rejected, varied between four days and two months in the peak hiring season. Unfortunately, at this time I cannot offer evidence to test the possibility that strategic decision making is occurring.

1.6 Policy Discussion and Next Steps

The extant literature provides evidence which suggests that by manipulating principal decisions, either through training principals or directly screening candidates at the district level, the quality of newly hired teachers can be improved (Jacob et al., 2018; Bruno & Strunk, 2019). To implement a screening policy based on a characteristic, the characteristic must be something that cannot be easily manipulated by the candidates. When relying on the district-wide estimates, college GPA is the most reliable prospect for a screener as it appears to be under-utilized and is not malleable by candidates. These properties suggest that the district could improve the classroom performance of recently hired teachers by establishing minimum GPA requirements or incentivizing principals to more strongly consider candidates with higher GPAs.

However, for this type of policy to improve hiring outcomes, principals must currently be making sub-optimal choices in their selection of candidates to receive job offers. Due to the success of the screening system studied in Bruno and Strunk (2019), principal decision misalignment with teacher performance is likely to be part of the reason for potentially sub-optimal candidate selections. The current paper, however, provides preliminary evidence that principal decisions may be more complicated than choosing the best unemployed teacher in the area. What appear to be poor decisions by principals may in fact be optimal, given they may face different applicant pools while competing with other principals to hire quality candidates.

These additional influences on the principals' choices have contrasting policy implications. If competition is a contributing factor, districts may want to use programs to promote their schools' appeal to candidates, such as bonus programs or other non-pecuniary benefits. However, if differences in applicant pools lead to misalignment between hiring and teacher quality predictors, then implementing screeners can actually exacerbate the hiring difficulties that high-needs schools face as the number of teachers in their pool is already limited and they may not be able to hire a candidate meeting the screening criteria. To correct for variation in principal selections due to differences in the pools of applicants, a district would need to take steps to alter the distribution of candidates. There are a variety of ways in which this might be accomplished, including providing information about school quality to candidates, restricting the number of candidates that can apply to more desirable positions, requiring candidates apply to multiple schools (with perhaps a preference ordering) and offering monetary inducements to work in "high-need" schools. Districts could also engage in active recruitment to bolster the pool quality and size for positions with inadequate applicant pools.

However, from the current analysis, altering the candidate pools is unlikely to close the teacher quality gaps in hiring as there are no readily observable systematic differences in the size and quality of the applicant pools. In addition, no readily observable principal characteristics are associated with "better" hires, so any targeted professional learning or interventions regarding talent recruitment and hiring need to be assigned based on hiring outcomes and not observable principal characteristics. Due to this finding, it is likely that the disconnect between the relation of GPA to hiring requests and GPA to teacher quality is not fully attributable to applicant pool differences, and is in some part principal error which may be possible to correct with more information or incentives to select candidates with more desirable observable characteristics.

Due to the finding that a pool with a greater portion of high GPA candidates is related with a selection of candidates with a higher GPA, it may be tempting to return to the notion of screening on GPA. If the goal is to hire candidates with higher GPAs this is a good strategy, but the use of GPA as a single measure of candidate quality can be problematic if other unobserved factors are significant determinants of teacher quality.

1.7 Tables

Table 1.1 Candidate and Hires Characteristics

	New to the District		All Candidates		All Hires	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Certified in Georgia*	0.680	0.466	0.733	0.442	0.855	0.352
Certified Outside of Georgia*	0.216	0.411	0.160	0.366	0.082	0.274
Did Not Report Certification Status	0.414	0.493	0.368	0.482	0.132	0.339
National Board Certified*	0.075	0.263	0.072	0.259	0.059	0.239
Did Not Report National Board Status	0.294	0.455	0.393	0.488	0.970	0.171
Student Taught in District*	0.146	0.353	0.183	0.387	0.317	0.466
Did Not Report Student Teaching	0.704	0.456	0.730	0.444	0.704	0.457
Some Teaching Experience*	0.345	0.475	0.356	0.479	0.364	0.481
More than Five Years Teaching Experience	0.174	0.379	0.244	0.430	0.404	0.491
Previously Worked in District*	N/A	N/A	0.259	0.438	0.490	0.500
Did Not Report Work History	0.026	0.160	0.024	0.154	0.022	0.147
Currently Under Contract*	0.185	0.388	0.195	0.396	0.308	0.468
Did Not Answer Previous Employment Questions	0.174	0.379	0.294	0.456	0.965	0.183
Found the Job through District Employee*	0.095	0.293	0.107	0.309	0.175	0.380
Did Not Report How Found Job	0.020	0.140	0.072	0.258	0.120	0.325
Advanced Degree*	0.524	0.499	0.565	0.496	0.683	0.465
Education Major*	0.535	0.499	0.572	0.495	0.706	0.456
Did Not Report Education	0.029	0.168	0.028	0.166	0.004	0.059
College GPA*	3.150	0.428	3.141	0.429	3.175	0.425
Did Not Report Any College GPA	0.314	0.464	0.310	0.463	0.197	0.398
Applied Before April	0.390	0.488	0.406	0.491	0.388	0.488
Average Application Date Percentile	46.517	27.667	45.628	27.578	49.153	24.713
Average Application Date Percentile Missing	0.091	0.287	0.093	0.291	0.066	0.249
Number of Positions Applied to	6.630	9.707	7.059	10.574	11.029	14.408
Applied to a Non-Standard Positions	0.318	0.466	0.345	0.475	0.370	0.483
GALLUP Score*	74.587	10.114	74.566	10.270	75.816	9.559
No GALLUP Score	0.672	0.469	0.699	0.459	0.543	0.498
Female*	0.789	0.408	0.786	0.410	0.779	0.415
Did Not Report Gender	0.062	0.241	0.114	0.317	0.148	0.355
Race Black*	0.759	0.428	0.785	0.411	0.772	0.419
Race Non-White Other*	0.026	0.160	0.025	0.157	0.024	0.152
Did Not Report Race	0.089	0.285	0.139	0.346	0.170	0.376
Number of Applicants or Hires±	11,048		14,884		1,128	

Notes: *All summary statistics for these fields is reported with the missing values suppressed. The values seen are the summary statistics for the applicants who answered those fields. In some cases the number of candidates who answered a question can be quite small. ±One observation per person per year.

Table 1.2 School and Principal Characteristics of the Schools who Hired Applicants

	All Hires	
VARIABLES	Mean	St. Dev
Middle School	0.172	0.378
High School	0.212	0.409
Other School Level	0.017	0.129
School Accountability (CCRPI) Score	47.430	31.965
School Accountability Score Missing	0.281	0.450
School Climate (STAR) Score	2.059	1.528
School Climate Score Missing	0.288	0.453
Received a School Grade of C or Higher	0.477	0.500
No GADOE School Grade	0.252	0.434
Number of Students in the School (100s)	6.003	4.803
Portion of Students Directly Certified	45.635	34.004
Portion of the Students Female	0.364	0.218
Portion of Students Hispanic	0.054	0.080
Portion of Students Black	0.615	0.421
Student Characteristics Missing	0.246	0.431
Principal’s Experience in the District	2.987	3.264
Principal’s Evaluation Score	12.270	7.402
No Principal’s Evaluation Score	0.259	0.438
Principal and Hire are Black	0.410	0.492
Principal and Hire are Female	0.267	0.443
No Principal Characteristics	0.253	0.435
Number of Applicants Hired to the District±	1,128	

Notes: ±One observation per person per year.

Table 1.3 Summary Statistics of Outcome Variables

	All			New		
	Mean	Standard Deviation	N	Mean	Standard Deviation	N
Applicants						
Requested for Hire	0.097	0.296	14,884	0.070	0.256	11,048
Hires						
Official Evaluation Score	19.898	2.616	743	19.787	2.526	385
Mean Student Growth Percentile	47.650	8.728	245	48.648	8.632	129
Persistence in Initial School	0.635	0.482	803	0.671	0.471	422
Persistence in District	0.690	0.463	922	0.721	0.449	462
Teacher Attendance	0.961	0.036	884	0.966	0.028	455

Table 1.4 Estimates of the Determinants of Hiring Requests, Teacher Productivity, Teacher Persistence and Teacher Attendance (All Applicants)

	Applicants	Applicants Who Are Hired				
	Hire Request	Official Evaluation Score	Mean Student Growth Percentile	Persistence in Initial School	Persistence in the District	Teacher Attendance
Certified in Georgia	0.035***	-0.150	2.496	0.026	0.093	-0.002
	(0.009)	(0.538)	(2.231)	(0.076)	(0.063)	(0.005)
Certified Outside of Georgia	0.026**	0.022	6.005**	-0.009	0.065	0.004
	(0.011)	(0.616)	(2.787)	(0.096)	(0.083)	(0.006)
National Board Certified	-0.009	2.710***				-0.003
	(0.015)	(0.968)				(0.008)
Student Taught in District	0.034***	-0.163	-0.339	-0.011	0.074	0.009**
	(0.009)	(0.387)	(2.314)	(0.062)	(0.060)	(0.004)
Previously Worked in District	0.002	0.186	-0.467	-0.052	-0.027	-0.005**
	(0.005)	(0.205)	(1.361)	(0.036)	(0.034)	(0.002)
Some Teaching Experience	0.001	-0.315*	-1.550	-0.078**	-0.010	-0.001
	(0.004)	(0.189)	(1.329)	(0.033)	(0.031)	(0.002)
Currently Under Contract	0.008	0.459	-10.286**	-0.110	-0.090	-0.012
	(0.009)	(1.488)	(4.816)	(0.190)	(0.172)	(0.012)
Found the Job through District Employee	0.023***	-0.099	-1.005	0.042	-0.004	-0.003
	(0.006)	(0.249)	(1.562)	(0.046)	(0.043)	(0.003)
Advanced Degree	0.016***	0.390*	2.498**	-0.121***	-0.081**	-0.005*
	(0.005)	(0.201)	(1.220)	(0.038)	(0.036)	(0.003)
Education Major	0.011**	-0.036	-0.670	-0.010	-0.003	-0.002
	(0.005)	(0.219)	(1.554)	(0.041)	(0.038)	(0.003)
College GPA	-0.003	0.837***	1.517	0.080*	0.052	0.005
	(0.006)	(0.250)	(1.662)	(0.045)	(0.042)	(0.003)
Average Application Date Percentile	0.000***	-0.015***	-0.035	-0.002***	-0.001*	0.000
	(0.000)	(0.004)	(0.025)	(0.001)	(0.001)	(0.000)
GALLUP Score	0.001*	0.010	0.094	0.002	0.002	-0.000
	(0.000)	(0.014)	(0.058)	(0.003)	(0.003)	(0.000)
Year Fixed Effects	X	X	X	X	X	X
Number and Type of Applications	X	X	X	X	X	X
Candidate Gender and Race	X	X	X	X	X	X
Principal and School Characteristics		X	X	X	X	X
Constant		14.778***	36.009**			
		(2.659)	(14.614)			
Observations	14,884	743	245	790	920	884
R-squared		0.250	0.310			

Notes: One observation per person per year. For all variables in the model, if the value was missing the variable value was set to zero, and for each variable there is a matching variable equal to 1 if the original variable was missing. Only regressions with linear specifications have marginal effects for the constant term.

Table 1.5 Estimates of the Determinants of Hiring Requests, Teacher Productivity, Teacher Persistence and Teacher Attendance (New Applicants)

	Applicants	Applicants Who Are Hired				
	Hire Request	Official Evaluation Score	Mean Student Growth Percentile	Persistence in Initial School	Persistence in the District	Teacher Attendance
Certified in Georgia	0.030***	0.035	-1.887	0.209*	0.115	-0.006
	(0.010)	(0.860)	(2.746)	(0.121)	(0.097)	(0.006)
Certified Outside of Georgia	0.030***	0.453	2.564	0.120	0.061	-0.005
	(0.011)	(0.908)	(3.372)	(0.133)	(0.112)	(0.007)
National Board Certified	-0.012	0.047				-0.009
	(0.014)	(0.997)				(0.021)
Student Taught in District	0.024***	-0.374	1.269	-0.047	0.052	0.013**
	(0.009)	(0.518)	(3.247)	(0.079)	(0.076)	(0.005)
Some Teaching Experience	-0.004	-0.072	-2.680	-0.073	-0.023	0.001
	(0.004)	(0.271)	(1.884)	(0.047)	(0.044)	(0.003)
Currently Under Contract	0.012*	1.664		0.081	-0.053	-0.019
	(0.007)	(1.229)		(0.411)	(0.364)	(0.022)
Found Job through District Employee	0.023***	-0.140	-1.018	0.072	-0.027	-0.006*
	(0.005)	(0.321)	(2.005)	(0.058)	(0.051)	(0.003)
Advanced Degree	0.014***	0.391	1.768	-0.170***	-0.095**	-0.004
	(0.004)	(0.257)	(1.625)	(0.050)	(0.045)	(0.003)
Education Major	0.008*	-0.083	2.539	0.070	0.048	-0.003
	(0.004)	(0.339)	(2.228)	(0.053)	(0.050)	(0.003)
College GPA	-0.003	0.790***	2.074	0.095	0.115**	0.002
	(0.005)	(0.293)	(2.493)	(0.061)	(0.054)	(0.003)
Average Application Date Percentile	0.000***	-0.014***	-0.094**	-0.001	-0.001	0.000**
	(0.000)	(0.005)	(0.040)	(0.001)	(0.001)	(0.000)
GALLUP Score	0.000	0.019	0.193***	0.001	0.001	0.000
	(0.000)	(0.019)	(0.066)	(0.003)	(0.003)	(0.000)
Number and Type of Applications	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
Candidate Gender and Race	X	X	X	X	X	X
Principal Characteristics		X	X	X	X	X
School Characteristics		X	X	X	X	
Constant		14.295***	-0.602			
		(3.525)	(21.585)			
Observations	11,048	385	129	413	460	455
R-squared		0.336	0.461			

Notes: One observation per person per year. For all variables in the model, if the value was missing the variable value was set to zero, and for each variable there is a matching variable equal to 1 if the original variable was missing. Only regressions with linear specifications have marginal effects for the constant term.

Table 1.6 Number and Quality of Applicants by School Characteristics and by Subject Area

	Number of Applicants		% of Candidates in the top Quintile of Applicant GPA	
	Mean	Standard Deviation	Mean	Standard Deviation
To All Schools	198.745	233.352	20.000	0.000
By Core Subjects				
Elementary	369.915	290.250	17.500	5.869
English	120.107	118.740	16.481	17.081
Social Science	134.277	138.101	12.135	5.253
Math	81.968	82.780	14.022	6.613
Science	76.516	72.955	12.050	5.204
By Number of Students in the School				
Less Than 500	207.456	299.004	15.403	10.821
Between 500 and 750	247.594	212.542	16.712	10.633
Between 750 and 1000	159.227	177.190	14.056	7.069
Greater than 1000	97.364	88.138	14.151	6.313
Missing	404.68	339.418	13.326	4.782
By School Level				
Elementary	371.287	290.958	17.551	5.862
Middle School	89.354	84.907	13.529	13.475
High School	112.281	122.761	13.921	5.914
Other School Level	81.091	31.536	12.457	3.419
By Percent of Students Directly Certified				
Less than 25	188.259	167.642	17.154	6.540
25 to 50	288.091	249.547	15.569	7.022
50 to 75	143.447	213.728	14.174	8.894
Greater than 75	228.630	227.833	15.638	10.501
Missing	404.68	339.418	13.326	4.782
By School Grade				
A	248.826	191.091	17.482	6.204
B	136.042	164.886	15.135	6.424
C	169.870	184.655	15.954	6.414
D	169.460	176.359	15.619	10.809
F	187.681	249.583	14.153	9.240

Table 1.7 Estimates of the Determinants of the Candidate Pool Size and Quality

VARIABLES	Total Size of the Pool	Total Size of the Pool Before the first hire request	% of Applicants in the top GPA quintile	% of Applicants in the top GPA quintile before first hire request
Middle School	-220.579***	-205.755***	-0.043	-0.036
	(77.127)	(61.715)	(0.037)	(0.045)
High School	-247.748*	-228.932*	-0.024	-0.055
	(134.627)	(130.100)	(0.064)	(0.093)
Other School Level	2.094	7.402	-0.066	-0.059
	(103.241)	(99.716)	(0.049)	(0.071)
Portion of Students	-1.075	-2.065	-0.000	-0.000
Directly Certified	(1.677)	(1.610)	(0.001)	(0.001)
GADOE School Climate	3.925	6.754	-0.003	-0.006
STAR Score	(12.868)	(12.413)	(0.006)	(0.009)
Number of Students	0.517	0.650	-0.002	-0.001
(100s)	(3.717)	(3.578)	(0.002)	(0.003)
Portion of Students	-294.847	-167.649	-0.045	-0.053
Hispanic	(211.934)	(203.296)	(0.101)	(0.145)
Portion of Students Black	-53.222	43.561	-0.081	-0.071
	(172.874)	(165.517)	(0.082)	(0.118)
GADOE School Grade A	-86.965	-69.931	-0.019	-0.023
	(62.450)	(59.119)	(0.030)	(0.042)
GADOE School Grade B	-65.623	-47.214	-0.015	-0.060*
	(48.039)	(46.024)	(0.023)	(0.033)
GADOE School Grade D	-13.973	6.747	0.010	0.004
	(37.669)	(36.397)	(0.018)	(0.026)
GADOE School Grade F	27.974	65.736*	0.000	-0.007
	(39.052)	(37.685)	(0.019)	(0.027)
Science	-256.321***	-246.111***	0.026	-0.025
	(95.278)	(91.940)	(0.046)	(0.066)
Math	-225.686**	-219.509**	0.011	0.014
	(102.652)	(99.212)	(0.049)	(0.071)
Social Science	-279.119*	-263.123*	-0.002	-0.043
	(144.253)	(139.351)	(0.069)	(0.100)
English	-283.504**	-262.394**	0.014	-0.012
	(117.420)	(113.462)	(0.056)	(0.081)
Middle School Science	200.917*	194.489*	-0.025	-0.039
	(118.764)	(107.382)	(0.057)	(0.077)
High School Science	178.540	176.938	-0.045	0.001
	(160.893)	(155.411)	(0.077)	(0.111)
Middle School Math	152.635	158.525	-0.028	-0.027
	(125.104)	(114.235)	(0.060)	(0.082)
High School Math	167.196	164.793	0.007	0.007
	(164.416)	(158.917)	(0.078)	(0.113)
Middle School English	240.104*	226.613*	0.044	0.009
	(141.762)	(129.858)	(0.068)	(0.093)
High School English	253.939	235.969	-0.008	0.006

	(176.652)	(170.713)	(0.084)	(0.122)
Middle School Social	234.702	221.917	-0.008	-0.028
Science	(160.221)	(149.781)	(0.076)	(0.107)
High School Social	287.744	274.808	-0.019	0.020
Science	(192.442)	(185.949)	(0.092)	(0.133)
Number of Applicants			-0.003	-0.007*
for Pool			(0.003)	(0.004)
Constant	478.299***	384.704***	0.287***	0.320***
	(122.235)	(117.173)	(0.059)	(0.085)
Observations	357	361	357	361
R-squared	0.446	0.408	0.122	0.110

Notes: Subjects omitted Elementary which was denoted as its own subject. School levels also omitted elementary. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 1.8 Estimates of the Determinants of the Grade Point Average of the Applicants who were selected by Principals for their first request

VARIABLES	Pool Characteristics	Pool and School Characteristics	Pool, School, and Principal Characteristics	Pool, School, Principal, and Subject Characteristics
Pool Characteristics				
Number of Applicants to School-Subject Before the First Request (100s)	0.040***	0.013	0.020	0.016
	(0.010)	(0.013)	(0.014)	(0.015)
Percent of Candidates before the First Request with a GPA in the top Quintile	0.866***	0.659***	0.668***	0.641***
	(0.137)	(0.144)	(0.153)	(0.157)
School Characteristics				
Middle School		-0.117	-0.054	-0.097
		(0.091)	(0.093)	(0.267)
High School		-0.111	-0.037	0.449***
		(0.095)	(0.099)	(0.125)
Other School Level		-0.276**	-0.255**	0.127
		(0.111)	(0.117)	(0.284)
Portion of Students Directly Certified		-0.003	-0.002	-0.002
		(0.003)	(0.004)	(0.004)
GADOE School Climate STAR Score		0.001	-0.008	-0.003
		(0.034)	(0.036)	(0.037)
GADOE School CCRPI Score		-0.002	-0.002	-0.001
		(0.003)	(0.003)	(0.003)
Number of Students (100s)		-0.013	-0.015*	-0.010
		(0.008)	(0.009)	(0.009)
Portion of Students Hispanic		-0.371	-0.314	-0.287
		(0.409)	(0.412)	(0.413)
Portion of Students Black		-0.122	-0.138	-0.130
		(0.334)	(0.361)	(0.363)
Principal Characteristics				
Principal Years of Experience			-0.003	-0.003
			(0.003)	(0.003)
Principals LKES Score			0.021	0.019
			(0.015)	(0.015)
Subject Controls				
Science				-0.550
				(0.338)
Math				-0.380
				(0.256)
Social Science				-0.169
				(0.331)
English				-0.541
				(0.334)
Middle School Science				0.489
				(0.421)
High School Science				0.019
				(0.346)
Middle School Math				0.418

				(0.352)
High School Math				-0.103
				(0.254)
Middle School English				0.591
				(0.425)
High School English				0.094
				(0.368)
Middle School Social Science				0.255
				(0.396)
High School Social Science				-0.328
				(0.336)
Constant	2.939***	3.678***	3.292***	3.237***
	(0.040)	(0.289)	(0.364)	(0.373)
Observations	293	293	293	293
R-squared	0.108	0.171	0.191	0.207

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Subjects omitted Elementary which was denoted as its own subject. School levels also omitted elementary. Outcome is the Candidate's GPA. The sample is all candidates who were selected first in a school-subject pool.

