Imperfect Information and Centralized School Choice*

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October 14, 2019

Abstract

As in many school districts around the world, prospective high-school students in Ghana are assigned to schools through the national Computerized School Selection and Placement System (CSSPS). Using administrative data on applications, we report various limitations in the behaviour of students, and matching outcomes show that approximately 15% of students end up unassigned, while almost 50% of schools have at least 1 vacancy. In order to rationalize choices in this setting, we build and estimate a model, where students engage in a costly search process to acquire information over school characteristics. The key insight of the model is that students may not be aware of all schooling options, and as such decisions are exerted without the full examination of all available options, which leads to potential sub-optimal choices. Our empirical application documents a substantial welfare loss: only a quarter of the efficient allocation is realized under the current allocation mechanism. Counterfactual simulations show that if a planner were to restrict choices and assign students using a rule as simple as " students prefer more selective schools", welfare would increase by 72%.

Keywords: school choice, uncertainty, consideration set, search.

JEL Classification Number: C53, D61, I20.

*This paper has benefited from helpful discussions with Attila Ambrus, Pat Bayer, and Todd Sarver as well as seminar and conference participants at Duke University, University of Virginia, and PeGnet.

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Introduction

Over the last 30 years, choice has become a key aspect of the assignment of students to schools. As such, most public school systems in the US are organized through a centralized coordinated assignment mechanism. Many recent empirical research on school choice highlights the potential welfare gain.[1]

In 2005, Ghana introduced the national Computerized School Selection and Placement System (CSSPS) to increase equity and access to quality senior high schools. The matching was based on the serial dictatorship algorithm, a popular strategy-proof mechanism, where priorities are determined by the student score at the Basic Education Certification Examination (BECE). Every spring, several hundred thousands students would submit a wish list of schools, and gain admission into one school at the end of summer, making it *de facto* one of the largest matching systems in the world.[2]

Yet, throughout the process, logistical considerations outweigh efficiency concerns. First, the timing introduces uncertainty, as rank-order lists (ROLs) are submitted prior to the examination that determined priority scores. Then, constraints were imposed in the length of rank ordered lists (4 in 2005, then 6 in 2008), which prompt agents to strategize over their submitted list. The short history of the program combined with the potential low involvement of parents may have worsen the potential welfare consequences of these implementation issues.

Three years after the introduction of the CSSPS, an analysis of application lists demonstrates that well established principles of students application under constraints such as the ordering of programs in admission chances are violated for almost 95% of the students, and as much as half (50%) of the students could have been admitted into a more selective school by changing the ordering of schools in their application. Matching outcomes show that approximately 15% of students end up administratively assigned.[3] The application behaviour of students led

[1] see Abdulkadiroglu and Sonmez (2003) for a foundational analysis and Abdulkadiroglu et al. (2011) for a review.

[2] A press report at the time of the introduction vows the merits of the program: " The system has not only brought about good governance but it put an end to anxiety, frustrations and confusion that qualify candidates were going through due to delays in the placement of such candidates, also to the benefits of the schools it has also help in ensuring that schools do not take more than their limits in order to hence good learning environment".

[3] Abdulkadiro?lu et al. (2005) report that 30% of students were administratively assigned under the decentralized application in NYC, motivating the switch to a coordinated assignment mecha-

to churning across admission cutoffs, especially for low and medium selectivity schools, and almost 50% of schools end up with at least 1 vacancy (including the very best schools).

Many scholars have documented the challenges faced by students from disadvantages background in school applications. The existence of applications mistakes (Pallais, 2015), or informational constraints (Hastings and Weinstein, 2008; Hoxby and Turner, 2015) are likely to hinder the objectives of school choice reforms. Yet, the school choice literature is cast in a view of the world where students and parents are informed about all the schooling opportunities. In this paper, we formally introduce incomplete information in a school choice problem.

We develop and estimate a model of school application in a large centralized allocation system. Our setting not only allows us to understand the choices of students, but also predict welfare under alternative policy arrangements. We show that the tension between competing explanations (preference for quality may not be strong, the existence of unsophisticated agents, . . .) may be resolved by the existence of incomplete information over schools attributes. In our model, students engage in an iterative and costly search among alternatives. A key implication of the model is that school choices are exerted without the full examination of all available options, which may lead to sub-optimal decisions. The optimal stopping structure of the model implies a dynamic utility trade-off between searching for alternative schools versus settling on the current consideration set. The dynamic trade-off along with the existence of search cost ensures that submitted ROLs may not be ranked monotonically in cutoffs, an important empirical finding in our data.

Our work is related to the recent literature on empirical market designs that is best summarized by Fack et al. (2019); Agarwal and Somaini (2018); Kapor et al. (2018); Calsamglia et al. (2018) among others.[4] While these papers introduce key innovations to the analysis of centralized school allocation systems, our setting differs with the existence incomplete information, which rationalizes the observation that students may choose an inferior option over a superior alternative. As

nism.