Table 1.9 Estimates of the Determinants of the Likelihood of Being Selected for a Hiring Request – All Applicants and Positions Combined Versus Separate Pools for Each Position

Hiring Requests-All Applicants			
	Probit	Probit	Conditional Logit
	Full Candidate Pool*	Candidates in the Clogit Pool±	Different Applicant Pools°
Certified in Georgia	0.035***	0.039**	0.065
	(0.009)	(0.017)	(0.131)
Certified Outside of Georgia	0.026**	0.026	0.039
	(0.011)	(0.017)	(0.440)
National Board Certified	-0.009	0.006	-0.115
	(0.015)	(0.016)	(0.258)
Student Taught in District	0.034***	0.043***	0.106**
	(0.009)	(0.013)	(0.016)
Previously Worked in District	0.002	-0.002	-0.008
	(0.005)	(0.008)	(0.722)
Some Teaching Experience	0.001	0.057	0.018
	(0.004)	(0.006)	(0.351)
Currently Under Contract	0.008	0.083	0.099***
	(0.009)	(0.012)	(0.002)
Found the Job through District Employee	0.023***	0.013	0.045
	(0.006)	(0.010)	(0.105)
Advanced Degree	0.016***	0.014*	0.001
	(0.005)	(0.007)	(0.963)
Education Major	0.011**	0.005	0.537**
	(0.005)	(0.008)	(0.030)
College GPA	-0.003	-0.028	0.215
	(0.006)	(0.296)	(0.396)
Average Application Date Percentile	0.000***	0.001***	0.000
	(0.000)	(0.000)	(0.687)
GALLUP Score	0.001*	0.001	0.000
	(0.000)	(0.000)	(0.976)
N	14,884	7,528	19,215

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The first two columns have one observation per person per year. The third column is one observation per applicant per school-subject-year.
*This column also appears in Table 1.4. ±This pool removes all candidates who applied after the first request that was placed.

Table 1.10 Estimates of the Determinants of the Likelihood of Being Selected for a Hiring Request – All Applicants and Positions Combined Versus Separate Pools for Each Position (New Applicants)

Hiring Requests-New Applicants			
	Probit	Probit	Conditional Logit
	Full Candidate Pool*	Candidates in the Clogit Pool±	Different Applicant Pools
Certified in Georgia	0.030***	0.035**	0.047
	(0.010)	(0.015)	(0.065)
Certified Outside of Georgia	0.030***	0.030**	0.084
	(0.011)	(0.015)	(0.079)
National Board Certified	-0.012	-0.004	-0.127
	(0.014)	(0.014)	(0.116)
Student Taught in District	0.024***	0.018	0.114**
	(0.009)	(0.012)	(0.061)
Some Teaching Experience	-0.004	-0.002	-0.007
	(0.004)	(0.006)	(0.024)
Currently Under Contract	0.012*	0.106	0.109**
	(0.007)	(0.010)	(0.043)
Found the Job through District Employee	0.023***	0.013*	0.050
	(0.005)	(0.007)	(0.034)
Advanced Degree	0.014***	0.014**	-0.004
	(0.004)	(0.006)	(0.840)
Education Major	0.008*	0.008	0.518
	(0.004)	(0.006)	(0.037)
College GPA	-0.003	-0.006	-0.007
	(0.005)	(0.007)	(0.034)
Average Application Date Percentile	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.001)
GALLUP Score	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)
N	11,048	5,396	8,373

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The first two columns have one observation per person per year. The third column is one observation per applicant per school-subject-year.
*This column also appears in Table 5. ±This pool removes all candidates who applied after the first request that was placed.

Table 1.11 Alternative Specific Conditional Logistic Regression of Principal Hiring Choice (Marginal Effects)

Probability the Choice Category was Selected	Characteristics of Choice Category				Marginal Effect on Principal's Hiring Request Choice	
	In Top 30% of all Applicant GPAs	More than Five Years of Experience	First 20% of Applicants	Certified	Principal Experience	Principal Evaluation Score
0.038	✓	✓	✓	✓	-0.002 (0.004)	0.002 (0.004)
0.016	✓		✓	✓	-0.004* (0.002)	-0.000 (0.001)
0.024	✓	✓		✓	0.004* (0.002)	0.003 (0.003)
0.074	✓			✓	-0.002 (0.005)	0.013* (0.007)
0.105			✓	✓	0.003 (0.006)	-0.003 (.004)
0.098		✓	✓	✓	-0.000 (0.006)	0.008 (0.006)
0.256		✓		✓	0.004 (0.008)	-0.019** (0.009)
0.168				✓	-0.013** (0.007)	0.005 (0.010)
0.000	✓	✓	✓		0.000 (0.000)	0.000 (0.000)
0.000	✓		✓		0.000 (0.000)	0.000 (0.000)
0.074	✓	✓			0.013 (0.010)	-0.004 (0.006)
0.031	✓				-0.003 (0.004)	-0.000 (0.004)
0.016			✓		0.002* (0.001)	0.000 (0.001)
0.000		✓	✓		0.000 (0.000)	0.000 (0.000)
0.062		✓			-0.005 (0.007)	-0.001 (0.003)
0.036					0.004 (0.003)	-0.003 (0.003)

Notes: ✓Category had this Characteristic.

1.8 Appendix 1

Table A1.1 Principal Decision Using Hired instead of Hiring Request

VARIABLES	All Hired	New Hired
Certified in Georgia	0.032***	0.033***
	(0.008)	(0.007)
Certified Outside of Georgia	0.016	0.022**
	(0.010)	(0.009)
National Board Certified	-0.050	-0.035
	(0.033)	(0.038)
Student Taught in District	0.034***	0.027***
	(0.009)	(0.008)
Previously Worked in District	-0.002	N/A
	(0.005)	
Some Teaching Experience	-0.002	-0.008**
	(0.004)	(0.004)
Currently Under Contract	-0.012	0.000
	(0.012)	(0.012)
Found the Job through District Employee	0.024***	0.020***
	(0.006)	(0.005)
Advanced Degree	0.013***	0.007**
	(0.005)	(0.004)
Education Major	0.010**	0.010**
	(0.004)	(0.004)
College GPA	-0.003	0.000
	(0.005)	(0.005)
Average Application Date Percentile	0.000***	0.000***
	(0.000)	(0.000)
GALLUP Score	0.000	-0.000
	(0.000)	(0.000)
Observations	14,884	11,048

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

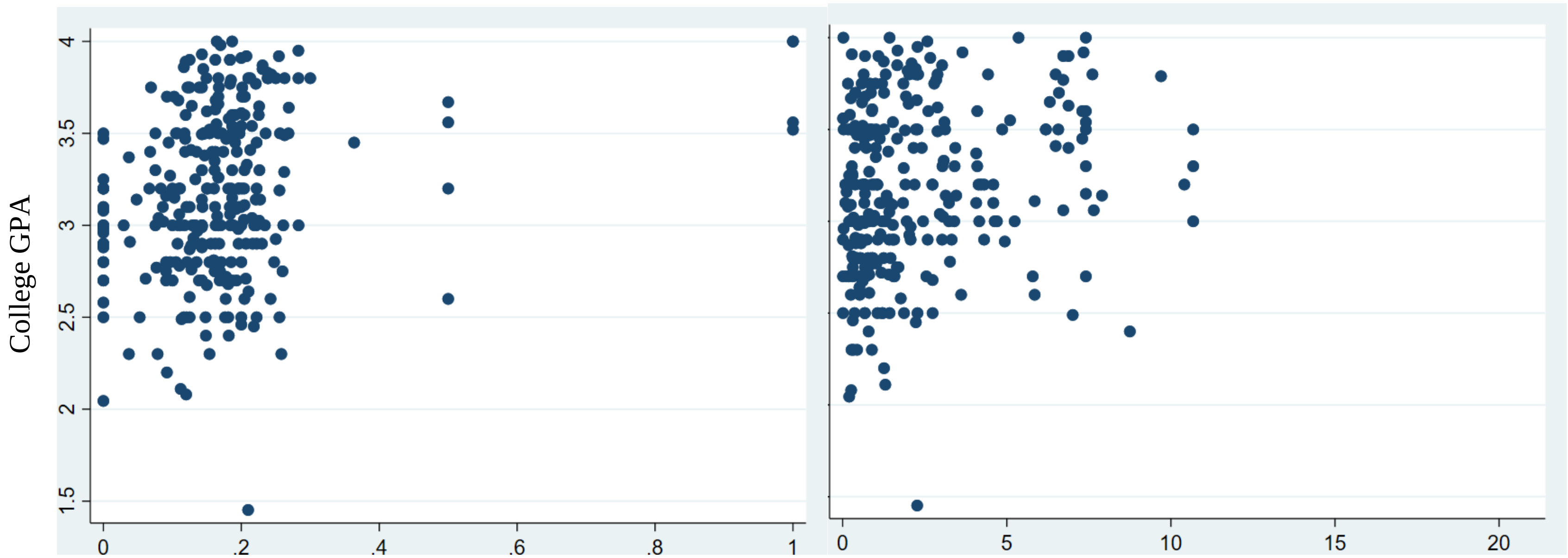
Table A1.2 Estimates of the Determinants of the Grade Point Average of the Applicants who were selected by Principals for all their Requests

VARIABLES	Pool Characteristics	Pool and School Characteristics	Pool, School, and Principal Characteristics	Pool, School, Principal, and Subject Characteristics
Pool Characteristics				
Number of Applicants to School-Subject (100s)	0.017***	0.013**	0.017***	0.016***
	(0.005)	(0.005)	(0.006)	(0.006)
Percent of All Candidates with a GPA in the top Quintile	1.381***	0.697***	0.662***	0.689***
	(0.297)	(0.218)	(0.223)	(0.222)
School Characteristics				
Middle School		-0.107**	-0.088*	0.051
		(0.049)	(0.048)	(0.146)
High School		-0.092**	-0.055	0.621***
		(0.046)	(0.051)	(0.082)
Other School Level		0.170	0.177	0.189
		(0.123)	(0.132)	(0.228)
Portion of Students Directly Certified		0.001	0.002	0.002
		(0.002)	(0.002)	(0.002)
GADOE School Climate STAR Score		0.002	-0.003	-0.002
		(0.018)	(0.018)	(0.019)
GADOE School CCRPI Score		0.002	0.002	0.002
		(0.002)	(0.002)	(0.002)
Number of Students (100s)		-0.000	-0.001	-0.000
		(0.005)	(0.005)	(0.005)
Portion of Students Hispanic		-0.400*	-0.369*	-0.371*
		(0.204)	(0.207)	(0.207)
Portion of Students Black		-0.364*	-0.401*	-0.388*
		(0.190)	(0.205)	(0.207)
Principal Characteristics				
Principal Years of Experience			-0.003**	-0.003*
			(0.002)	(0.002)
Principals LKES Score			0.018**	0.017**
			(0.007)	(0.007)
Subject Controls				
Science				0.006
				(0.197)
Math				0.011
				(0.282)
Social Science				-0.259
				(0.249)
English				0.039
				(0.296)
Middle School Science				-0.099
				(0.242)
High School Science				-0.699***
				(0.203)
Middle School Math				-0.101
				(0.319)
High School Math				-0.738***

				(0.281)
Middle School English				-0.208
				(0.332)
High School English				-0.701**
				(0.304)
Middle School Social Science				0.032
				(0.284)
High School Social Science				-0.398
				(0.254)
Request Order	-0.003	-0.003*	-0.003*	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	2.906***	3.204***	2.947***	2.887***
	(0.049)	(0.194)	(0.202)	(0.206)
Observations	1,143	1,143	1,143	1,143
R-squared	0.045	0.087	0.097	0.105

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Outcome is the Candidate's GPA. The sample is all candidates who were selected with a control for selection order.

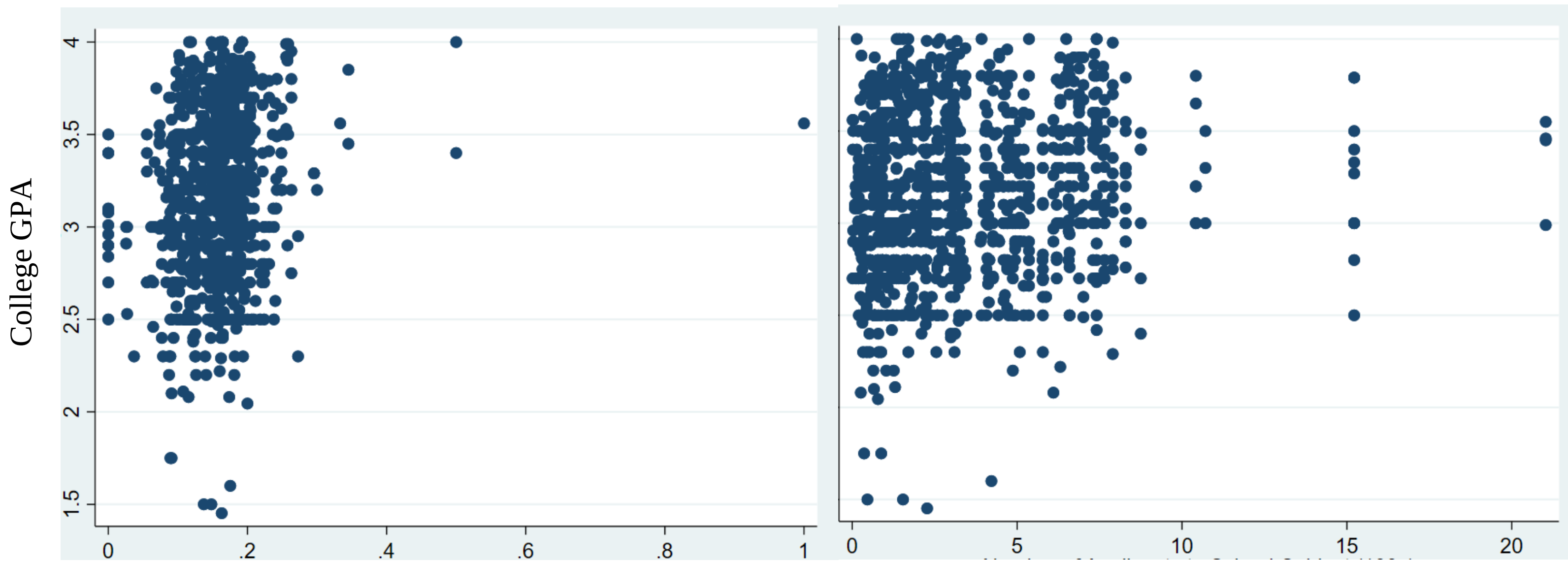
Figure A1.1 Relation of GPA of First Selected Candidates to Number of Applicants and Portion of the Pool with a High GPA



Fraction of Candidates in the Top Quintile of GPA before the First Request

Number of Applicants to School-Subject before the first request (100s)

Figure A1.2 Relation of GPA of All Selected Candidates to Number of Applicants and Portion of the Pool with a High GPA



Fraction of All Candidates in the Top Quintile of GPA

Number of Applicants to School-Subject

Table A1.3 Alternative Specific Conditional Logistic Regression Selection Probabilities

Characteristics of Choice Category								
In Top 30% of all Applicant GPAs	More than Five Years of Experience	First 20% of Applicants	Certified	Percent Selected	Average Number of Type in the Pool	Standard Deviation of Type in the Pool	Predicted Percent Selected	Standard Deviation On Estimated Percent Selected
✓	✓	✓	✓	0.037	2.305	1.770	0.044	0.016
✓		✓	✓	0.045	4.130	4.297	0.033	0.091
✓	✓		✓	0.044	3.071	3.693	0.042	0.038
✓			✓	0.104	6.646	8.678	0.107	0.049
		✓	✓	0.141	13.665	13.925	0.145	0.120
	✓	✓	✓	0.119	7.421	8.419	0.132	0.090
	✓		✓	0.243	10.608	14.226	0.321	0.129
			✓	0.205	21.022	27.025	0.222	0.107
✓	✓	✓		0.000	1.290	0.643	0.000	0.000
✓		✓		0.017	2.058	1.835	0.009	0.095
✓	✓			0.048	1.452	1.035	0.098	0.058
✓				0.026	3.041	4.105	0.036	0.013
		✓		0.045	7.528	22.512	0.045	0.132
	✓	✓		0.020	2.444	3.759	0.007	0.084
	✓			0.055	3.697	9.208	0.077	0.074
				0.061	13.579	51.565	0.054	0.068

Notes: ✓Category had this Characteristic.

2 Where They Stop Nobody Knows: What Drives Teacher Placement Decisions?

2. 1. Introduction

To understand the labor market, how workers and firms come together to produce goods and services, it is vital to understand how workers enter a given firm. To understand this, there are two sides, the firms' hiring decisions and the workers' employment decisions. The preferences workers have over firms drive their decisions by affecting their search efforts and their probability of accepting an offer from a firm. Hence, understanding worker preferences is crucial to labor market research.

Much of the research on worker preferences has focused on the wage differences needed to compensate for disparities in non-pecuniary workplace benefits and conditions. However, school districts typically utilize fixed salary schedules across schools. These schedules do not allow for salary to offset the undesirable aspects of a school. Prior work has documented that the combination of teacher preferences and rigid pay schedules can lead to disparities in student access to quality teachers. Policymakers are concerned that teacher sorting across schools may limit access to high-quality teachers, particularly for minority, impoverished, or low-performing students. Teacher sorting may occur in the job market for hiring new teachers (Sass et al., 2012; Reininger, 2012) as well as through post-hire differential patterns of teacher mobility.[13] The disparity in access to quality teachers has lasting impacts as teacher quality affects not only their student's academic outcomes, but also their students' lifetime earnings.[14]

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[13] Darling-Hammond 2001; Viadero 2002; Gordon & Maxey 2000; Goldhaber et al., 2007; Feng & Sass 2017

[14] Rivkin et al., 2005; Aaronson et al., 2007; Kane et al., 2008; Chetty et al., 2011, Chetty et al., 2014

District policies can possibly mitigate disparities in access to high-quality teachers. Some policies that have been tested are bonuses for high-performing teachers to remain in or to transfer to low-performing schools, state bonus schemes for teachers in high-poverty and low-performing schools, or differential retention programs. Analysis of the Talent Transfer Initiative showed that monetary incentives might have to be very large to induce highly effective teachers to transfer to low-performing schools. The teachers who transferred could improve student scores on math and reading exams in elementary schools, but had no impact on math or reading scores for middle school students (Glazerman et al., 2013). A North Carolina bonus scheme for math, science, and special education teachers working in high-poverty or low-performing schools significantly reduced teacher turnover (Clotfelter et al., 2008). Similarly, a selective retention bonus scheme for highly effective teachers in low-performing schools in Tennessee led to improved teachers retention in tested grades and subjects (Springer et al., 2016) and improved student test-score gains (Springer et al., 2019). Further, targeted recruitment strategies may reduce disparities in the supply of new teachers resulting from teachers' geographic preferences (Reininger, 2012; Boyd et al., 2005a).

The fact that teachers have preferences over the characteristics of their workplace means that to address disparities in access to effective teachers, policymakers must know how teacher preferences vary and the compensating differentials required to offset those preferences. In chapter 1, I found evidence that apparent errors in principal hiring decisions that affect the initial distribution of teachers may partially stem from differences in the pool of applicants, as well as from sub-optimal use of information by principals. Hence, in this chapter, I examine how teachers' preferences affect their application behavior and thereby affect principals' hiring choice sets. The results can inform schools' and districts' decisions regarding teacher recruitment policies or adjustments to the application process. For example, the findings can shed light on the existing differences in application behavior which can be targeted to improve the principals' hiring choice sets.

The teacher preference research is extensive and ever-growing, to add to that literature in a meaningful way I focus on how candidate preferences affect the choice of where to apply. While the majority of the literature uses labor market decisions such as transfers and initial placements to determine teacher preferences, few prior studies examine the teacher's decision of where to apply. Those that do consider only particular segments of the applicant pool, such as inter-school transfers of existing teachers (Boyd et al., 2011), application choices at job fairs (Engel et al., 2014), or recent college graduates (Cannata, 2010), or focus on specific aspects such as the role of geography (Goff & Bruecker, 2017). Leveraging a partnership with an Atlanta metropolitan area school district, the present research will employ rich data that covers both initial and transfer applications, which does allow me to compare part of my results to the findings of Boyd et al. 2011. I estimate the teacher's choices to apply to a school by using conditional logistic choice models.

I find that in relation to schools with a Governor's Office of Student Achievement (GOSA) School Report Card letter grade of C, teachers are more likely to apply to a school with a grade of F and less likely to apply to schools with a grade of A, B, or D. This is an odd result that warrants further investigation in the future but could be due to a variety of factors including differences in accountability pressures, variation in resources, and differences in recruitment. I also find that, in accordance with the current preference literature, school climate scores are positively correlated with current employee application likelihoods, however, the opposite is true for teacher applicants who are new to the district. The difference could be due to differences in information availability, recruitment efforts, or randomness in applications of new teachers, and warrants further investigation. Increases in the proportion of students "directly certified" (a measure of poverty) negatively impacts only the application likelihood of current teachers, but there is a positive relationship between the number of students and the application likelihoods for all teachers. The portion of minority students, Black or Hispanic, in a school is negatively correlated with the likelihood of a candidate applying to work in the school, Black teaching applicants do have increased application likelihoods to schools with greater portions of black students. Of the principal characteristics examined, only the principal's years of experience is positively related to application likelihood for all teacher subsamples. The principal's evaluation score and principal tenure in the school either have negative or no relation with the likelihood of an application submission. When the interaction of applicant teaching experience with key school characteristics[15] are added to the analysis, they only show a significant relationship for current teachers. However, when the applicant's college GPA is interacted with the same key school characteristics as applicant teaching experience as well as the principal characteristics,[16] it only has statistically significant impacts for new teachers. The inclusion of these interactions minimally impacts the magnitude of the relations discussed previously.

[15] These characteristics are the GOSA Report Card Grade Dummy Variables, the GADOE School Climate Score, the number of students, and the percent of students who are Black, Hispanic, or Directly Certified.
[16] These characteristics are the principal's experience, years in the current school, and their official evaluation score.

The next section reviews the employee preference literature for teachers and is followed by section 3, which details the hiring processes of the participating district. Section 4 discusses the data, and section 5 details the methodology. Section 6 provides the results while section 7 summarizes and concludes this essay.

2.2. Literature Review

Researchers have long examined the relationships between workplace characteristics and employee placement and mobility decisions. As the current work is focused on teacher employment preferences, this section will review the research specific to teacher workplace preferences. The teacher preference research includes analyses of teacher job applications, initial placements, job satisfaction, and teacher mobility decisions. In these studies, researchers have considered several factors affecting teacher labor market decisions, including school characteristics, salary, student population demographics, teacher peer groups, school facilities, administrative support, mentoring, and geography.

Perceived job difficulty varies with the attributes of schools and the students who attend them. Given fixed salary schedules, schools often cannot offer higher wages to compensate for undesirable workplace characteristics. The most common payment schedule is where a teacher's salary depends solely on their years of teaching experience and educational attainment. Salaries may vary across districts, however, and there is evidence that teachers will transfer to nearby districts that have higher salaries or remain in schools with higher salaries when wage variation exists.[17] However, some research

[17] Imazeki, 2005, Feng 2014, Feng 2009

finds that when teachers exit the profession, it is not in search of higher pay.[18] Taken together, these findings suggest that salary is an important factor in placement decisions throughout a teacher's work history, but that due to rigid wages, non-pecuniary factors are more important in subsequent transfer or exit decisions. This conclusion is further supported by its own body of research.[19] However, as a contrast, the Talent Transfer Initiative offered substantial bonuses of twenty thousand dollars to high performing teachers if they transferred to high-needs schools. Few teachers even participated in the information session, let alone accepted the bonuses to transfer to low-performing schools (Glazerman et al., 2013).

An additional body of research shows that teachers tend to move away from urban schools and schools with high portions of minority or low-income students.[20] Urban schools also have lower application rates during the hiring process.[21] Further research demonstrates that the movement away from schools with high portions of minority students is driven largely by the choices of white teachers. Black and Hispanic teachers seem to prefer schools with student and teacher[22] or principal demographics (Grissom & Keiser, 2011) similar to their own. Additionally, teachers were found to move away from schools with substantial disciplinary problems (Feng, 2009, 2010). Teachers were also found to prefer supportive administrators and peers as well as mentorship opportunities.[23]

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[18] Podgursky et al., 2004; Scafidi et al., 2006; Stinebrickner, 2002

[19] Clotfelter et al., 2011, Hanushek & Rivkin 2007, Feng 2009

[20] Boyd et al. 2011; Lankford et al., 2002; Hanushek et al., 2004; Boyd et al., 2005a,b; Imazeki, 2005, Scafidi et al., 2007; Feng, 2009; Goldhaber et al., 2011; Clotfelter et al., 2011; Feng & Sass, 2017; Goldhaber et al., 2015; West & Chingos, 2009; Neild et al., 2003; Hanushek & Rivkin 2007

[21] Levin & Quinn, 2003; Levin et al., 2005; Liu et al., 2008; Donaldson, 2013

[22] Strunk & Robinson 2006; Hanushek & Rivkin, 2007

[23] Smith & Ingersoll, 2004; Ingersoll, 2001; Horng, 2009; Loeb et al., 2005

Location has also been shown to strongly affect teacher employment decisions. Teachers more frequently accept an initial placement in the area where they grew up (Reininger, 2012, Boyd et al., 2005a), where they attended college (Boyd et al., 2005a), close to their current home address (Boyd et al., 2005b, Boyd et al. 2013, Engel & Cannata, 2015), with a shorter commute (Engel et al., 2014; Horng 2009), or in a specific type of geography (Goff & Bruecker, 2017). In addition, teachers are found to prefer schools that have characteristics like those of their hometown (Boyd et al., 2005a). The geography of the district can affect subsequent mobility decisions as well. For example, transient teachers are less likely to move to geographically isolated districts (Neild et al., 2003).

Engel, Jacob, and Curran (2014) found that school characteristics strongly predicted application choices when studying behavior at the Chicago Public Schools job fair. However, Cannata (2010) found that if school-specific information is limited, teachers may make application decisions based on characteristics of the district as a whole. Both of these papers also find that applicants prefer schools with lower portions of minority students

The hiring process can also affect labor supply decisions by imposing additional constraints on teacher choices. For example, increases in the amount of screening and certification requirements are negatively correlated with the number of candidates (Delfgaaw & Dur, 2007; DeVaro, 2005). However, the direction of causation is not entirely clear, as the supply of candidates can affect the way schools structure their hiring process (Rynes & Barber, 1990, Ryan & Tippins, 2004). Winter et al. (2004) find the attractiveness of a job offering to teachers is positively correlated with hiring-process factors such as ease, length, and timeliness. Similarly, Rynes and Barber (1990) find that decreasing the application process length and the number of steps enhanced the attractiveness of a job to candidates. In addition to the hiring process, laws dictating evaluation standards can affect teacher choices. For example, the accountability standards imposed by the No Child Left Behind Act unintentionally exacerbated supply problems faced by high-needs schools by making schools with low-performing students less attractive to teachers (Rutledge et al., 2010).

2.3. The School District's Hiring Process

Each year the studied school district, located in the Atlanta metropolitan area, fills roughly 600 teaching positions. Applications for these positions occur year-round but are concentrated in the period from January to August, as shown in Figure 1. Historically, a teacher candidate's information would be available to principals in a hiring portal upon the submission of an online application and a simple background and credential check. For the past several years, however, the district has implemented changes to the teacher hiring process. The main change has been to provide principals additional information about teacher candidates through scores from a compatibility screener, GALLUP TeacherInsight, and a video interview tool, HireVue. In January 2019, obtaining a minimum score on the TeacherInsight test became a requirement for a candidate to enter the teacher candidate pool available to principals. However, this paper only studies applications through May 2018. The GALLUP TeacherInsight and HireVue tools are only applied to teachers new to the current district. The current teachers instead are limited by a transfer window which begins in March and ends in April.

Any candidate accepted into the candidate pool can apply for specific school-subject positions or to generic pools such as middle-school math. Principals can then review the applications and offer interviews to candidates. After the interviews, principals make hiring requests to the district's Human Resources Department, who then extends a formal offer (provided the candidate does not already have an outstanding offer from another school in the district). A teacher must reject their current offer to receive further offers from within the district.

2.4. Data

2.4.1 Partner District Administrative Data

For the bulk of the analysis, I use employment and hiring data from the Human Resources Department of the studied school district. This means I have, when available, all information collected about every applicant during the hiring process, not just those that are hired. The data also include this information for the transfer process. The applicant's address at the time of application was used to generate distance-to-school measures and the specific addresses will not be available to the researcher.

2.5. Model

This work builds upon the methodology used by Boyd et al. 2011, in their study of teacher retention and school choices regarding teacher transfer hires in New York City. However, in contrast to Boyd et al., I use all applications (both new and transfers), not just applications from currently-employed teachers seeking to transfer. In addition, I focus more on the impact of school characteristics, as opposed to the characteristics of the teacher.

While a variety of models have been employed by other researchers, the approach of Boyd, et al., seems most relevant for the current analysis. For example, I do not use the methods of Biasi (2019) as they emphasize preferences over payment methods, and no significant policy changes occurred in the districts and period I study. In addition, I use the method from Boyd et al., to capitalize on the application data, which were not available for Boyd et al. (2013). There are also several related papers in the compensating-wage literature, such as Lavetti (2020), which utilize changes in wages and benefits over time to identify worker preference. That approach is not feasible in the present context, where there were no significant changes in compensation or benefits. Other papers directly use employer- to-employer transfers analyzed within the revealed preference framework as Sorkin (2018). However, the revealed-preference literature either focuses on the direction of flows of workers or uses choice experiments to pin down the value of specific firm characteristics (Maestas et al., 2018; Wiswall & Zafar, 2017), their methods, however, are infeasible for this work.

For this work, the characteristics of schools studied have previously been studied and found to have effects on teacher preference in the prior literature. School quality measures of the GOSA school report card grade (performance and demographics) and the GADOE school climate measures (quality of school environment) are included to capture applicant preferences over readily available quality measures. Then due to the extensive literature about teacher flight from high-needs schools, I incorporated variables to represent the school's minority (percent of black or Hispanic) and poverty (percent of students directly certified for aid) status. Black and Hispanic were separated due to the studied district being primarily black in students and staff, so percent minority as an aggregate variable may not have accurately demonstrated preferences. As the studied district is highly urban with no internal variation, this factor of traditionally high-needs schools was excluded. As defined by the number of students, the school's size was included to further capture preferences over readily observable school aspects. The principal characteristics were included as they are the primary interaction of the candidate with the school and, to a large extent, represent the school's administrative environment.

The applicant characteristics chosen for interactions were also carefully selected. Firstly applicant race with student race due to the extensive literature showing that by including the interaction, the results can be substantially different in magnitude and potentially even reverse the effects. In the previous chapter, applicant GPA represented applicant quality, so in this chapter, applicant GPA is interacted with all of the preference aspects to study if quality had noticeable effects on preferences, which could contribute to disparate distributions of quality teachers. There is similar reasoning behind including interactions with and applicant's teaching experience as this candidate aspect has been strongly related with teacher performance in the literature.

2.5.1 Research Question: Which Schools are more likely to Receive Applications?

Conditional on applying to the district, teachers can choose to apply to any school with an opening. The likelihood of a teacher applying to a school is modeled as a conditional logistic function.[24] This particular estimation method was chosen to represent the application choice of teachers who must choose what schools to apply to amongst a set of alternatives. This approach allows unobserved characteristics of teacher to be

[24] In addition to the conditional logit specification, a traditional logit estimation was run on the same analysis sample which yielded very similar results and is therefore not being added to this paper.

accounted for and provides more precise estimation of the teachers' preferences. The model includes the interactions between each school's characteristics and a key set of each teacher's characteristics. The model can be represented as:

$$\Pr\left(Y_j \middle| Y_j \epsilon \{Revelant\ Openings\}\right) = \frac{\exp(x'_{ij}\beta)}{\exp\left(x'_{ij}\beta\right) + \sum_{i' \epsilon I^{\wedge} j} \exp(x'_{i'j}\beta)} \quad (1)$$

where i represents the school-subject in question and j all other alternatives. The choice set is constructed to be all schools with at least one hiring request in the school-level/subjects the teacher applied to in the year of application. Therefore, equation (1) represents the odds of choosing alternative i of their choice set. The probability is a function of the characteristics of the school they apply to and the interactions with key teacher characteristics. When using conditional logit, due to the estimation being within a teacher's choice set, any initial location effects and any teacher characteristic effects that are not interacted with the school drop out of the model since there is no variation. The analysis is split into applicants who have never worked in the district denoted as "New" pool, the transfer or "Current" applicant pool, and the combined or "All" applicant pool.

In the analysis, I estimate seven specifications. The first only includes a single measure of school quality, the letter grade assigned to the school in the Governor's Office of Student Achievement (GOSA) Georgia School Grades Report, with a grade of C being the omitted category. These grades are assigned based on the school performance on state assessments, the schools demographics, the graduation rate, and other accountability measures. In the second specification, I control for a set of characteristics I will group as "other school characteristics" including the Georgia Department of Education (GADOE) school climate score, the percent of students directly certified,[25] school size (measured by the number of students enrolled), the percent of students who are Black, and the percent of students who are Hispanic. In the third specification, I control for both sets of school characteristics (school grade and specific school characteristics). Then in the fourth, I also control for the characteristics of the principal of the school, namely their experience, evaluation score, and their years in the school. These three sets of controls are then used in the remaining three specifications, where in the fifth I also control for the interaction of student and applicant race. Then instead of applicant race, I interact the school grade and specific school characteristics with applicant teaching experience. In the last specification the characteristics as well as the principal characteristics are interacted with applicant GPA (a proxy for teacher quality) instead of experience. These key characteristics were selected based on prior research that demonstrates these school and applicant aspects are important to the labor market decisions of teachers.

2.6. Results

The estimation results for the sample of new applicants to the district are presented in Table 2.2. The first set of variables introduced are dummy variables for the school receiving a give GOSA School Report Card letter grade. The first specification includes only these variables and yields estimates that schools with a letter grade of F receive more applications than schools with a C grade, but that schools of other grades receive fewer applications. This result is true for all six specifications including these variables. This result may seem odd, as it suggests that teachers are most willing to apply

[25] The students determined to be eligible for free or reduced-price meal based on certification directly from government agencies without the need for households to verify the need of the child.

to the schools rated the worst level. However, there are a few reasons this result can be plausible, and the underlying truth is likely to be a combination of factors. First, accountability pressure in high-ranked schools can cause intrinsic pressure to not apply to higher-ranked schools. The preference for less accountability pressure has been shown in Feng, Figlio, & Sass (2018). Further, these low-ranked schools may offer the lure of additional resources and rewards, as argued in Dizon-Ross, 2020. These additional benefits could be an extrinsic motivation towards applying to lower-ranked schools. There is also the possibility that higher-graded schools may be better able to utilize personal networks and thus reach out and determine their hire quickly, not leaving the window open long enough for most applicants to submit (Engel & Finch, 2015). In addition to the applicant motivations that could cause the estimates, the model is unable to account for the prevalence of alternatives due to following the Independence from Irrelevant Alternatives property meaning if a certain school aspect is overly prevalent in the possible options the model is unable to decrease its weight in the estimates. Therefore, due to the prevalence of F ranked schools in the district, the estimated result may appear if applicants apply randomly. However, I do not think this is the reason, as in that case, D ranked schools should also have a positive point estimate, which they do not.

In addition to the GOSA letter grades, the number of students in the school, a descriptor of student poverty, the GADOE school climate score, and the portion of Black or Hispanic students were also incorporated into the analysis. The three non-race variables have interesting estimated impacts on application probabilities for the sample of new applicants; they differ from prior research findings regarding teacher preferences.

For all specifications, the number of students is positively related with application submission probabilities. There is the possibility that this sample of teachers finds appeal in larger schools, which may offer a larger professional learning community. It is more likely a result of the short-comings in the data set construction. As the choice set is made at the teacher-subject-school level, and any applications within that category are counted. Larger schools probably have more positions, increasing the likelihood that at least one of those positions appeals to the applicant. In addition, if the applicant applied to any positions in lower levels but were primarily targeting positions for a higher level this result could also occur. For example, if an applicant submitted an application for any middle school math position, all middle school math positions were placed in their choice set, but if that applicant was primarily applying to high schools which are by nature larger schools the estimate could be positive.

Traditionally, in the teacher preference literature, the proportion of students experiencing poverty is associated with lower application probabilities and increased likelihood of teacher exit from a school. For the sample of new teachers though, there is either no relationship or a positive relation among student poverty and application probabilities. This could coincide with the reasoning that struggling schools receive more resources, which balances with the teachers' preference to teach more economically advantaged students. There is also the possibility that applicants to this district are aware that the district has a large portion or disadvantaged students, and therefore, that information does not factor into their choices. I posit that this same reasoning can be applied to the finding that the school climate score has a negative correlation with application probabilities.

Across specifications and samples there is a large negative relationship between the percent of students who are Black and the probability of the average candidate applying to a school. However, while together with the large effect on its own of the portion of Black students, the total effect is still negative, the likelihood a black candidate applies to a school increases with the proportion of students in the school who are black. There is also a negative correlation between the percentage of students who are Hispanic and the probability that the average candidate will apply to a school. This negative correlation is even greater for Black candidates. These results support the previous research findings on teacher mobility that indicate white teachers are more likely to exit schools with high proportions of non-white students.

New applicants are more likely to apply to schools with more experienced principals. Taken in isolation, this result could support the previous finding that teachers prefer more supportive principals[26] or indicate that teachers prefer schools with greater staff stability. But when the negative estimated relationship with the principal's duration in the school is also considered, the former explanation seems unlikely. The two variables association with application probabilities could indicate that teachers may be willing to follow a principal or be attracted by a change in a school led by an experienced principal.

In the sixth specification, the GOSA School Grade variables, the school climate, size, as well as student poverty and race, are interacted with applicant experience. In the new-applicant sample, none of the coefficients on the interactions between applicant experience and school characteristics are statistically significant, indicating that the impact of school characteristics on candidate choices do not differ between new

[26] Ingersoll, 2001; Horng, 2009; Loeb et al., 2005

applicants who have never taught and those with prior experience in other school districts. This result is not surprising as most new applicants have no prior experience, and those that do typically have few years of experience.

The final set of interactions is between the applicant's college GPA (a proxy for candidate quality) and the principal characteristics and the characteristics previously interacted with experience. Within the sample of new applicants, the likelihood of an prospective teacher to apply to schools with higher climate scores, greater portions of Hispanic students, and to Grade A, D, and F schools (relative to Grade C Schools) increases with higher applicant GPAs. Further, applicants having a higher GPA makes them less likely to apply to schools where the principal has a higher evaluation score or more experience. The direction of the interaction with principal evaluation scores, principal experience, and Grade-F interactions further compound on the existing effect of those variables when un-interacted on application submission likelihoods. The other significant interaction effects have directions opposing the un-interacted variable estimates, which with large enough magnitude could reverse the total effect at large enough GPA values. However, as GPA is on a scale of zero to four, there is no GPA an applicant can have to make the total effect positive. For example, the school having a Grade of A, the effect of the applicant having a GPA of four would still be -0.125 ($-0.233 + (.027\times4)$). Having a higher GPA makes the estimates of the total effect closer to the current teacher sample, so possibly candidates with higher college GPAs are better able to gather information about their possible options.

In discussing the results from the current-teacher sample I will compare my findings those of Boyd et al. (2011). Though they employ different sample construction and techniques, the two paper's estimations yield similar results. Both studies find negative effects of the percent of students who are Black or Hispanic. Though the student population with the largest effect is different, (Hispanics in my sample and Blacks in Boyd et al, 2011); I believe this is due to the differences in the racial composition of the teachers (my sample is predominantly black while theirs has a large Hispanic population). Both studies find that greater student poverty and worse school climates are associated with lower probabilities of application to a school.

The main area where we both have significant estimates, but opposing results, is school size. This result could be due to their inclusion of the school level (elementary, middle, high), and my sample construction, which as discussed for the new applicant estimation, is likely to have this unexpected positive result since larger schools having more openings for a single "position," and the fact that different levels of schools are different sizes so if enough teachers prefer a high school when those are in their choice set this could lead to this positive effect of school size.

There are a few areas where the results from the current-teachers and new-applicant samples differ substantially; estimates for the effects of the school climate score, student poverty, and the interactions with GPA and experience all have qualitatively different estimated impacts on application probabilities. Current teachers follow the expected preferences regarding school climate scores and student poverty, while new applicants do not. A possible explanation for this difference is that current teachers have greater knowledge of the school system and are better able to direct their applications to the more desirable schools. Another possible reason is that current teachers may value "easier" teaching environments relatively more than do new teachers who could have shorter planning horizons. All current-teacher sample members have varying amounts of experience, while the reported GPAs have less variation. Therefore, the current-teachers sample has applicant experience interactions as statistically significant and GPA insignificant, which is a reverse of the new-applicant estimates.

Because the distance to a school has been shown to be an important element of teacher preference over schools (Horng, 2009; Boyd et al., 2013; Engel & Cannata, 2015; Engel at al., 2014; Boyd et al., 2005b), I also estimate application probability models that account for the distance between a teacher's residence and each school. Unfortunately, address information is missing for many applicants, which lead to a roughly 50 percent reduction in the sample size. Further, it is likely that this reduced sample consists of a greater portion of fully completed applications. I believe this completion rate inference to be true due the fact that in every specification of new sample (Table 2.4), the direction of the relations are maintained, the magnitude is slightly increased, and the significance of the point estimates actually increased. For the sample of current teachers (Table 2.5), the inclusion of the distance variable generally either reduces or has no appreciable effect on the magnitude of the point estimates. This could suggest that location is a more important factor once a teacher is already in a position, and is seeking a transfer. In addition to the effect the inclusion of the distance variable has through the sample change, the distance point estimates are significant and, as expected, indicate that increases in distance to a school reduce the likelihood a candidate will apply, similar to the application choices at the Chicago job fair studied by Engel, Jacob, and Curran in 2014.

2.7. Conclusion

This research provides an analysis of teacher application preferences in an Atlanta Metropolitan area school district. My main contribution to the extensive teacher preference literature is using the applications of prospective teachers to examine the preferences of teachers entering a school district. The majority of my findings for new teachers is consistent with the prior teacher preference research. Still, there are several notable exceptions: the school climate, student poverty, school size, and the GOSA School Report Card Grade. The new applicants were less likely to apply to schools with a higher climate score and more likely to apply to a school with a higher portion of economically disadvantaged students. This finding could result if positions in struggling or difficult schools are more likely to be supported with increased resources, or the vacancy is open longer due to the search being more difficult to complete and, therefore, more likely to be up during any given window an applicant is applying. The odd result for applicants being more likely to apply to schools with more students could also be due to the search duration of the school leading the position to be open for a longer time or could be a result of the sample construction whereby larger schools should have more vacancies posted, but I am unable to observe and therefore account for total vacancies.

I also found that applicants were more likely to apply to schools with a GOSA School Report Card letter grade of F, and less likely to apply to the other grades as compared to grade C schools. There are several possible reasons. There is a higher prevalence of grade F schools in the school district and if applicants apply somewhat randomly is could seem they prefer grade F schools. In that case, though, there should also be an increase in applications to grade D schools, and there is not. It could also be the preferences against accountability pressures previously found in Feng, Figlio, and Sass (2018) presenting in the application behavior, or preferences for increased resources and rewards that may be allocated to low-ranked schools, as shown in Dizon-Ross (2020). Furthermore, the result may due to the window of time the vacancy is posted in the higher graded schools is too short for the applicants to complete their submission. Engel and Finch (2015) found that higher-graded schools may have principals able to utilize their personal networks to quickly complete their hiring process.

In general, my findings for current teachers are also consistent with those from previous studies in the teacher preference literature. The primary exceptions are the GOSA School Report Card and the number of students in a school, though they could be explained by the factors discussed above for new applicants results discussed above. Also, my results indicate a negative relationship between application probabilities and the evaluation scores of a school's principal. This evaluation score effect could mean that the evaluation is capturing portions of the principal's performance, which are unappealing to teachers, and current teachers can capitalize on this information due to informal information networks and apply elsewhere. If this is the reason behind the evaluation result, then the evaluating entity may want to consider changing the measure to better reflect the ability of the principal to attract teachers.

Together the findings for the new applicants and current teachers could support the notion that teachers, as they progress in the profession, increasingly value "easier-to-teach" positions and leverage their knowledge of the school system to obtain them. Regardless, the differences mean that efforts to change a school's appeal to candidates should account for potentially varying impacts prospective teachers. For example, if a school is attempting to attract current teachers, they should demonstrate that the school climate is improving even if they cannot affect the student population. For both current and new teachers, the distance of the school from their residence had a negative relation with application probabilities. Therefore if the system was able to offer housing subsidies to live close to the schools, they may be able to entice more applicants to those schools.

2.8. Tables

Table 2.1 Summary Statistics

	All		New		Current		All	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Min	Max
Applied to the position	0.116	0.321	0.108	0.310	0.160	0.366	0	1
GADOE School Climate Score (STAR)	3.118	1.057	3.120	1.053	3.110	1.077	0	5
GADOE School Climate Score (STAR) missing	0.050	0.217	0.049	0.216	0.053	0.224	0	1
Percent of Students Directly Certified	60.270	26.438	60.230	26.454	60.474	26.356	0	91.9
Percent of Students Directly Certified Missing	0.025	0.155	0.024	0.151	0.030	0.170	0	1
Number of Students (100s)	6.665	2.669	6.648	2.643	6.754	2.802	0	20.09
Percent of Students Black	0.775	0.314	0.775	0.313	0.773	0.317	0	1
Percent of Students Hispanic	0.075	0.101	0.076	0.101	0.074	0.100	0	0.540
GOSA Report Card Grade A	0.110	0.313	0.110	0.313	0.109	0.312	0	1
GOSA Report Card Grade B	0.073	0.260	0.073	0.260	0.073	0.261	0	1
GOSA Report Card Grade C	0.107	0.308	0.109	0.311	0.096	0.294		
GOSA Report Card Grade D	0.302	0.459	0.305	0.461	0.286	0.452	0	1
GOSA Report Card Grade F	0.365	0.481	0.360	0.480	0.386	0.487	0	1
Principal Experience	10.670	9.778	10.676	8.982	10.638	9.078	0	42.5
Principal Experience Missing	0.105	0.307	0.105	0.306	0.106	0.308		
Principal Evaluation Score	16.814	2.055	16.836	2.048	16.700	2.086	12	23
Principal Evaluation Score Missing	0.062	0.241	0.060	0.237	0.073	0.260	0	1
Principal Years in the School	3.791	2.812	3.805	2.804	3.720	2.847	0	17
Principal Years in the School Missing	0.060	0.237	0.061	0.240	0.051	0.221	0	1
Black Applicant	0.806	0.395	0.807	0.395	0.803	0.398	0	1
White Applicant	0.171	0.377	0.171	0.376	0.1773	0.378	0	1
Non-White Other Applicant	0.023	0.149	0.023	0.149	0.024	0.153	0	1

Applicant Race Missing	0.148	0.355	0.126	0.332	0.262	0.440	0	1
Applicant College GPA	2.174	1.497	2.103	1.516	2.521	1.346		
Applicant College GPA Missing	0.334	0.472	0.359	0.480	0.209	0.407	0	1
Applicant Teaching Experience	2.881	5.297	2.079	4.344	6.922	7.403	0	56
Applicant Teaching Experience Missing	0.019	0.138	0.022	0.146	0.008	0.086	0	1
Applicant Distance to the School	171.768	581.807	189.967	620.486	64.872	224.677	0.059	14045
Applicant Distance to the School Missing	0.452	0.498	0.438	0.496	0.522	0.500	0	1
N	533,806		446,423		87,383			

Notes: N is for the total sample. These summary statistics are unsuppressed in the regressions the mean will be lower because all missing values are replaced with zero and an indicator for missing is included.

Table 2.2 Application Estimations for New Applicants-Relevant School Level-Subject Choice Set

		1	2	3	4	5	6	7
GOSA Report Card Grade	Grade A	-0.043***		-0.150***	-0.171***	-0.174***	-0.169***	-0.233***
		(0.006)		(0.005)	(0.010)	(0.010)	(0.010)	(0.015)
	Grade B	-0.118***		-0.097***	-0.122***	-0.123***	-0.121***	-0.126***
		(0.007)		(0.005)	(0.008)	(0.008)	(0.008)	(0.010)
	Grade D	-0.046***		-0.007***	-0.015***	-0.015***	-0.014***	-0.058***
		(0.004)		(0.003)	(0.002)	(0.002)	(0.003)	(0.006)
	Grade F	0.048***		0.043***	0.024***	0.024***	0.025***	0.010**
		(0.004)		(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
Other School Characteristics	GADOE School Climate Score (STAR)		-0.012***	-0.003***	-0.005***	-0.005***	-0.006***	-0.007***
			(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Percent of Student Directly Certified		0.002***	-0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Number of Students (100s)		0.004***	-0.000	0.002***	0.002***	0.001***	0.001**
			(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Percent of Students Black		-0.183***	-0.204***	-0.246***	-0.304***	-0.245***	-0.263***
			(0.018)	(0.011)	(0.016)	(0.012)	(0.016)	(0.024)
	Percent of Students Hispanic		-0.344***	-0.409***	-0.397***	-0.356***	-0.399***	-0.544***
			(0.019)	(0.014)	(0.023)	(0.023)	(0.023)	(0.037)
Principal Characteristics	Experience				0.004***	0.004***	0.004***	0.006***
					(0.000)	(0.000)	(0.000)	(0.000)
	Evaluation Score				-0.000	-0.000	-0.000	0.001
					(0.000)	(0.000)	(0.000)	(0.001)
	Years in the School				-0.001***	-0.001***	-0.001***	-0.001**
					(0.000)	(0.000)	(0.000)	(0.000)

Percent of Student Race Interacted with Applicant Race	Black × Black	0.081***	
		(0.008)	
	Black × Non-White Other	0.024	
		(0.017)	
	Hispanic × Black	-0.068***	
		(0.017)	
	Hispanic × Non-White Other	-0.086	
		(0.055)	
Interacted with Applicant Experience	GOSA Report Card Grade A		-0.001
			(0.001)
	GOSA Report Card Grade B		0.000
			(0.001)
	GOSA Report Card Grade D		-0.000
			(0.000)
	GOSA Report Card Grade F		-0.001
			(0.000)
	GADOE School Climate Score (STAR)		0.000
			(0.000)
Interacted with Applicant Experience	Percent of Student Directly Certified		-0.000
			(0.000)
	Number of Students (100s)		0.000*
			(0.000)
	Percent of Students Black		-0.000
			(0.002)
	Percent of Students Hispanic		0.001
			(0.002)

Interacted with Applicant College GPA	GOSA Report Card Grade A							0.027*** (0.003)
	GOSA Report Card Grade B							0.003 (0.002)
	GOSA Report Card Grade D							0.018*** (0.002)
	GOSA Report Card Grade F							0.005*** (0.002)
	GADOE School Climate Score (STAR)							0.001* (0.000)
	Number of Students (100s)							-0.000 (0.000)
	Percent of Student Directly Certified							-0.000 (0.000)
	Percent of Students Black							0.010 (0.004)
	Percent of Students Hispanic							0.066*** (0.009)
	Principal Years in the School							-0.000 (0.000)
	Principal Evaluation Score							-0.000*** (0.000)
	Principal Experience							-0.001*** (0.000)
	N	444,403	444,403	444,403	444,403	444,403	444,403	444,403

Notes: For each of the non-interacted variables there is a non-reported indicator equal to one if the variable was missing and zero if not.

Table 2.3 Application Estimations for Current Teachers-Relevant School Level-Subject Choice Set

		1	2	3	4	5	6	7
GOSA Report Card Grade	Grade A	0.004		-0.176***	-0.145***	-0.147***	-0.149**	-0.167***
		(0.011)		(0.010)	(0.013)	(0.013)	(0.015)	(0.022)
	Grade B	-0.068***		-0.117***	-0.110***	-0.108***	-0.086***	-0.118***
		(0.012)		(0.011)	(0.014)	(0.013)	(0.013)	(0.020)
	Grade D	-0.053***		0.008	-0.004	-0.004	0.012*	-0.016
		(0.008)		(0.007)	(0.005)	(0.005)	(0.007)	(0.013)
	Grade F	-0.037***		0.046***	0.023***	0.022***	0.041***	0.017
		(0.008)		(0.008)	(0.007)	(0.007)	(0.009)	(0.013)
Other School Characteristics	GADOE School Climate Score (STAR)		0.008***	0.010***	0.007***	0.007***	0.005**	0.009**
			(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
	Percent of Student Directly Certified		-0.001***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	Number of Students (100s)		0.010***	0.004***	0.003***	0.004***	0.004***	0.003**
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Percent of Students Black		0.037	-0.097***	-0.080***	-0.163***	-0.123***	-0.078
			(0.039)	(0.365)	(0.029)	(0.030)	(0.034)	(0.054)
	Percent of Students Hispanic		-0.031	-0.279***	-0.210***	-0.212***	-0.252***	-0.188***
			(0.036)	(0.032)	(0.028)	(0.036)	(0.036)	(0.059)
Principal Characteristics	Experience				0.002***	0.002***	0.002***	0.002***
					(0.000)	(0.000)	(0.000)	(0.001)
	Evaluation Score				-0.005***	-0.005***	-0.005***	-0.005***
					(0.001)	(0.001)	(0.001)	(0.001)
	Years in the School				-0.001	-0.001	-0.001	-0.001
					(0.001)	(0.001)	(0.001)	(0.001)

Percent of Student Race Interacted with Applicant	Black × Black	0.135***	
		(0.020)	
	Black × Non-White Other	-0.003	
		(0.049)	
	Hispanic × Black	0.005	
		(0.034)	
	Hispanic × Non-White Other	-0.076	
		(0.123)	
Interacted with Applicant Experience	GOSA Report Card Grade A		0.001
			(0.001)
	GOSA Report Card Grade B		-0.004***
			(0.001)
	GOSA Report Card Grade D		-0.003***
			(0.001)
	GOSA Report Card Grade F		-0.003***
			(0.001)
	GADOE School Climate Score (STAR)		0.000
			(0.000)
Interacted with Applicant Experience	Percent of Student Directly Certified		-0.000**
			(0.000)
	Number of Students (100s)		-0.000
			(0.000)
	Percent of Students Black		0.007**
			(0.003)
	Percent of Students Hispanic		0.007**
			(0.003)

Interacted with Applicant College GPA	GOSA Report Card Grade A							0.009 (0.007)
	GOSA Report Card Grade B							0.004 (0.005)
	GOSA Report Card Grade D							0.005 (0.004)
	GOSA Report Card Grade F							0.002 (0.004)
	GADOE School Climate Score (STAR)							-0.001 (0.001)
	Number of Students (100s)							0.000 (0.000)
	Percent of Student Directly Certified							-0.000 (0.000)
	Percent of Students Black							-0.001 (0.019)
	Percent of Students Hispanic							-0.009 (0.012)
	Principal Years in the School							0.000 (0.000)
	Principal Evaluation Score							0.000 (0.000)
	Principal Experience							-0.000* (0.000)
	N	86,747	86,747	86,747	86,747	86,747	86,747	86,747

Notes: For each of the non-interacted variables there is a non-reported indicator equal to one if the variable was missing and zero if not.

Table 2.4 Application Estimations for New Applicants-Including a Distance Variable

		1	2	3	4	5	6	7
	Distance to the School	-0.000*	-0.000*	-0.000*	-0.000*	-0.000	-0.000*	-0.000*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GOSA Report Card Grade	Grade A	-0.055***		-0.181***	-0.223***	-0.225***	-0.221***	-0.306***
		(0.008)		(0.007)	(0.014)	(0.014)	(0.014)	(0.023)
	Grade B	-0.122***		-0.127***	-0.155***	-0.156***	-0.155***	-0.161***
		(0.008)		(0.008)	(0.013)	(0.013)	(0.013)	(0.016)
	Grade D	-0.046***		-0.003	-0.017***	-0.018***	-0.017***	-0.058***
		(0.005)		(0.004)	(0.004)	(0.004)	(0.004)	(0.009)
	Grade F	0.045***		0.076***	0.039***	0.039***	0.042***	0.044***
		(0.005)		(0.006)	(0.005)	(0.005)	(0.006)	(0.008)
Other School Characteristics	GADOE School Climate Score (STAR)		-0.006***	-0.000	-0.006***	-0.006***	-0.006***	-0.008***
			(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	Percent of Student Directly Certified		0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Number of Students (100s)		0.007***	0.001**	0.003***	0.003***	0.002***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Percent of Students Black		-0.089***	-0.137***	-0.227***	-0.288***	-0.223***	-0.194***
			(0.025)	(0.020)	(0.019)	(0.022)	(0.021)	(0.033)
	Percent of Students Hispanic		-0.189***	-0.353***	-0.412***	-0.361***	-0.414***	-0.565***
			(0.026)	(0.019)	(0.026)	(0.029)	(0.027)	(0.047)
Principal Characteristics	Experience				0.004***	0.004***	0.004***	0.007***
					(0.000)	(0.000)	(0.000)	(0.001)
	Evaluation Score				0.002**	0.002**	0.002**	0.004***
					(0.001)	(0.001)	(0.001)	(0.001)
	Years in the School				-0.002***	-0.002***	-0.002***	-0.002***
					(0.000)	(0.000)	(0.000)	(0.001)

Percent of Student Race Interacted with Applicant	Black × Black	0.092***	
		(0.011)	
	Black × Non-White Other	0.013	
		(0.028)	
	Hispanic × Black	-0.079***	
		(0.025)	
	Hispanic × Non-White Other	-0.178**	
		(0.090)	
Interacted with Applicant Experience	GOSA Report Card Grade A		-0.001
			(0.001)
	GOSA Report Card Grade B		0.000
			(0.001)
	GOSA Report Card Grade D		-0.000
			(0.001)
	GOSA Report Card Grade F		-0.002**
			(0.001)
	GADOE School Climate Score (STAR)		0.000
			(0.000)
Interacted with Applicant Experience	Percent of Student Directly Certified		0.000
			(0.000)
	Number of Students (100s)		0.000
			(0.000)
	Percent of Students Black		-0.002
			(0.004)
	Percent of Students Hispanic		0.001
			(0.003)

Interacted with Applicant College GPA	GOSA Report Card Grade A							0.036***
								(0.005)
	GOSA Report Card Grade B							0.004
								(0.004)
	GOSA Report Card Grade D							0.016***
								(0.003)
	GOSA Report Card Grade F							-0.004
								(0.003)
	GADOE School Climate Score (STAR)							0.001
								(0.001)
	Number of Students (100s)							-0.000
								(0.000)
	Percent of Student Directly Certified							0.000*
								(0.000)
	Percent of Students Black							-0.010
								(0.012)
	Percent of Students Hispanic							0.068***
								(0.014)
	Principal Years in the School							0.000
								(0.000)
	Principal Evaluation Score							-0.001***
								(0.000)
	Principal Experience							-0.002***
								(0.000)
	N	254,964	254,964	254,964	254,964	254,964	254,964	254,964

Notes: For each of the non-interacted variables there is a non-reported indicator equal to one if the variable was missing and zero if not.

Table 2.5 Application Estimations for Current Teachers-Including a Distance Variable

		1	2	3	4	5	6	7
	Distance to the School	-0.000**	-0.000**	-0.000**	-0.000**	-0.000*	-0.000**	-0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GOSA Report Card Grade	Grade A	-0.029*		-0.167***	-0.114***	-0.116***	-0.116***	-0.134***
		(0.016)		(0.013)	(0.016)	(0.015)	(0.017)	(0.027)
	Grade B	-0.096***		-0.121***	-0.095***	-0.095***	-0.078***	-0.106***
		(0.016)		(0.017)	(0.020)	(0.019)	(0.018)	(0.027)
	Grade D	-0.025**		0.021**	0.003	0.002	0.011	-0.018
		(0.011)		(0.009)	(0.006)	(0.006)	(0.008)	(0.014)
	Grade F	-0.036***		0.045***	0.010	0.009	0.019**	-0.001
		(0.011)		(0.010)	(0.007)	(0.007)	(0.009)	(0.015)
Other School Characteristics	GADOE School Climate Score (STAR)		0.001	0.004	0.001	0.002	0.002	0.001
			(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
	Percent of Student Directly Certified		-0.002***	-0.003***	-0.002***	-0.002***	-0.001**	-0.001**
			(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	Number of Students (100s)		0.008***	0.002	0.001	0.001	0.002	0.002
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
	Percent of Students Black		0.105**	-0.047	-0.026	-0.106***	-0.072*	-0.029
			(0.053)	(0.054)	(0.035)	(0.031)	(0.038)	(0.060)
	Percent of Students Hispanic		0.085*	-0.162***	-0.091***	-0.066	-0.132***	-0.036
			(0.050)	(0.052)	(0.033)	(0.045)	(0.037)	(0.069)
Principal Characteristics	Experience				0.001***	0.001***	0.001***	0.002***
					(0.000)	(0.000)	(0.000)	(0.001)
	Evaluation Score				-0.006***	-0.006***	-0.006***	-0.007***
					(0.001)	(0.001)	(0.001)	(0.001)
	Years in the School				-0.001	-0.001	-0.001	-0.002
					(0.001)	(0.001)	(0.001)	(0.002)

Percent of Student Race Interacted with Applicant Race	Black × Black	0.122***
		(0.026)
	Black × Non-White Other	0.013
		(0.053)
	Hispanic × Black	-0.038
		(0.039)
	Hispanic × Non-White Other	-0.184
		(0.155)
Interacted with Applicant Experience	GOSA Report Card Grade A	0.000
		(0.001)
	GOSA Report Card Grade B	-0.004**
		(0.002)
	GOSA Report Card Grade D	-0.002*
		(0.001)
	GOSA Report Card Grade F	-0.002*
		(0.001)
	GADOE School Climate Score (STAR)	-0.000
		(0.000)
Interacted with Applicant Experience	Percent of Student Directly Certified	-0.000**
		(0.000)
	Number of Students (100s)	-0.000
		(0.000)
	Percent of Students Black	0.009**
		(0.004)
	Percent of Students Hispanic	0.008**
		(0.004)

Interacted with Applicant College GPA	GOSA Report Card Grade A							0.008 (0.008)
	GOSA Report Card Grade B							0.004 (0.006)
	GOSA Report Card Grade D							0.008* (0.005)
	GOSA Report Card Grade F							0.004 (0.005)
	GADOE School Climate Score (STAR)							0.000 (0.001)
	Number of Students (100s)							-0.000 (0.001)
	Percent of Student Directly Certified							-0.000 (0.000)
	Percent of Students Black							0.001 (0.020)
	Percent of Students Hispanic							-0.021 (0.022)
	Principal Years in the School							0.000 (0.001)
	Principal Evaluation Score							0.000 (0.000)
	Principal Experience							-0.000* (0.000)
	N	42,267	42,267	42,267	42,267	42,267	42,267	42,267

Notes: For each of the non-interacted variables there is a non-reported indicator equal to one if the variable was missing and zero if not.

3. Who Knew? An Experimental Examination of Information Effects on a Teacher Labor Market

3.1 Introduction

Several studies find that teachers are the most important school provided input into a child's education,[27] in addition to being an anecdotal truth believed by most people. However, there has been shown to be a disparity in access to quality teachers between key student sub-groups. The disparity can occur due to differential job mobility patterns[28] or in the hiring process,[29] making the teacher labor market of particular interest.

Further research has shown that the quality of the match between the teacher and the school, how well the teacher fits in with their peers and students can also affect the teacher's ability to contribute to their students' growth.[30] An additional benefit of a good teacher-school match is that it increases the likelihood of prolonged tenure at the school, which is of particular interest as experience is a teacher aspect positively related to student achievement consistently.[31] Improving the way teachers match to schools during the hiring process seems an attractive intervention to improve equity in accessibility and quality of education. Lastly, improving teacher tenure through improving their matches to schools decreases the teacher turnover rate and, in turn, decreases the pecuniary and non-pecuniary costs of turnover,[32] allowing those resources to be directed into further helping student achievement.

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[27] Rivkin et al., 2005; Aaronson et al., 2007; Kane et al., 2008
[28] Darling-Hammond, 2001; Viadero 2002; Gordon & Maxey, 2000; Goldhaber et al. 2007; Feng & Sass, 2017
[29] Sass, et al., 2012; Reininger, 2012
[30] Jackson, 2013
[31] Chingos & Peterson, 2011; Staiger & Rockoff, 2010; Rivkin et al., 2005; Clotfelter et al., 2006; Dobbie, 2011; Wiswall, 2013; Papay & Kraft, 2015; Rockoff, 2004
[32] Milanowski & Odden 2007; Guin, 2004

The possible benefits of improving matching in the teacher labor market stress the importance of identifying behaviorally stable and efficient matching procedures between teachers and schools. In this chapter, I use a laboratory experiment to examine the effect of information about the teachers' competitors on (i) teachers' choices of signaling their quality, (ii) the efficiency of the matching market, and (iii) the market stability. The experimental design allows the identification of the effect of the information as I control for the environment, namely the productivity of teacher-school pairing, a challenging task for observational data. A novel feature of the experimental design is the integration of the matching mechanism and (Spence) signaling model. These two models, widely used in economic literature, will be described in detail later in this paper.

Matching markets theory offers a framework to model the teacher labor market I am examining. The matching markets framework was initially designed to represent the marriage market and the housing market (Gale & Shapley 1962) but has since been used in many contexts such as medical residency placements (Roth & Xing, 1994, 1997; Kagel & Roth, 2000; Roth, 1984, 1991) organ transplants (Roth et al., 2005), and school assignments (Abdulkadiroğlu et al. 2005; Chen & Sönmez, 2006). The procedure I use will be called the school hiring (SH) mechanism for the rest of this paper. The model is based on the partner school district studied in the two other chapters of this dissertation. However, in the markets modeled, there are varying levels of information. I examine the effect of information about competitors on applicants' choices and how school assignments are affected by teachers' strategic actions. It is hard to identify quality teachers in the hiring process. A lot of the initial judgment stems from credentials, which should be easier to achieve for high-type teachers when aligned adequately to teacher quality. Examples of possible ability signals are licensure test scores, college selectivity, college grade point average, and the degrees obtained.

Embedding a signaling model of applicant productivity in a two-sided matching market is the main contribution of this experiment to the existing experimental economics literature. Hopkins first developed the combination of the Spence model with the matching markets framework in 2012. The concept of combining a two-sided matching market with signaling was further expanded by Coles et al. (2013). However, Hopkins focused on the effects of matching markets on the signaling equilibrium, and Coles et al. focused on signals of interest. I use a two by two design of homogenous or heterogeneous preferences over partners and additional versus no additional information in my experiment. The purpose of the experiment is to generate data than can inform on the effect of information on signaling investments and the market efficiency and stability of the observed matches.

I examine information value in a lab setting for several reasons. The first being that any policy interventions should be evidence based before being imposed on the actual labor market. Creating that data as a survey has a problem regarding the difficulty of ensuring the salience of answers and being unable to represent the market's two-sided nature. Then, even if I could find districts following the treatments, the administrative data would be so complicated that empirical identification would still be difficult. The data issues are especially true for estimating market efficiency and payoffs, given that many of the benefits teachers and schools receive from a given match cannot clearly be measured due to being subjective. Besides, in the actual labor market, schools and teachers can seek additional information outside of the signals, through methods such as interviews, phone calls, and personal connections. Many of these interactions are never recorded, thus muddling that aspect of an empirical analysis.

Further there are a plethora of hiring process variations which can affect the match outcomes, such as teachers using the placement as a way to transfer somewhere more preferred (indicating the markets are unstable),[33] collective bargains,[34] and other policies that can disrupt placement planning.[35] More importantly, when empirically studying the existing labor market, both the schools' and teachers' true preferences are unknown, meaning the market must be stable to allow for the calculation of self-sorting (Boyd et al., 2013). The market I am interested in studying empirically is not stable based on the large amounts of mobility.[36] A further complication preventing studying this question using observational data is that the geographic area I am studying has many competing sub-markets causing the system to be very complex and challenging to empirically model. Creating a controlled market and observing participants' decisions in this market, I can develop an initial understanding of how information can affect applicants' behavior in a two-sided matching market with the SH mechanism.

In light of these difficulties arising from asymmetric information, when and what agents know becomes crucial. In the experiment, all signaling investments are simultaneous in one treatment (the baseline), whereas in another treatment, investments are sequential. That is, investments occur in random order and workers observe all earlier investments. Also, to examine how the degree of competitiveness in the labor market

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[33] Reininger 2012; Boyd et al. 2005a,b; Boyd et al. 2013
[34] Strunk et al. 2018; Levin et al., 2005
[35] DeArmond et al., 2010; Cohen-Vogel et al., 2019; Heneman & Milanowski 2004, 2007
[36] Ingersoll, 2001; Hanushek et al., 2004; Scafidi et al., 2007; Clotfelter et al., 2011; Feng, 2009; Jackson, 2013; Goldhaber et al., 2011

affects the outcomes, I induce two preference sets in the experiment. I used these two preference sets to study agents' choices when preferences are identical (competitive) or heterogeneous (reduced competition).

The theoretical model (discussed in section 3.3) guided the parameterization of the experiment. The participants in the experiment were Georgia State University students recruited using the ExCEN online recruiter. After participants completed the matching markets portion of the experiment, I also collected their demographic information and behavior on a risk elicitation task, to control for individual idiosyncratic characteristics.

Data from the experiment suggests that heterogeneous preferences decrease agents investment amounts when not participating in the information treatment. Further, the information treatment negatively impacts investment amounts when preferences are homogenous. The information treatment also leads to the signaling investments revealing worker type less often. The treatment has no effect however on market efficiency, but the preferences being homogenous does result in higher efficiency. The information treatment negatively affects firms' payoffs when preferences are heterogeneous, but positively affects firms' payoffs when preferences are homogenous. However, no single firm type bore the brunt of the effects of information. Regarding market stability, the stability was higher for when the preferences were homogenous.

3.2 Literature Review:

In 1962, the matching markets framework was formalized by Gale and Shapley to model college admissions and marriage market stability. This initial paper proposed the Deferred Acceptance procedure, where agents from one side (the man or applicant) issue an offer to one agent from the other side (the woman or college). The side receiving offers can receive multiple offers and decides which to keep. Rejected agents then issue offers to their next preferred, and so forth until no more rejections occur. The mechanism is strategy-proof for the applicants (no applicant has an incentive to misrepresent their preferences) and stable (no pair of applicant and college would both prefer each other over their assigned partner). However, markets using Deferred Acceptance are not always efficient, so in some cases, agents' total payoffs could increase in a non-equilibrium solution (Roth, 1982).

The Deferred Acceptance mechanism is widely used and studied; however, for this experiment, the matching procedure studied bears greater similarity to the Priority (Boston) matching algorithm. The Priority algorithm is most easily described in the context of student placements to Boston Public Schools in the early 2000s, such as in the works of Abdulkadiroğlu et al. (2005) and Chen & Sönmez (2006). The schools each have a priority ranking of all students based on several factors such as siblings, distance, etc. While knowing the schools at which they had priority, students created a preference ranking of schools to be submitted to the system for the assignment procedure. In the first round, schools accepted any students within capacity constraints. If they had a surplus of applicants, they retained students in the order of priority. Students who were not assigned enter the second round of placements. The same procedure takes place at their second-ranked school, but if the seat has already been filled, being a priority student will not allow the student to receive a spot in the school. The matching procedure continues for as many rounds as are needed to assign each student a school. This assignment procedure gives students (the agents placing active offers or rankings) a strong incentive to strategically order their preferences, such that schools for which they have priority are ranked higher on their submitted preferences than in their true preferences. The strategic ranking allows the students to receive a better final assignment than if they submitted their true preferences. The primary difference between the Priority mechanism and the School Hiring mechanism used in this paper is that those being proposed to can reject an offer even if their quota is not full. This should not change the theoretical properties that we would expect in a priority matching environment.

In addition to school assignment procedures, the Priority procedure has also appeared in US and European medical student residency markets. The procedure was the most commonly used unstable algorithm. The residency markets often were unstable (leading to next period rematching) or matched unreasonably early. When introducing various procedures into these markets as field experiments, the early matching only decreased modestly under the priority algorithm, and instability increased (Roth, 1984, 1991).

For this experiment, agents also cannot defer acceptance, and thus workers must reject their current offer to receive future offers. These workers may then accept a less preferred partner early in the market to avoid the outcome of no or worse matches. The main difference from the traditionally studied Priority algorithm is that for one side of the market type (true productivity) is private information. Those agents must then use a costly signal to demonstrate their type. Agents still have incentives to misrepresent their preferences or type (act strategically) to make a better match like in the original Priority procedure. This paper aims to determine if additional information regarding competitor actions or the competition created by similar preferences impacts strategic behavior.

The model incorporated into two-sided matching markets to characterize the incomplete information regarding agent type is the Spence signaling model (Spence 1973). In the model, workers know their productivity, but this information is not known to firms. Agents signal their productivity by making costly investments where cost is inversely related to productivity. Firms then observe signaling investments. The workers can chose investment amounts (a separating equilibrium) that allow firms to determine worker types or the workers can choose to invest the same amount (a pooling equilibrium) or other amounts which result in firms being unable to determine worker type. In the original (Spence) signaling game, their investments did not increase productivity, and thus any amount of investment was socially inefficient. In this experiment, the investment will be productivity increasing, with the increases occurring at units 1, 4, and 7 to mimic preparation program completion effects, allowing the investment to represent a properly-aligned signal of teacher quality.

Both the Spence Signaling Game and Matching Markets have been extensively tested experimentally, and developed theoretically, in isolation. Researchers have tested variation in the Spence Signaling game regarding the equilibrium type,[37] behavior,[38] and the signal's purpose.[39] The research within the Matching Markets literature has covered a variety of matching mechanisms[40] comparative statics (Hopkins, 2012), levels of asymmetric information,[41] utility transferability (Becker, 1973, 1974), market types,[42]

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[37] Brandts & Holt, 1992; Banks et al., 1994; Cho & Kreps, 1987
[38] Cooper & Kagel, 2003; Potters & van Winden, 1996
[39] Coles et al., 2013; Miller & Plott, 1985; Kübler et al., 2008
[40] Gale & Shapley, 1962; Shapley & Scarf, 1974; Roth, 1982, 1984, 1991; Roth & Xing, 1994, 1997; Hylland & Zuckhauser, 1972; Abdulkadiroğlu & Sönmez, 1999; Sönmez & Ünver, 2011; Chen & Sönmez, 2003
[41] Hopkins, 2012; Bikhchandani, 2017; Ehlers & Masso, 2015; Chen & Sönmez, 2003; Coles et al., 2013; Hoppe et al., 2009
[42] Gale & Shapley, 1962; Roth & Xing, 1997; Roth, 1991; Roth et al., 2004; Chen & Sönmez, 2006

and preference types (Becker, 1973, 1974). The listed research listed are examples in a large body of experimental and theoretical work. This work shows that properties of matching market outcomes can vary dramatically with the information environment.

Other experimentalists and theorists have developed research regarding the effects of introducing varied preferences of the agents to study the impact on behavior and prevent preference-specific results. Additional researchers have introduced information asymmetry into two-side matching markets. Coles et al., 2013 developed a matching market experiment that introduced signals as an element of the market. In their market, the signals were to demonstrate interest or enthusiasm for the match in a congested hiring market as preferences were private information. Also, in their experiment the worker quality is known to firms and thus public information. The researchers show that signals benefit searchers, do not harm employers, and work best under balanced markets. For the signal to work, the number of signals must be limited. The study also examined the effects of block correlated preferences, which are useful when firms have multiple attributes by allowing for idiosyncrasies within worker preferences. In their experiment, they have only one block, and the match's quality does not change due to the preferences, so just being able to create any match is the target outcome.

In my model and experimental design, I draw upon various previous studies on signaling games and matching procedures but did focus on insights from works focused on the role of information on the market performance. This paper is not the first to theoretically combine the two models (that honor goes to Hopkins, 2012). Still, it is the first to examine it experimentally, and the focus of the theory is substantially different to reflect the questions of interest in the experiment.

3.3 Theoretical Model

3.3.1 Assumptions

1) There is a one-to-one matching between teachers and schools.
2) There is a set of schools seeking to fill one teaching position.[43]
3) The sets of possible investment levels, teacher types, and school types are finite.

3.3.2 Information Environment

All agents' preferences over agents on the other side of the market are unknown to the other agents and are private information. The school types are public information, known to all. Each teacher knows their true value over matching with any possible school. Teacher type is private information, known only to the teacher. All agents know the set of possible teacher and school characterizations or types. The differences between types are modeled by varying the matches' productivity, and their investment cost represents the teacher's general productivity. There are three types of workers and three types of firms in the experiment. In each market, there is one of each type of firm and worker. Members of the market are unable to directly associate a type with a given teacher. Teachers attempt to signal their types to the schools by making costly investments. The investments are visible to all schools, all teachers when offers are being made, and any teacher investing afterward in the Information treatment. Assigning the match benefits induces the agents' preferences towards their possible partners. The schools can infer a teacher's true type from their investment choice. There are high, medium, and low general productivity teacher types represented in their investment cost,

[43] This assumption appears to be strong, given that schools have many teachers and are often hiring more than one in a year. However, this assumption operates using the concept that the positions available at a school are often vastly different, resulting in disparate search efforts, and thus the final match is similar to a one-to-one match.

which are 10, 20, and 30, respectively. The firm types are 1, 2, and 3 defined by their preference structure (which is identical in the competitive treatment) and the differential productivity of their matches.

3.3.3 Wage Structure

Given that I am modeling the teacher labor market, I use a somewhat novel wage structure. Generally, in the teacher labor market, the wage structure is rigid, with salary being determined by where the teacher's experience and educational attainment place them in a fixed salary schedule. The schedule means all new teachers with a bachelor's degree earn essentially the same starting wage within a school system. Due to this rigidity, non-pecuniary benefits of the match drive teacher preferences over schools (Scafidi et al., 2007; Hanushek & Rivkin, 2007). These benefits consist of location (Boyd et al., 2005a, b; Reininger, 2012), the characteristics of the student population at the school, the perceived quality of the faculty and leadership, and a range of other factors.[44] Instilling non-pecuniary preferences in the participants would not be salient, so to parameterize these benefits, there is a school-specific wage the teachers received upon a match. The benefits vary by the match and change only once during the experiment. I could have parameterized investment with no productivity returns, as Spence did in his 1973 work. However, as the teacher wage has an adjustment to salary schedule based on degree attainment, I decided to have the hybrid fixed payments as in Table 3.1. These payments jump at specific investment values but remain the same in the interim.

[44] Lankford et al., 2002; Hanushek et al., 2004; Imazeki, 2005; Feng, 2009; Feng & Sass, 2017; Goldhaber et al., 2015; West & Chingos 2009

In the experiment, teachers and schools always receive a payment of 300 for matching with their top choice, 200 from the second, and 100 from the bottom choice. Table 3.2 presents the two preferences sets. The first set of preferences were chosen to be the most competitive, given that all participant preferences are identical. The second set of preferences decreases competition and increase the discordance between agents' preferences over the other side. The choice of these two sets of preferences was to prevent the results from being preference structure dependent.

3.3.4 Investment

Given the parameterization, the investment which will afford a teacher the greatest payoff at each firm is 7 for a high type teacher, 4 for medium, and 1 for low. If the teacher adopts a maximin strategy or believes that they have an equal probability of matching with any given school, these would be the teachers' optimal investment. There would be a separation of investment, revealing the teacher types.[45]

The maximum payoff for the market requires that high types invest 7, medium types invest 4, and low types invest 1 resulting in investment payoffs of 100, 40, and 10. If investments for each type deviate, this causes their investment payoff to decrease, decreasing the maximum possible total payoff for the market. If a worker cannot make a match, the cost of over-investment is greater as they also do not receive the payment for investment.[46] If they can make a match, overinvestment is offset for most types by the additional pay from investment, especially for high type workers.[47] Under the

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[45] Separation occurring is likely to be impacted by workers making strategic investments to obtain more preferred matches. This is not studied directly in this paper, but the theory is discussed in Appendix A.
[46] For high types, if they make no match and have invested nine instead of their maximin seven, or lower values like six, they receive a payoff of negative ninety versus negative seventy or sixty.
[47] For high types, if they invest eight instead of seven their payoff is ninety plus the match payoff instead of when they underinvest at six only receiving sixty plus the match payoff.

competitive (homogenous) preferences, it is expected that the overinvestment will be greater, as agents have the most direct benefit of presenting themselves as the high type.

If the worker achieves a better match of one rank by investing more, the worker's payoff always increases. This means that under the competitive preferences, where the highest investor should match with the best firm, an agent will invest more than their competitors' investment when they can. Due to the incentive to misrepresent their type, agents are more likely to do so when they have more information about their competitors' actions and are thus able to pick their apparent type decreasing the likelihood investment is in a type revealing ranking.[48]

Hypothesis 1: Agents will invest more when the preference rankings are homogenous.

Hypothesis 2: Agents will invest more if they observe higher competitor investment under competitive preferences.

Hypothesis 3: Agents are less likely to engage in separating investment in the information treatment.

[48] In preference set 1, (7, 4, 1) is not an equilibrium because the medium worker has an incentive to deviate and invest 8. (7, 4,1) is also not an equilibrium in preference set 2 as the low type worker has incentive to deviate and invest 8, or the high and medium type workers have incentive to deviate and invest 1. However, there is a partial pooling equilibrium in the simultaneous investment game of 9, 9, 1. High has no incentive to deviate as the expected payoff from investing 9 due to ties being broken randomly is 330, which is greater than the most profitable deviation of investing 7 and earning 300. The medium worker has no incentive to deviate as the expected payoff from investing 9 is 240, which is equal to the payoff from the most profitable deviation of investing 4 and being assigned to firm 2 (as high's investment is 9). Low has no incentive to deviate as low's payoff from investing 1 is 110 which is larger than the most profitable deviation of investing 9, which results in and being equally likely assigned to either firm and an expected payoff of 100. For preference set 2, non-type revealing separating equilibrium is (7, 0, 8). High type has no reason to deviate because as they receive 300 and the expected payoff of their next best investment 0 is 250. The medium type has no reason to deviate because while they could obtain more at 4 this would make 0 the best option for the high type decreasing medium types payoff at four. Low type has no incentive to deviate as their next best payoff is 210 when investing 1 as opposed to their current payoff of 230.

3.3.5 Matching Mechanism

In the experiment, I use a decentralized design where offers are transmitted directly from schools to teachers to elicit behavior as similar to the real labor market as possible, given that the actual market is decentralized. The other matching market possibility is centralized, where all agents list their preferences and submit them to a central matching organization. It is important to reemphasize that the primary difference between this mechanism, and the priority matching mechanism is that those being proposed to can reject an offer even if their quota is not full. This should not change the theoretical properties that we would expect in a priority matching environment.

3.3.5.1 The School Hiring Mechanism

1) Teachers know school types, own type, and the distribution of competitor types. They also know all of their possible payoffs from each combination of investment and match.
2) After observing the available information, teachers choose an amount of investment.
3) Once a teacher's investment is chosen, they apply to all schools. This is the point when schools can observe the teachers' investments.
4) Schools cannot observe true types, but they do observe all investments and make decisions on offers to workers.
5) Round 1.
    a. Schools issue their first an offer to a teacher.
    b. Teachers only receive up to one offer at a time.
        i. If multiple schools issue an offer to one teacher, the offer from the school ranked highest by that teacher is presented to the teacher.
    c. The teachers then accept or reject the offer.
        i. If the teacher accepts, the match is implemented, removing both the teacher and the school from the market. Offers can continue to be received, but they will be automatically rejected.
        ii. The teacher must reject the offer to receive future offers.

6) Round k.
    a. Any school rejected in round k-1 issues an offer to the next teacher in their list that has not previously rejected the school.
    b. Teachers only receive up to one offer at a time.
        i. If multiple schools issue an offer to one teacher, the offer from the school ranked highest by that teacher is presented to the teacher.
    c. The teachers then accept or reject the offer.
        i. The teacher must reject the offer to receive future offers.

7) End: The rounds continue until no more rejections occur.[49]

3.3.6 Market Efficiency and Payoffs

In this experiment's parameterization, under preference set 1, the maximum total payoff is 1350 points and can be achieved in any matches. As long as the workers invest their maximin amount, the surplus will just be redistributed. However, under preference set 2, the maximum total payoff is 1450 in a single match outcome (S1T2, S2T3, and S3T1), but this match outcome is not stable. As market efficiency is in terms of total possible payoff, if agents invest the maximin amount and enter a stable match outcome, efficiency would be lower in preference set 2. If the efficiency is not lower, then this is due to the deviation in investment in preference set 1 being substantially higher.

Hypothesis 4: There will be a decrease in efficiency under preference set two because the max payoff is greater than in preference set one, but achieving the maximum outcome is unlikely.

Hypothesis 5: Due to agents deviating from the maximin investment by more with additional participant information and under the homogenous preferences, payoffs will be lower in those treatments.

[49] This matching mechanism reporting format is based from the work Chen and Sönmez (2006).

3.3.7 Market Stability

In the case of a separating investment equilibria and workers following a sincere acceptance strategy, the SH mechanism produces a stable matching. As teachers gain more information about their competitors' actions, they will be better able to represent themselves favorably. The deceptive representation can lead to increased instability as it is more likely for a teacher-school pair who prefer each other cannot match due to the firm not being able to discern type accurately.

Hypothesis 6: When teachers have more information about competitors' actions, the outcomes will be less stable.

3.3.8 Risk

There are several ways the risk attitudes of agents may affect the outcomes. There is strategic risk in the teachers' choices in the simultaneous investment game as they learn the schools' preferences during the rounds or other teachers' investments. The optimality of their investment is dependent on the choices of competitors. Teachers may over invest to ensure they have a greater investment than their competitors under the competitive preference rankings. The probability of matching with a given school is affected by how their investment ranks affect school offers. Since the SH mechanism requires teachers to accept or reject an offer, there is the risk a teacher may remain unmatched in the case of rejecting an offer. Thus risk-averse teachers would be more likely to accept an early offer from a less preferred school. Risk-averse schools are more likely to issue offers to a less-preferred teacher if the perceived probability of acceptance from the most-preferred worker is low enough.

3.4 Experimental Design

3.4.1 Treatments

There are four treatments in this experiment. Participants took part in a market where the teachers were making simultaneous or sequential investments and were then matched to a school using the SH matching procedure. These two investment structures which affect participants' information were implemented as a between-subject design. The information treatment is crossed with competitive preferences (preference set 1) and less competitive preferences (preference set 2). Participants experienced both sets of preferences, and thus this was a within-subject implementation.

When teachers invested simultaneously, each teacher chose their investments without any knowledge of the other teachers' investment decisions. However, they do view their competitors' investments during the market decision. This design is the most similar to the true market as applicants cannot control the composition of their competing cohort of applicants. However, they may be able to gather information during the interview process about where they stand and how likely they are to receive an offer. However, this lack of information adds an additional component of strategic risk to their decision. The second treatment of sequential investments was implemented to examine the effects of added information on investment decisions. In this treatment, teachers chose their investments one at a time in random order and could view the preceding workers' investments. To better separate the differences between the two treatments' investment behavior and allow the participants to understand the game better, all participants in the first few rounds (part one stage one) of the experiment made signaling investment decisions and were automatically matched to schools.

Seven sessions were run in total. In five of the sessions, the participants completed the automated firm portion, the active firms and workers portion, and the risk task. In the other two sessions, the participants could not complete the active firm portion due to technical difficulties. Three of the completed sessions had sequential investing, with a total of 66 participants. The other two completed sessions had simultaneous investing with a total of 42 participants. The decisions from the incomplete sessions were in the simultaneous investment environment. This resulted in 208 rounds of Simultaneous investment with the same preferences and automated firms and 142 in the same environment with heterogeneous preferences. In the rounds, where firms were also agents, there were 41 rounds in the homogenous, simultaneous treatment, 61 rounds in the homogenous, sequential treatment, 45 rounds in the heterogeneous, simultaneous treatment, and 89 rounds in the heterogeneous, sequential treatment.

3.4.2 Implementation

In the second and third stages of part one of the experiment, the teachers and schools were both active participants. The participants were Georgia State University students recruited using the ExCEN online recruiter. The participants were recruited for seven separate sessions, and in each session, there was only one information treatment, making this a between-subjects design. The experimental set up allowed for comparison within participants of the effects of the different parameterizations.

In part one stage one (the first few (seven to ten) rounds), all participants were teachers (called workers in the experiment), and the assignment to schools (called firms in the experiment) was automatic based on the rank order of their investments. This means that in the portion where the firms were automated participants only experienced preference set 1. In the remaining (13 to 20) rounds, participants were split equally into the roles of teachers or schools. Half of the rounds, termed part 1 stage 2, teachers and schools were randomly assigned a unit investment cost and their preference from either 1 or 2. Then in part 1 stage 3, the participants remained as either a teacher or a school, randomly assigned a unit investment cost, and followed the other preferences. The ordering of preferences 1 and 2 was varied between sessions.

In each round, participants matched with a new group to better represent the teacher labor market. Matching in this manner has been shown not to simulate one-shot game behavior resulting in systematic differences from perfect stranger matching in public goods games (Botelho et al., 2009). However, it does simulate a market where the teachers have rapid turnover and compete with similar sets of competitors through their careers. Besides, it is not feasible to complete this experiment with perfect stranger matching due to the requisite number of participants to complete the matchings.

3.4.2.1 Decision Tasks

1. In each round a "teacher" chooses an investment between 0 and 9. The treatment determines investment order, which is randomized in the sequential treatments. (Figures 3.1 and 3.2)
2. "Schools" know their own preferences over types but can't observe teachers' types. They issue offers to teachers after observing teachers' investments. (Figure 3.3)
3. Teachers know their preferences over schools. They make decisions on whether to accept or reject an outstanding offer knowing that acceptance ends the game. (Figures 3.4 and 3.5)

4. Steps 2 and 3 are repeated until there are no rejections or all possible firm offers have been extended. This results in a maximum of three offers and six decisions per round.

5. Once matches are finalized, the participants’ payoffs for the round are revealed, both the round and the stage average. The round payoff is shown to all members of the group. (Figures 3.6 and 3.7)

3.4.2.2 Risk Task

After completing the first two phases of the experiment, the participants completed a risk elicitation section consisting of up to 50 tasks. Each task consists of a choice between two lotteries, Left and Right. The participants knew one task would be randomly selected using a dice roll, and that they would be paid based on the resolution of the lottery they had selected for the random task. Between the 50 tasks, the possible prizes of the lotteries and the probabilities of each prize were varied. The task design emulated Harrison and Ng (2016). Each lottery had up to three prize states, with each probability being a multiple of twenty-five percent. The order the tasks administered were randomized between participants. The first three sessions had different tasks and the number of tasks due to calibration, timing, and technical issues. (Figure 3.8)

3.4.2.3 Demographic Survey and Participant Summary Statistics

The sessions ended with a demographic survey of participants' gender, parent income, parental education, major, college grade point average, and race. 132 participants completed the demographic survey in six sessions. In the seventh session, technical difficulties prevented the administration of the demographic survey. The summary statistics of their answers are reported in Table 3.3. The majority of the participants were black. There was a fairly wide range of parental income and education. The participants had an average GPA of 3.7.

3.4.2.4 Payment

The participants were paid the sum of the average payoff from all rounds in part 1 separated by stage, and the outcome after the resolution of the lottery in the randomly-selected risk task.

Each round, the payoff was determined and recorded electronically following the investment decisions and the realized payoffs. Then to determine the outcome of the risk task, the proctor went to each participant and rolled a pair of dice to determine which risk task was chosen for implementation and then used dice or a spinner app to resolve the lottery. The total payment amount was written on a slip of paper for the participant to take to another proctor for payment. Only the experimenters, not the other participants, saw the payment outcomes; this ensured the experiment utilized a single-blind payment procedure.

Participants were informed of this payment method before the experiment began. The payment mechanism's salience was assured due to maintaining an appropriate average payoff of $24.6, with a minimum payoff of $9 and a maximum payoff of $55. The experiment duration was two hours or less, including the time needed to explain the instructions and pay the participants, so the average payoff was higher than the minimum wage.

3.5 Results

In this experiment, I examine the effects of the information treatment and preference set variation on participant investment decisions, market efficiency and payoffs, and market stability. For each outcome, I estimate the effects separately for each preference set. Each agent in the market had different incentives, so I estimate the effects by participant type for investment amounts and market payoffs. I split this investment analysis into changes to investment amount and the prevalence of participants selecting a type-revealing separating equilibrium. Except for individual market payoffs and the estimation of each worker types' likelihood to invest the most, each estimation has two specifications. The first includes controls to the information treatment, the firms being active participants, and period and session fixed effects. The second includes the participants' demographic and risk preference information. The additional variables account for the effects that participants' idiosyncratic characteristics could have on the decisions. For market efficiency and payoffs, I also estimate a specification including a binary variables for homogenous preferences and information treatment interacted with homogenous preferences.

3.5.1 Signaling Decision

Result 1: Heterogeneous preferences decrease investment amounts when participants are not in the information treatment.

Support: In the rounds with simultaneous investment, all types invest more when the preferences are homogenous. In the information treatment, the amount is higher for high and low types under the heterogeneous preference set (Table 3.4). Then, when estimating the investment amount, the constant term (the baseline investment amount) is not statistically different for heterogeneous preferences than for homogenous preferences except for high type workers where there is an increase (Tables 3.5, 3.6, and 3.7).

Result 2: The information treatment negatively impacts the investment amount when preferences are homogenous.

Support: Under homogenous preferences, the information treatment negatively impacts the amount of worker signaling investment. The decrease in investment due to information, while holding other factors constant, brings the medium and low type workers' investment closer to the most efficient (for the market) investment amount. During the rounds with the heterogeneous preference set, high types also invest closer to the efficient amount (Tables 3.5, 3.6, and 3.7). Under the same preferences, all workers invest less in the investment treatment, and the medium type worker also invests less in the information treatment under heterogeneous preferences. Though the largest treatment effect that can be seen is that low type workers invest substantially more on average under different preferences (Table 3.4).

To further investigate this phenomenon, I studied which worker types invest the most. When examining the averages, the high type is less likely to be the greatest investor in the information treatment when there are heterogeneous preferences (Table 3.4). When empirically estimating the probabilities of being the highest investor, the information treatment has a statistically significant negative effect on high types in both preference sets (Table 3.8). This is to be expected because in the simultaneous signaling game with homogeneous preferences, a high type invests 7, 8, or 9. A risk-averse type would invest 9 to increase the likelihood of a preferred match with an additional cost of only 20 points. However, in the sequential signaling game, the risk-averse type would also invest 9 when they move first and probably second, but their investment is the max of seven and the largest Observed Maximum Investment when moving last. Therefore high types are expected to invest less in the sequential game.

Result 3: The signaling investments are less informative when there is additional information on competitors' actions and heterogeneous preferences because the portion of the time investments are type revealing decreases.

Support: For investments to reveal type (be separating), the investment amounts need to be negatively related to their investment costs. The high type workers invest the most, the middle second, and the low type the least. There is a smaller separation between types when there is sequential investment except for high types in preference set 2 when the averages are compared. When looking at the portion of the time the investments are completely separating, this is lower in the treatment in preference set 2 (Table 3.4). The remaining pooling outcome possibility that is not reported is when there are no ties, and the order is not type revealing.

When agents have homogenous preferences, and the firms are also participants, the likelihood of investment separation increases. The information treatment decreases separation likelihoods under both preference sets, but the effect is greater when preferences are heterogeneous. In homogenous preferences, the information treatment also increases the likelihood of two participants selecting the same investment amount (Table 3.9). A scatter plot of the average investment in a period shows consistent investment separation (Figure 3.9). The investment is also mainly separated within treatments on average. When comparing the plots for the information treatment (Figures

3.10 and 3.12) to the non-information treatment plots (Figures 3.12 and 3.13), there is less separation in the information treatment.[50]

3.5.2 Market Efficiency and Payoffs

Result 4: The information treatment has no impact on market efficiency, and the market efficiency is higher when the preferences are homogenous.

Support: Market efficiency estimations, as defined by the realized payoff divided by the maximum payoff (1350 for preference set 1 and 1450 for preference set 2), are reported in Table 3.10. When examining the information treatment point estimates, there is no statistical impact. However, when the constant terms are studied, it is revealed that when preferences are homogenous, the market is closer to the efficient outcome. The impact of the preferences may be because only investments can impact the total market payoff when there are homogenous preferences (the difference between matches is the distribution of the wealth). In contrast, under heterogeneous preferences, the match can affect the maximum total payoff as well.

Result 5: The information treatment has a negative impact on the firms' payoffs when preferences are heterogeneous, and these decreases for firms in total are not consistently at the detriment of a single firm type.

Support: On average, firms receive a higher payoff when there are homogenous preferences in the information treatment and the most negative outcome when preferences are heterogeneous in the information treatment (Table 3.4). The information treatment negatively impacts total firm payoff when estimating across all rounds with

[50] There were no consistently estimated period effects, so there appears to be little participant learning over the course of a session.

controls for preferences set and information treatment interacted with the preference set. However, the negative impact of the information treatment is mostly negated by the positive impact of the information treatment interacted with the homogenous preference set (Table 3.11). Further, while there are no estimated impacts of the information treatment in the estimates separated by preference type, each group's baseline payoff amount is higher when the preferences are homogenous (Tables 3.12 and 3.13). When examining the payoffs by individual type, none of the firm types are negatively impacted by the information treatment under either preference set (Table 3.14). Within worker types, the high-type worker is negatively impacted by information under homogenous preferences, which matches the fact they underinvest when preferences are homogenous. Medium type workers are positively impacted by information under heterogeneous preferences but negatively impacted when preferences are homogenous on average. This outcome may reverse when taking into account participant risk preferences. Low type workers are unaffected by the information treatment. (Table 3.4 and 3.15).

3.5.3 Market Stability

Result 6: The information treatment does not impact market stability, which is greater when preferences are homogenous.

Support: When examining the portion of matches from the set of stable matches in Table 3.16, there are no statically significant estimates regarding the impact of the information treatment. In contrast, when examining the same preference terms, it can be seen that a greater portion of the matches are from the stable outcome when the preferences are the same; this may because the workers do not prefer the stable match in preference set 2 and therefore, may attempt more vigorously to alter the outcome.

3.6 Conclusion

In this experiment, I was able to identify that subjects do change their investment behavior when they possess additional information regarding their competitors' actions and between preference structures. Further, market efficiency can decrease when workers have additional information, but this decrease depends on the market's preference structure. The data suggest that the differences caused by the treatments are larger for schools on average. The most negative effect on payoffs occurs when examining the impact of the information treatment within the heterogeneous preferences. The greatest positive difference being homogenous preferences over heterogeneous preferences within the information treatment. The workers' average payoffs decrease the most when moving from preference set 2 to preference set 1 within the information treatment. Still, their payoffs are always higher in preference set 2 than preference set 1 and in the information treatment on average.

Overall the interaction of the Spence signaling game and two-sided matching markets leads to interesting participant behavior. In this labor market, it appears best to not let the teachers observe their competitors' investments if the goal is to promote the schools' welfare, mainly when the preferences of schools and teachers are varied.

3.7 Tables

Table 3.1 Cost of Signal by Type and Fixed Investment Payoff

Investment	0	1	2	3	4	5	6	7	8	9
Fixed Payment	0	40	40	40	120	120	120	170	170	170
High Type Worker	0	10	20	30	40	50	60	70	80	90
Medium Type Worker	0	20	40	60	80	100	120	140	160	180
Low Type Worker	0	30	60	90	120	150	180	210	240	270

Table 3.2 Preference Parameterization

	Preference Set 1			Preference Set 2		
	Top	Second	Bottom	Top	Second	Bottom
Teacher High	1	2	3	1	2	3
Teacher Medium	1	2	3	1	3	2
Teacher Low	1	2	3	3	2	1
School 1	1	2	3	3	2	1
School 2	1	2	3	2	3	1
School 3	1	2	3	1	2	3
Payoff	300	200	100	300	200	100

Table 3.3 Participant Summary Statistics

	All		Information Treatment		Not Treated		All	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Min	Max
Education Level	1.809	0.596	1.862	0.583	1.758	0.609	1	3
GPA	3.748	0.516	3.769	0.493	3.727	0.542	2	4
Gender	0.344	0.477	0.292	0.458	0.394	0.492	0	1
High Father's Education	0.206	0.406	0.277	0.451	0.136	0.346	0	1
High Mother's Education	0.252	0.436	0.323	0.471	0.182	0.389	0	1
High Father's Income	0.573	0.497	0.615	0.490	0.530	0.502	0	1
High Mother's Income	0.481	0.501	0.523	0.503	0.439	0.500	0	1
White	0.137	0.346	0.231	0.424	0.045	0.210	0	1
Hispanic	0.092	0.290	0.108	0.312	0.076	0.267	0	1
Black	0.695	0.462	0.661	0.477	0.727	0.448	0	1
Non-White Other	0.174	0.381	0.092	0.292	0.258	0.441	0	1
Percent Risk Choice with Riskier Option	0.392	0.167	0.365	0.150	0.419	0.179	.04	.86

Notes: 131 participants reported their demographic information.

Table 3.4 Investment and Market Outcomes When Firms are Participants

Preferences over other side of the market	**Same**		**Different**	
Signaling Game	**Simultaneous N=41**	**Sequential N=61**	**Simultaneous N=45**	**Sequential N=89**
Investments				
High Type Workers	6.927 (1.603) [2, 9]	6.311 (1.639) [1,9]	6.422 (1.196) [4,8]	6.427 (1.269) [4,9]
Medium Type Workers	5.682 (2.360) [1,9]	5.344 (1.806) [1,8]	4.489 (2.232) [0,9]	4.247 (2.352) [1,9]
Low Type Workers	3.512 (2.481) [1,9]	3.311 (2.446) [0,9]	3.000 (2.384) [0,9]	4.315 (2.410) [1,9]
Market Outcomes				
Efficiency and Distribution				
Workers Payoff	689.756 (150.988) [350,940]	650.656 (111.383) [380,750]	702.000 (149.721) [230,950]	697.303 (199.845) [270,950]
Firms Payoff	504.878 (107.124) [200,600]	550.820 (95.957) [300,600]	517.778 (119.257) [200,700]	446.067 (139.036) [200,900]
Total Payoff	1194.634 (199.187) [650,1340]	1201.475 (199.030) [750,1350]	1219.778 (201.297) [690,1440]	1143.371 (244.310) [610,1400]
Distribution Across Types				
High Type Workers	305.122 (115.285) [-90,400]	287.377 (136.356) [-80,400]	314.444 (121.123) [-80,400]	296.405 (142.041) [-90,400]
Medium Type Workers	218.781 (118.178) [-160,340]	199.672 (114.192) [-140,340]	214.000 (120.405) [-140,340]	226.966 (125.394) [-180,340]
Low Type Workers	165.854 (135.185) [-240,310]	163.607 (111.101) [-210,310]	173.556 (103.202) [-120,310]	173.933 (110.130) [-240,310]
Type 1 Firms	182.927 (91.931) [0,300]	222.951 (84.446) [100,300]	208.889 (87.444) [100,300]	142.697 (78.172) [0,300]
Type 2 Firms	165.854 (85.469) [0,300]	181.967 (78.546) [0,300]	175.556 (82.999) [0,300]	135.955 (90.763) [0,300]
Type 3 Firms	156.098 (83.812) [0,300]	145.902 (107.353) [0,300]	133.333 (82.572) [0,300]	167.416 (80.869) [0,300]

Separation and Pooling Decisions				
High Type Workers Invest Most	0.537 (0.505) [0,1]	0.541 (0.502) [0,1]	0.555 (0.503) [0,1]	0.472 (0.502) [0,1]
Medium Type Workers Invest Most	0.268 (0.449) [0,1]	0.197 (0.401) [0,1]	0.089 (0.288) [0,1]	0.135 (0.343) [0,1]
Low Type Workers Invest Most	0.073 (0.264) [0,1]	0.098 (0.300) [0,1]	0.044 (0.208) [0,1]	0.157 (0.366) [0,1]
Completely Separating Investment	.293 (.461) [0,1]	0.361 (0.484) [0,1]	0.311 (0.468) [0,1]	0.112 (0.318) [0,1]
Partially Pooling Investment	.293 (.461) [0,1]	0.426 (0.499) [0,1]	0.467 (0.505) [0,1]	0.506 (0.503) [0,1]
Completely Pooling Investment	0 (0) [0,0]	0.016 (0.128) [0,1]	0.022 (0.149) [0,1]	0.022 (0.149) [0,1]

Notes: Means, Standard deviation in parentheses, and then the minimum and maximum in square brackets.

Table 3.5 Investment of High Type Teachers

	Same			Different
VARIABLES	No Descriptors	Descriptors	No Descriptors	Descriptors
Information Treatment	-2.136***	-2.193***	-0.328	-2.873***
	(0.539)	(0.518)	(0.556)	(0.676)
Active Firms	-0.672	-0.607		
	(0.541)	(0.764)		
Percent of Risky Choices Selected		0.859		3.146***
		(0.713)		(0.970)
Observed Maximum Investment		0.006		0.010
		(0.046)		(0.038)
Education Level 2		0.632**		0.856**
		(0.293)		(0.352)
Education Level 3		0.725		-0.124
		(0.507)		(0.246)
GPA Reported		0.149		-0.983**
		(0.245)		(0.435)
Gender		0.399		-0.410
		(0.290)		(0.640)
Father had Higher Education		-0.602*		2.332***
		(0.354)		(0.640)
Mother had Higher Education		0.311		1.256***
		(0.312)		(0.323)
Black		-0.518*		-0.766**
		(0.287)		(0.276)
Constant	5.689***	4.866***	6.520***	9.961***
	(0.401)	(0.997)	(0.866)	(1.505)
Period Fixed Effects	X	X	X	X
Session Fixed Effects	X	X	X	X
Observations	452	394	134	134
R-squared	0.264	0.328	0.065	0.316

Notes: The dependent variable is the investment amount of the worker in a single round. Active firms is a binary indicator for if the rounds were after stage 1 of part 1. Percent of Risky Choices Selected is the number of choices in the risk task the participant selected the one with greater variance in outcomes divided by total number of completed choices. Observed Maximum Investment of others is zero for the simultaneous game and first investors, and the maximum of the earlier investors for the second and third investors in the sequential game. Education level 2 is some college and Education level 3 is college degree or greater. Gender is a binary variable equal to 1 if the participant was female. Mother and Father had a Higher Education means the parent in question had a master’s degree, a doctorate, or a professional degree.

Table 3.6 Investment of Medium Type Teachers

	Same		Different	
VARIABLES	No Descriptors	Descriptors	No Descriptors	Descriptors
Information Treatment	-0.777	-1.085*	-2.100	-1.655
	(0.523)	(0.621)	(1.532)	(1.828)
Active Firms	-0.046	-0.458		
	(0.691)	(0.954)		
Percent of Risky Choices Selected		1.327		0.525
		(0.927)		(1.796)
Observed Maximum Investment		0.022		0.087
		(0.048)		(0.088)
Education Level 2		0.358		0.467
		(0.329)		(0.528)
Education Level 3		0.661		0.347
		(0.526)		(1.632)
GPA Reported		-0.243		-1.180*
		(0.279)		(0.620)
Gender		-0.164		-0.060
		(0.397)		(1.110)
Father had Higher Education		-0.736*		-0.832
		(0.374)		(0.847)
Mother had Higher Education		0.395		-0.107
		(0.336)		(1.054)
Black		-0.442		-0.719
		(0.354)		(0.836)
Constant	5.048***	5.601***	4.438**	8.255**
	(0.454)	(1.236)	(1.820)	(3.845)
Period Fixed Effects	X	X	X	X
Session Fixed Effects	X	X	X	X
Observations	452	396	134	134
R-squared	0.128	0.166	0.356	0.486

Notes: Dependent variable is the investment amount of the worker in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.7 Investment of Low Type Teachers

	Same		Different	
VARIABLES	No Descriptors	Descriptors	No Descriptors	Descriptors
Information Treatment	-0.332	-1.019*	0.945	-0.033
	(0.553)	(0.575)	(1.830)	(2.369)
Active Firms	-0.003	0.960		
	(0.836)	(0.929)		
Percent of Risky Choices Selected		-0.132		-0.700
		(0.939)		(6.568)
Observed Maximum Investment		0.109**		0.084
		(0.054)		(0.084)
Education Level 2		0.325		1.372*
		(0.347)		(0.717)
Education Level 3		-0.036		-1.520
		(0.652)		(2.804)
GPA Reported		0.523*		-0.549
		(0.268)		(1.760)
Gender		0.297		0.610
		(0.351)		(1.531)
Father had Higher Education		-0.671*		-2.464
		(0.383)		(1.604)
Mother had Higher Education		-0.616		1.368
		(0.398)		(1.738)
Black		-0.211		-0.916
		(0.457)		(1.413)
Constant	3.870***	2.367*	6.197**	8.449
	(0.367)	(1.285)	(2.428)	(6.134)
Period Fixed Effects	X	X	X	X
Session Fixed Effects	X	X	X	X
Observations	452	397	134	134
R-squared	0.102	0.151	0.206	0.408

Notes: Dependent variable is the investment amount of the worker in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.8 Teachers Invest the Most

	Same			Different		
VARIABLES	High	Medium	Low	High	Medium	Low
Information Treatment	-0.072	0.119**	0.124	-0.222**	0.322**	0.051
	(0.067)	(0.053)	(0.098)	(0.088)	(0.151)	(0.191)
Active Firms	0.116*	0.007	-0.052			
	(0.066)	(0.056)	(0.047)			
Percent of Risky Choices Selected	-0.028	0.337**	0.115	-0.066	-0.830*	-0.118
	(0.196)	(0.143)	(0.102)	(0.216)	(0.465)	(0.501)
Observed Maximum Investment	-0.014	-0.021**	0.000	-0.016	0.009	0.016*
	(0.010)	(0.009)	(0.005)	(0.019)	(0.012)	(0.009)
Education Level 2	0.056	0.047	-0.001	0.105	0.077	0.072**
	(0.065)	(0.048)	(0.038)	(0.080)	(0.104)	(0.036)
Education Level 3	0.040	0.138	-0.022	0.095	0.006	0.295
	(0.097)	(0.090)	(0.064)	(0.112)	(0.081)	(0.238)
GPA Reported	-0.030	-0.044	0.017	-0.134**	0.037	
	(0.053)	(0.033)	(0.027)	(0.064)	(0.028)	
Gender	0.128*	-0.061	0.031	0.227**	0.410**	
	(0.067)	(0.056)	(0.041)	(0.091)	(0.171)	
Father had Higher Education	-0.187**	-0.167***	-0.088*	-0.020	0.099	
	(0.078)	(0.065)	(0.051)	(0.123)	(0.106)	
Mother had Higher Education	0.016	0.059	-0.125**	0.329***	-0.247	0.354**
	(0.079)	(0.044)	(0.058)	(0.043)	(0.152)	(0.170)
Black	-0.068	-0.033	0.024	-0.469***	-0.291*	-0.305***
	(0.065)	(0.053)	(0.042)	(0.099)	(0.170)	(0.085)
Observations	394	396	397	134	134	85

Notes: Dependent variable is an indicator if the worker type of the column invested the most in their group without tying their competitors in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.9 Investment Separation-Same vs Different Preferences

VARIABLES	Same Separating	Same Partial Pooling	Same Full Pooling	Different Separating	Different Partial Pooling	Different Full Pooling
Information Treatment	-0.094**	0.115**	0.020	-0.177***	0.039	0.000
	(0.040)	(0.046)	(0.017)	(0.061)	(0.091)	(0.027)
Active Firms	0.143***	-0.070	-0.042			
	(0.044)	(0.056)	(0.029)			
Observations	452	452	452	134	134	134

Notes: Separating is if Worker 10 invested more than worker 20 who invested more than worker 30. Partial Pooling is if two participants invested the same amount. Full Pooling is if all three participants invested the same amount.

Table 3.10 Market Efficiency

	All Preferences No Descriptors	All Preferences Descriptors	Same Preferences No Descriptors	Same Preferences Descriptors	Different Preferences No Descriptors	Different Preferences Descriptors
Information Treatment	-0.072*	-0.053	0.016	-0.009	-0.068	-0.024
	(0.038)	(0.058)	(0.099)	(0.116)	(0.047)	(0.073)
Same Preferences	0.082*	0.075*				
	(0.042)	(0.044)				
Information x Same	0.010	0.019				
Preferences	(0.053)	(0.055)				
Average Percent Risky		-0.103		-0.007		-0.075
Choices Selected		(0.186)		(0.303)		(0.248)
Average GPA		0.108		-0.011		0.219**
		(0.071)		(0.123)		(0.088)
Percent Female		0.053		0.046		0.022
		(0.081)		(0.117)		(0.116)
Percent Black		0.057		0.015		0.085
		(0.078)		(0.119)		(0.105)
Percent with High		0.070		-0.066		0.309***
Mother's Income		(0.068)		(0.096)		(0.102)
Percent with High		-0.045		-0.017		-0.128
Mother's Education		(0.086)		(0.134)		(0.115)
Session Fixed Effect	X	X	X	X	X	X
Period Fixed Effect	X	X	X	X	X	X
Constant	0.797***	0.350	0.908***	0.952*	0.815***	-0.115
	(0.088)	(0.321)	(0.055)	(0.522)	(0.109)	(0.406)
Observations	236	225	102	97	134	128
R-squared	0.158	0.182	0.147	0.142	0.165	0.290

Notes: Dependent variable is the sum of the payoffs to a group divided by the maximum possible payoff (1350 under homogenous preferences and 1450 under heterogeneous preferences) in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.11 Market Payoffs-All

VARIABLES	(1) Workers No Descriptors	(2) Firms No Descriptors	(3) Total No Descriptors	(4) Workers Descriptors	(5) Firms Descriptors	(6) Total Descriptors
Information Treatment	9.110	-113.899***	-103.768*	18.540	-141.789***	-75.309
	(23.436)	(29.770)	(53.941)	(29.980)	(44.997)	(82.204)
Active Firms	-21.786			-23.412		
	(28.662)			(35.901)		
Same Preferences	9.563	-13.031	29.429	-5.469	-13.640	19.193
	(23.357)	(32.482)	(58.855)	(25.672)	(33.750)	(61.657)
Information x Same Preferences	-40.324	108.819***	15.161	-24.727	110.682***	27.331
	(24.915)	(41.550)	(75.286)	(27.272)	(42.413)	(77.483)
Average Percent Risky Choices Selected				-57.054	58.631	-148.083
				(68.224)	(143.497)	(262.151)
Average GPA				12.851	54.994	157.704
				(21.832)	(54.454)	(99.480)
Percent Female				11.985	80.764	75.141
				(25.218)	(62.490)	(114.161)
Percent Black				-10.849	90.199	81.992
				(25.735)	(60.540)	(110.599)
Percent with High Mother's Education				35.371	14.391	105.378
				(25.743)	(52.832)	(96.517)
Percent with High Father's Education				5.374	-84.724	-64.731
				(28.954)	(66.701)	(121.854)
Session Fixed Effect	X	X	X	X	X	X
Period Fixed Effect	X	X	X	X	X	X
Constant	679.512***	493.778***	1,155.906***	649.993***	194.383	506.251
	(28.223)	(68.578)	(124.259)	(99.388)	(247.575)	(452.288)
Observations	586	236	236	514	225	225
R-squared	0.089	0.188	0.105	0.092	0.223	0.132

Notes: Dependent variable is the sum of the payoffs of all workers, firms, or participants in a group in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.12 Market Payoffs-Same

VARIABLES	(1) Workers No Descriptors	(2) Firms No Descriptors	(3) Total No Descriptors	(4) Workers Descriptors	(5) Firms Descriptors	(6) Total Descriptors
Information Treatment	-3.324	9.524	22.143	-1.075	-25.635	-11.834
	(13.712)	(61.507)	(134.008)	(18.965)	(65.418)	(155.975)
Active Firms	-9.546			-21.042		
	(21.797)			(28.904)		
Average Percent Risky Choices Selected				0.887	-39.175	-9.974
				(48.980)	(171.544)	(409.011)
Average GPA				-5.864	-35.377	-14.969
				(15.351)	(69.709)	(166.208)
Percent Female				12.197	87.724	61.665
				(17.498)	(66.492)	(158.537)
Percent Black				-11.448	40.029	20.637
				(18.069)	(67.250)	(160.343)
Percent with High Mother's Education				6.086	-70.188	-89.760
				(18.165)	(54.317)	(129.508)
Percent with High Father's Education				4.641	-21.685	-22.400
				(20.393)	(75.793)	(180.713)
Session Fixed Effect	X	X	X	X	X	X
Period Fixed Effect	X	X	X	X	X	X
Constant	668.365***	553.810***	1,226.324***	691.275***	683.412**	1,285.462*
	(13.279)	(34.320)	(74.775)	(67.673)	(295.726)	(705.099)
Observations	452	102	102	386	97	97
R-squared	0.115	0.330	0.147	0.107	0.388	0.142

Notes: Dependent variable is the sum of the payoffs of all workers, firms, or participants in a group in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.13 Market Payoffs-Different

VARIABLES	(1) Workers No Descriptors	(2) Firms No Descriptors	(3) Total No Descriptors	(4) Workers Descriptors	(5) Firms Descriptors	(6) Total Descriptors
Information Treatment	-32.657	-65.718	-98.375	67.183	-102.359	-35.177
	(52.679)	(39.782)	(67.917)	(85.979)	(64.654)	(106.261)
Average Percent Risky Choices Selected				-239.415	130.979	-108.436
				(291.493)	(219.196)	(360.255)
Average GPA				187.820*	129.603*	317.423**
				(103.496)	(77.827)	(127.911)
Percent Female				-16.028	47.264	31.236
				(136.578)	(102.703)	(168.796)
Percent Black				-4.023	127.585	123.563
				(122.773)	(92.323)	(151.734)
Percent with High Mother's Education				286.069**	162.090*	448.159***
				(119.615)	(89.948)	(147.832)
Percent with High Father's Education				-19.692	-166.161	-185.853
				(135.435)	(101.844)	(167.383)
Session Fixed Effect	X	X	X	X	X	X
Period Fixed Effect	X	X	X	X	X	X
Constant	779.354***	402.076***	1,181.430***	65.640	-231.957	-166.316
	(122.932)	(92.836)	(158.491)	(475.805)	(357.795)	(588.046)
Observations	134	134	134	128	128	128
R-squared	0.196	0.168	0.165	0.268	0.245	0.290

Notes: Dependent variable is the sum of the payoffs of all workers, firms, or participants in a group in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.134 Payoff of Schools

	Same Preferences			Different Preferences		
VARIABLES	1	2	3	1	2	3
Information Treatment	23.740	71.263	-6.087	-24.761	31.317	-5.529
	(98.945)	(60.319)	(72.444)	(15.348)	(41.678)	(18.053)
Percent of Risky Choices Selected	30.770	-179.172**	210.473***	12.069	-40.876	-29.006
	(47.091)	(83.965)	(63.071)	(30.581)	(91.792)	(41.968)
Education Level 2	-23.162	33.549		-5.146	6.192	
	(37.740)	(34.929)		(8.817)	(18.947)	
Education Level 3	-30.599	-52.317	-57.808***	59.585***	-39.677	17.727
	(44.663)	(38.785)	(16.844)	(14.305)	(32.767)	(10.487)
GPA Reported	120.889***	-3.473	-3.117	-38.120***	-12.825	-94.695***
	(25.497)	(25.009)	(31.711)	(9.366)	(20.409)	(13.707)
Gender	28.624	41.632*	18.073	49.564***	-32.957*	28.636
	(34.632)	(21.929)	(30.873)	(11.842)	(16.796)	(17.171)
Father had Higher Education	53.075	-	-78.706**	49.629***		4.177
	(44.650)		(30.533)	(8.792)		(14.471)
Mother had Higher Education	-56.776***	0.672	32.979	-38.104***	-0.846	-25.141*
	(9.064)	(26.565)	(22.254)	(12.237)	(17.316)	(11.944)
Black	26.659	-38.272	-33.098	-50.729***	-3.276	-16.304*
	(18.583)	(24.167)	(53.459)	(13.126)	(18.285)	(8.813)
Period Fixed Effects	X	X	X	X	X	X
Session Fixed Effects	X	X	X	X	X	X
Observations	97	102	102	134	128	134

Notes: Dependent variable is the payoff of an individual firm in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.145 Payoff of Teachers

	Same Preferences			Different Preferences		
VARIABLES	High Same	Middle	Low	High	Middle	Low
Information Treatment	-81.506***	43.578**	28.229	0.049	-66.183*	45.173
	(22.532)	(21.954)	(17.847)	(70.584)	(33.522)	(36.276)
Active Firms	-29.747	-2.193	-2.515			
	(28.151)	(38.740)	(38.800)			
Percent of Risky Choices Selected	59.690*	6.271	1.466	-66.300	-100.711**	-196.799*
	(33.834)	(29.638)	(28.642)	(110.202)	(38.572)	(108.693)
Observed Maximum Investment	-2.548	-1.853	-0.241	-11.277	6.467	-5.204**
	(2.694)	(2.234)	(1.965)	(6.878)	(4.800)	(2.377)
Education Level 2	32.733**	33.639***	0.821	-34.916	-19.060**	7.022
	(12.650)	(11.568)	(9.349)	(40.002)	(8.925)	(20.057)
Education Level 3	25.585	38.043**	10.714	-44.259**	-117.788***	-11.127
	(17.016)	(16.287)	(19.009)	(18.795)	(37.268)	(53.524)
GPA Reported	13.038	-9.291	-0.922	-0.213	17.401	-21.897
	(11.559)	(9.665)	(8.407)	(37.321)	(13.021)	(24.290)
Gender	3.268	3.932	-6.150	13.207	-2.672	-8.068
	(11.783)	(12.047)	(9.413)	(44.059)	(23.796)	(30.659)
Father had Higher Education	-36.921***	-5.997	-4.936	104.674	6.218	16.658
	(11.951)	(13.795)	(9.982)	(65.089)	(12.831)	(18.450)
Mother had Higher Education	-10.571	17.322	-9.810	43.808	-20.501	-71.955***
	(11.559)	(11.984)	(11.680)	(27.790)	(14.521)	(17.046)
Black	-16.042	-17.205	10.528	112.372***	3.730	13.610
	(11.863)	(12.470)	(9.757)	(37.524)	(17.664)	(33.276)
Period Fixed Effects	X	X	X	X	X	X
Session Fixed Effects	X	X	X	X	X	X
Observations	394	396	397	134	134	134

Notes: Dependent variable is the payoff of an individual worker in a single round. All explanatory variables are as defined in the note of Table 7.

Table 3.16 Market Stability

VARIABLES	School Stable No Descriptors	School Stable Descriptors
Information Treatment	-0.113	-0.048
	(0.073)	(0.089)
Active Firms	-0.097	-0.102
	(0.090)	(0.107)
Same Preferences	0.209***	0.242***
	(0.073)	(0.077)
Information x Same	-0.013	-0.043
Preferences	(0.078)	(0.081)
Average Percent Risky		-0.196
Choices Selected		(0.203)
Average GPA		-0.050
		(0.065)
Percent Female		0.113
		(0.075)
Percent Black		-0.048
		(0.077)
Percent with High Mother's		-0.016
Income		(0.077)
Percent with High Mother's		0.010
Education		(0.086)
Session Fixed Effect	X	X
Period Fixed Effect	X	X
Constant	0.194**	0.417
	(0.088)	(0.296)
Observations	586	514
R-squared	0.190	0.196

Notes: Dependent variable is the percent of matches in a group in a single round that are part of the stable market outcome. All explanatory variables are as defined in the note of Table 7.

3.8 Figures

Figure 3.1 Simultaneous Investment Screen

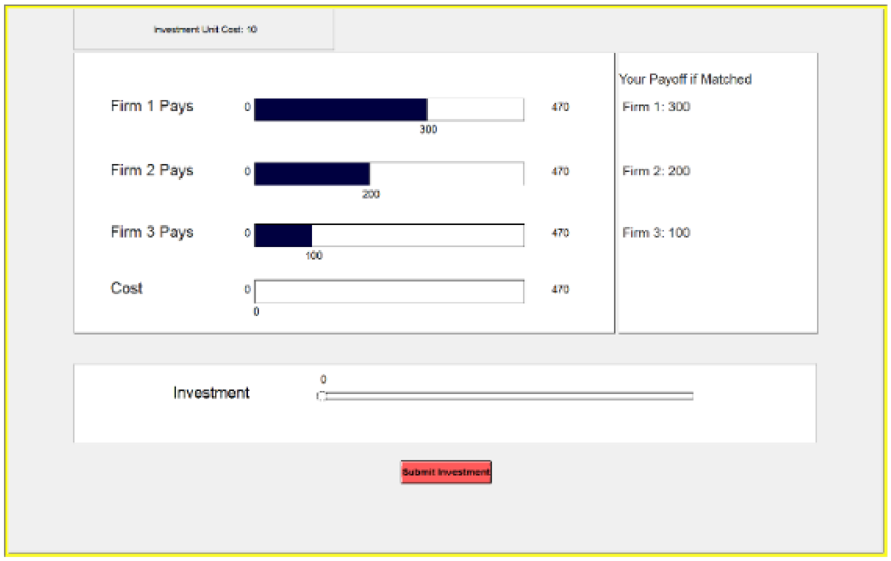


Figure 3.2 Sequential Investment Screen

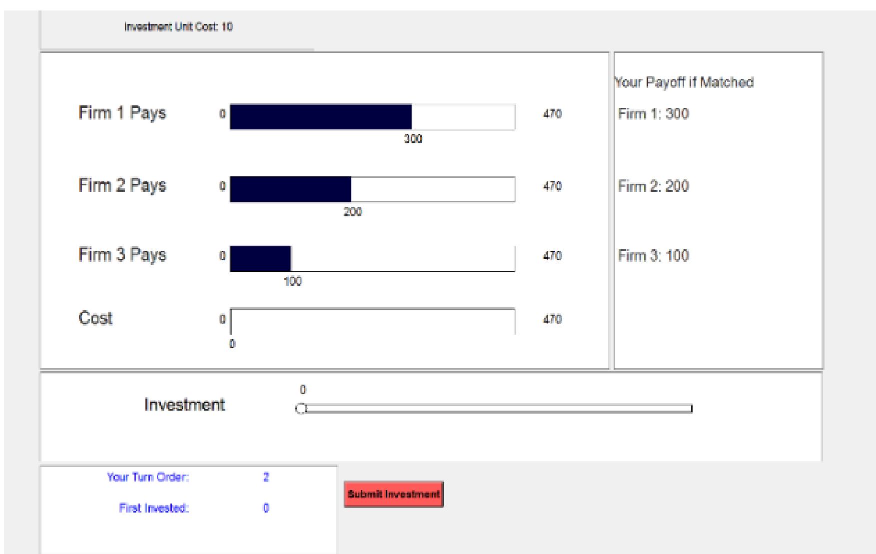


Figure 3.3 Firm Investment Screen

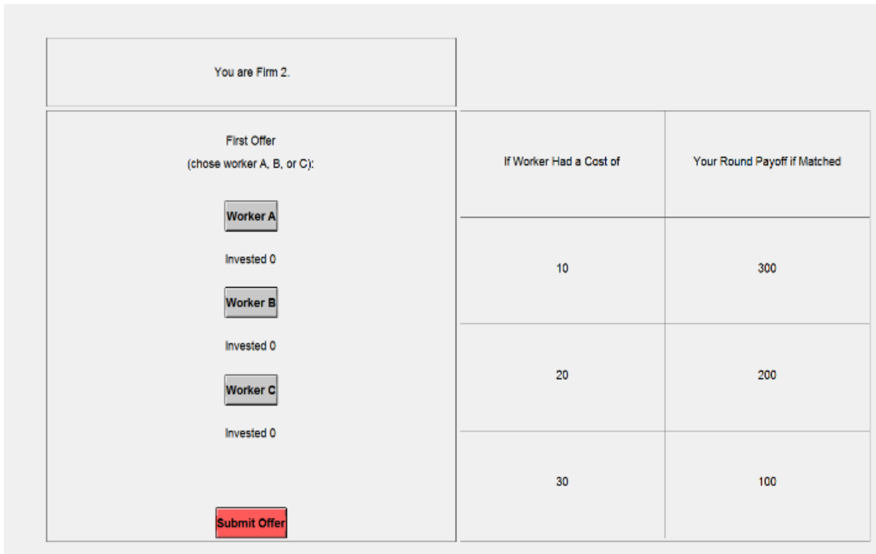


Figure 3.4 Worker Decision Screen - Offer

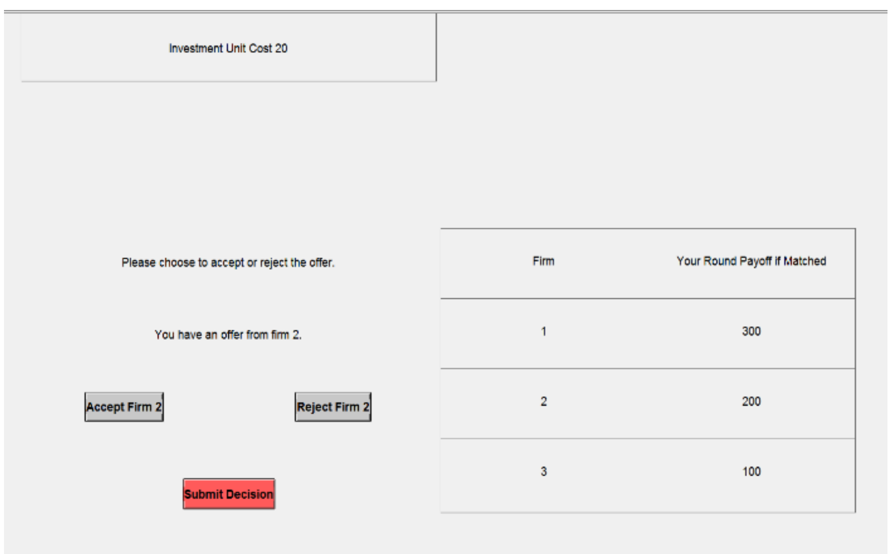


Figure 3.5 Worker Decision Screen - No Offer

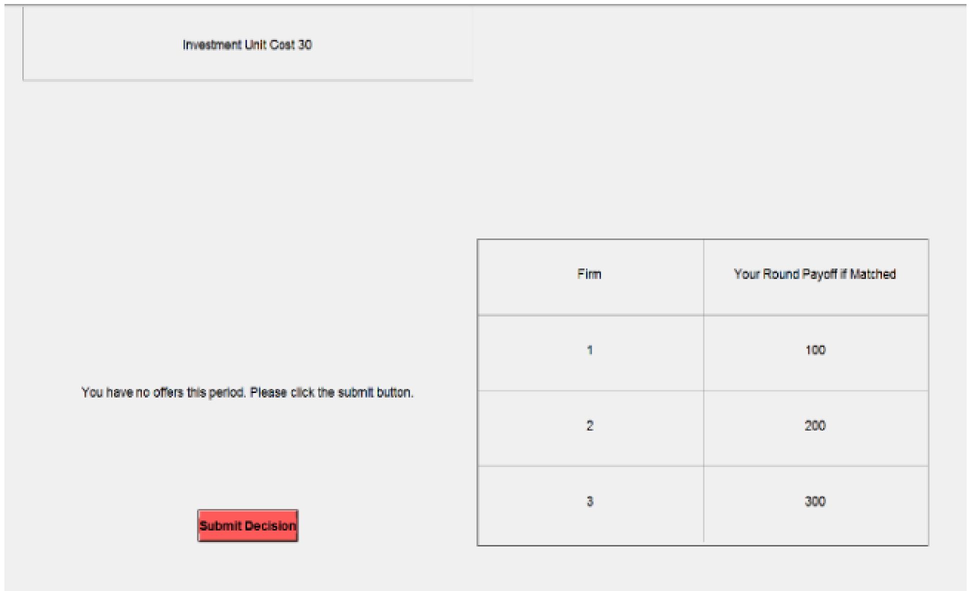


Figure 3.6 Market Match Outcomes

Figure 3.7 Match Outcome Payoff Screen

Figure 3.8 Risk Task Example

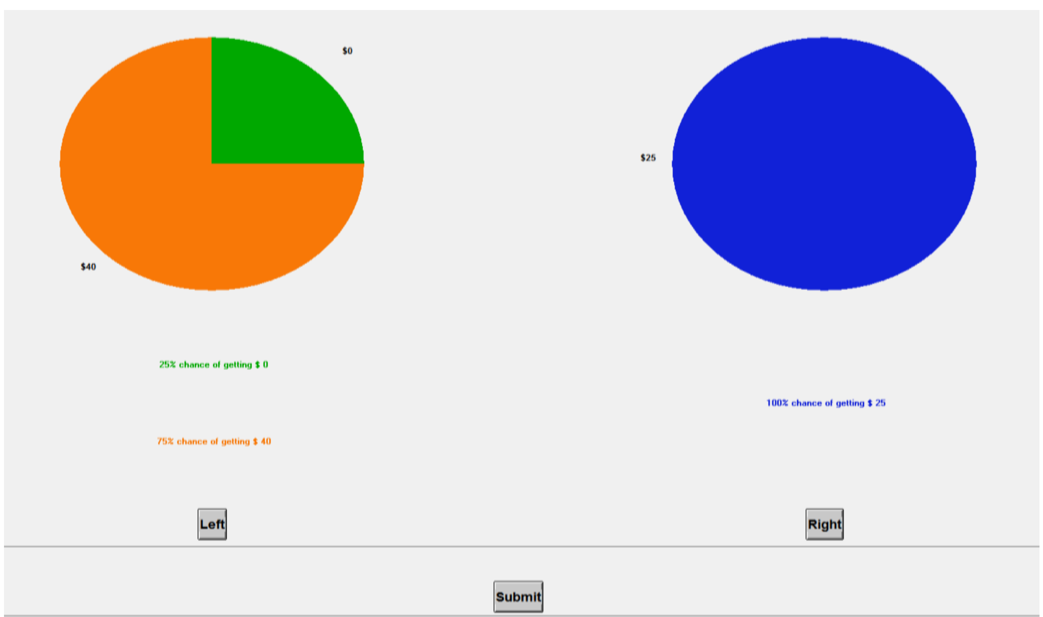


Figure 3.9 Investment Scatter Plot-All Workers

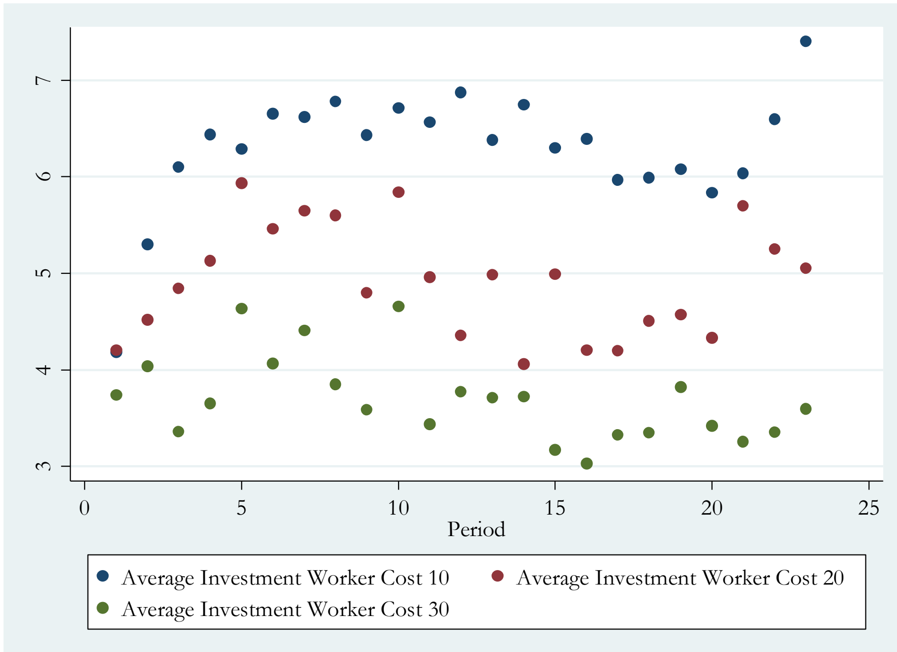


Figure 3.10 Investment Scatter Plot –Information Treatment and Same Preferences

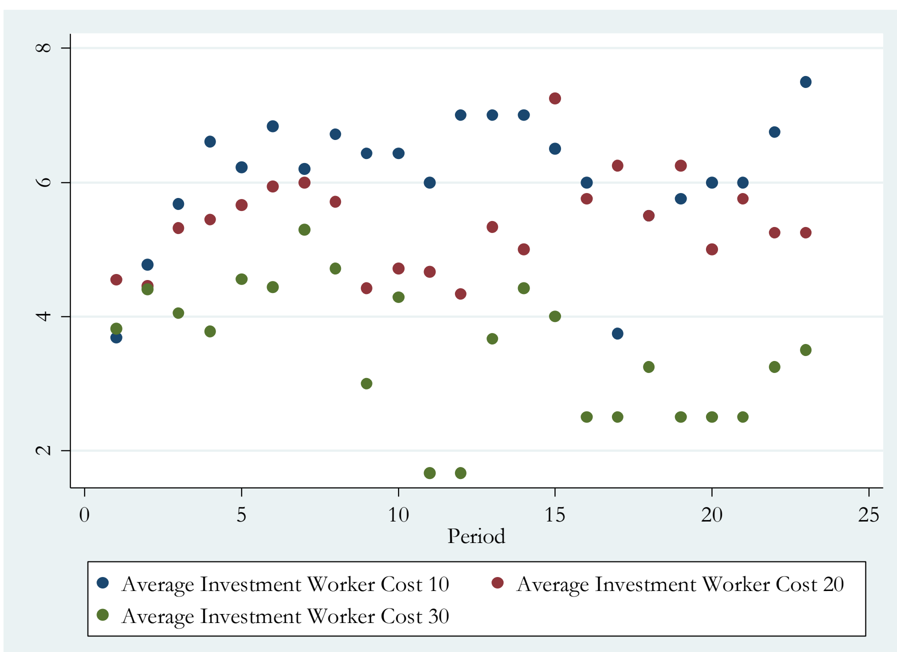


Figure 3.11 Investment Scatter Plot –Information Treatment and Different Preferences

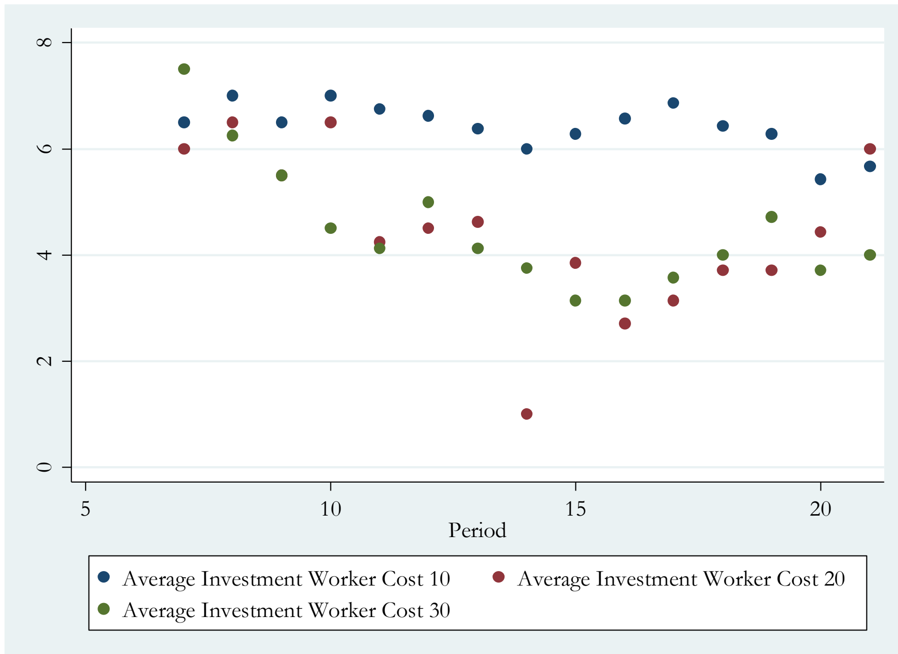


Figure 3.14 Investment Scatter Plot –Not Information Treatment and Same Preferences

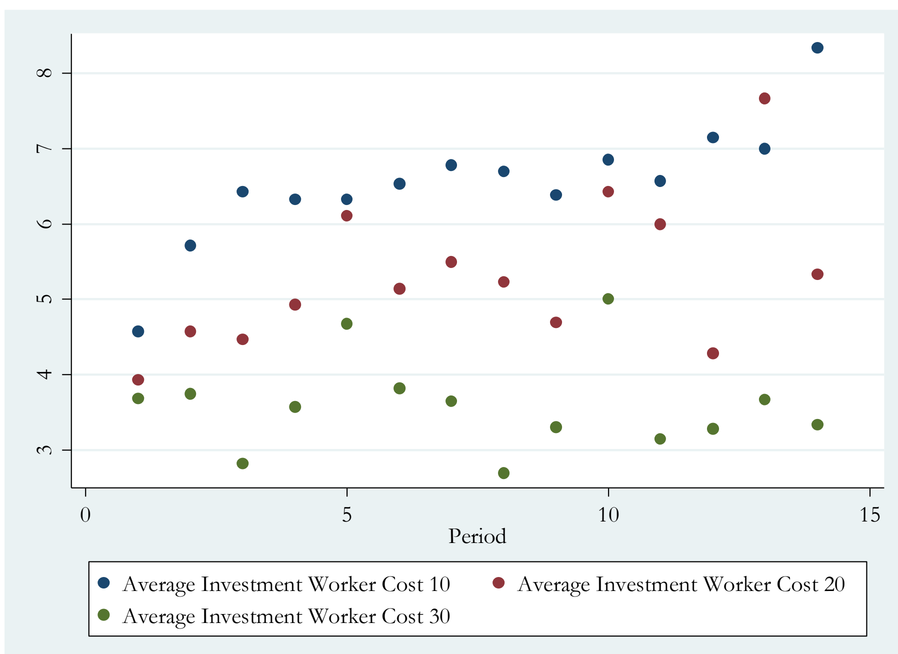
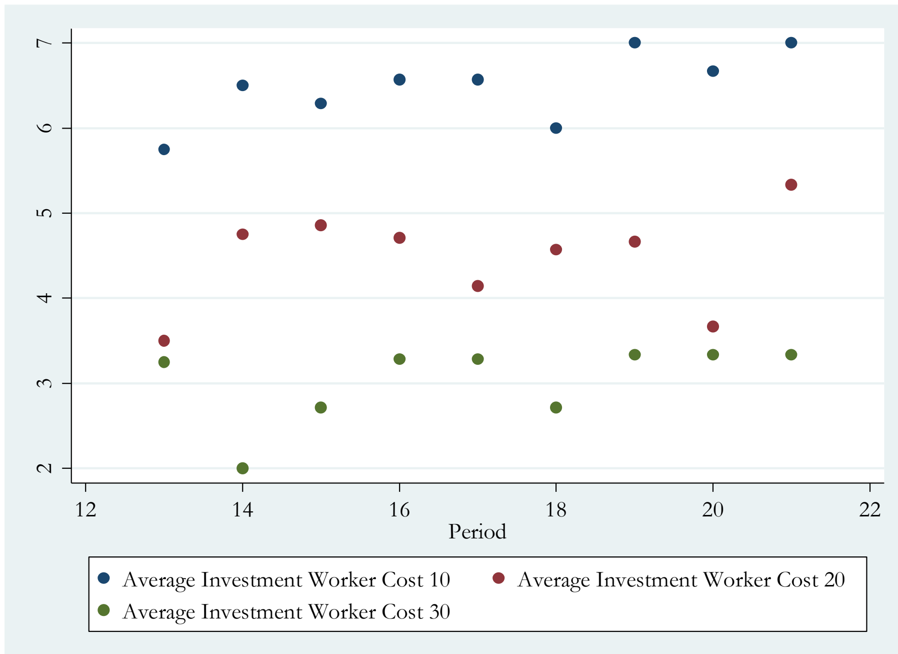


Figure 3.13 Investment Scatter Plot –Not Information Treatment and Different Preferences



3.9 Appendix A. Strategic Behavior

Strategic behavior is likely to occur in the worker investment decisions as the benefits of matching with their preferred school (100 for every rank higher) outweigh the investment benefits of selecting the maximin investment amount[51]. If the worker achieves a better match of one rank by investing more the worker's payoff always increases. The considerable boost from better matches gives the teachers incentives to invest strategically to attract a more preferred firm and attempt to receive a higher overall payoff. This strategic action requires workers to know what type their firm prefers, which is likely to occur with the rapid turnover and thus repeated participation of teachers in the teacher labor market. An example of the strategic investment in the true teacher labor market could be the amount of education they complete or the credentials they achieve to improve their chances of a better placement. In the market, teachers can also strategically accept or reject offers.

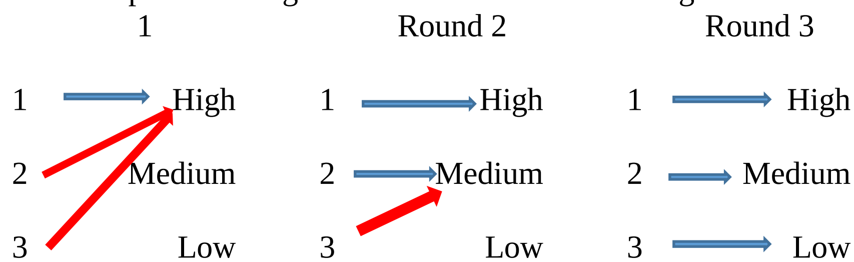
By a similar token as workers rejecting a firm if they believe they can receive a better offer, schools can strategically order their offers. If multiple firms make offers to the same worker simultaneously, the system presents only the worker's most preferred option. The mechanism is not strategy-proof for schools in any information environment as schools can obtain a better match by issuing an offer to a teacher who is not their most preferred teacher but who would be more likely to accept an early offer, particularly in preference set 1. Making an offer to their most preferred teacher might result in losing

[51] The max additional payoff from the investment is 100 for high types (170 (investment payoff)-70 (investment cost)), then 40 for medium (120 (investment payoff)-80 (investment cost)), and 10 for low types (40 (investment payoff)-30 (investment cost)).

their second-best candidate while waiting for the best candidate to reject their offer. Suppose a firm expects to be automatically rejected by their most preferred worker. In that case, the firm may choose instead to offer the job to their second preferred worker first if they have a better chance of being accepted by that worker. In the case of a separating investment equilibrium and a sincere workers' acceptance strategy (workers accepting their first offer), in preferences set one, a strategic offer by school three would be to make the first offer to the worker with the second highest level of investment rather than the top investor as illustrated below in Example 2. However, in the same set of assumption under preferences set 2, there are no such incentives for strategic offers.

The examples assume a separating investment equilibrium (worker types are perfectly revealed) and workers following a sincere acceptance strategy (workers will accept their first offer)[52]. In this case, Firm 3 can obtain a better match by issuing an offer to the medium type worker first. Under heterogeneous preferences, if workers accept their first offer, then the round will end due to the firms' disjoint first preference.

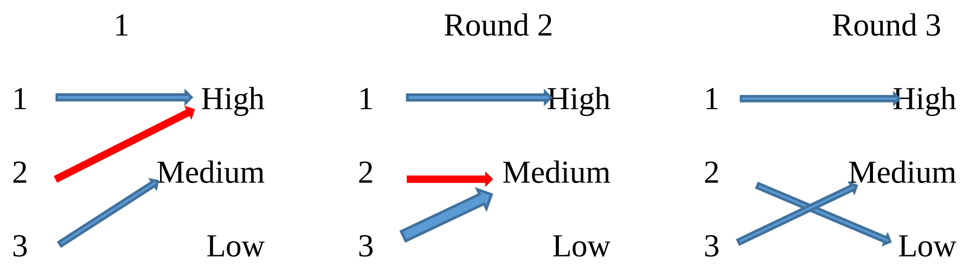
Example 1-Homogenous Preferences Non-Strategic Behavior



*Blue Arrow -the school is kept. Red arrow -the school is rejected.

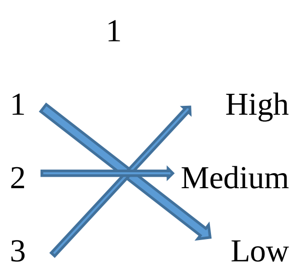
[52] This second assumption is for ease of the example, this is likely to be the case, if a participant is risk averse and fears not matching.

Example 2-Homogenous Preferences Strategic Behavior



*Blue Arrow -the school is kept. Red arrow -the school is rejected.

Example 3-Heterogeneous Preferences



*Blue Arrow -the school is kept. Red arrow -the school is rejected, Black is no match

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