[4]The predominant focus in the empirical school choice literature has been on lottery-based admission and the Boston mechanism (see Abdulkadiroglu and Sonmez, 2003). The recent literature tries to quantify the welfare gains associated with changing the allocation mechanism. Related literature also includes Abdulkadiroglu et al. (2017); Walters (2018).

such, our work is related to a large literature on search frictions that dates back to Stigler (1961).[5] The notion that individuals engage in search over products is highly studied in IO (Goeree, 2008; Honka et al., 2017; Dinerstein et al., 2018).

We estimate the model using administrative data from Ghana's senior high school choice system in the year 2008, when students were allowed to rank a maximum of 6 programs. Our empirical strategy, based on the method of simulated moments, estimates preference parameters that match the empirical characteristics of students' ranked choices to the ones predicted under the optimal portfolio choice model. We show that preferences for schools, beliefs about admission chances and consideration sets can be separately identified under random search using our data. Moments used in the estimation include summary characteristics of students as well as chosen programs.

Our estimated parameters are as expected, indicating individuals' preferences for school quality and its proxy and a dis-utility associated with technical programs. We also find that search costs are high, which implies that consideration sets are relatively small. The median consideration set consists of 10 choices, which implies that submitted ROLs are not monotonically ranked in admission probability.

Then, we quantify the welfare implications of school choice in the presence of incomplete information of school characteristics. Our analysis of welfare shows that a quarter of the efficient allocation is realized. Since the large majority of the welfare losses are incurred by low ability students, our findings suggest that the initial objective to increase equity in access to higher education may be negated. Further computations show that 58.7% of the welfare loss can be attributed to the inability of students to gather information about all alternatives, while the remaining 41.3% is due to uncertainty (test score and coordination frictions).

Finally, since the planner may be more informed about schooling opportunities than students, we study whether restricting choice could be welfare improving. Counterfactuals outcomes will depend largely on the information set of the planner. Our simulations show that a planner, who is only interested in assigning the best student to the most selective school, would increase welfare by 72%.

The rest of the paper is organized as follows. In Section 1, we describe our

[5] A recent literature in decision theory analyzes the role of information and rational inattention in individual choice (see Caplin and Dean, 2011; Sims, 2003).

data and report several empirical regularities. Section 2 describes the model, while estimation and identification are discussed in section 3. The estimation results are presented in Section 4. Section 5 presents a welfare analysis. Finally, section 7 discusses alternative models, and concludes.

1 Motivation

Our data comes Ghana, where the national school system consists of six years of primary school, three years of junior high school (JHS), and three years of senior high school (SHS). In contrast to most developed nations, high-school graduation is the final degree for almost 80% of our sample: Duflo et al. (2017) report that under 20% of SHS graduates enroll in tertiary education directly after senior high school. Starting in 2005, students completing junior high school apply for admission to senior high school through a centralized application system.

Students apply to specific academic programs within a school and can submit a ranked list of up to six choices. Available programs include agriculture, business, general arts, general science, home economics, visual arts, and several occupational programs offered by technical or vocational institutes. After submitting their ranked lists of choices, students take a standardized Basic Education Certification Exam (BECE). The application system then allocates students to schools based on a serial dictatorship.[6]

Students who are unassigned at the end of the algorithm are administratively assigned to a nearby program with remaining vacancies.

[6] In practice, the algorithm is implemented as a student-proposing deferred acceptance. The algorithm is as follows:

- Step 1: Each student i applies to the first school in her ordered portfolio of choices. Each school s tentatively assigns its seats to applicants one at a time in order of students' exam scores, and rejects any remaining applicants once all of its seats are tentatively assigned.
- Step k: Each student who was rejected in round $k-1$ applies to the next school in her ordered portfolio of choices. Each school compares the set of students it has been holding to the set of new applicants. It tentatively assigns its seats to these students one at a time in order of students' exam scores and rejects remaining applicants once all of its seats are tentatively assigned.
- The algorithm terminates when no spaces remain in any of the choices selected by rejected students. Each student is then assigned to her final tentative assignment.

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Our data consists of the universe of junior high schools (grades 6-9) in 2008. The data consists of individual wishes along with BECE scores as well as admission outcomes.[7]

In the remaining of this section, we study in detail individuals' application behavior as well as admission outcomes, revealing some regularities that will guide our modeling strategy.

1.1 Descriptive Statistics

This section reports the basic statistics behind our data. We focus first on the characteristics of the students, before considering the schools.

The full sample of students in 2008 consists of 340,823 students, among which, 160,936 students (47%) passed the qualifying exam and are therefore considered for the matching.[8]

Table 1 reports the basic characteristics of students. Over half of the students (53.2 %) are male and the average age is 17. Geographically, almost 40% of students are located the Ashanti and Accra (capital) regions. Student performance on the BECE exam ranges from 185 to 469 points out of a possible 600. As such, students have very heterogenous chances of gaining admission to any given program. Table 1 also reports that younger male students are over-represented among higher test score students. Similarly, high test score students are over-represented in the Accra and Ashanti regions. In the absence of information on family background, we proxy it using measures of academic success at the junior high school level (average BECE score, and BECE pass rate).

[7] We programmed the matching algorithm and checked the consistency between applications and admission outcomes, and we find a 99% matching rate. The inconsistency between data on matching and our simulated matches occurs when the individual did not fill all choices. It is possible that the admission office administratively assigned all students with missing choices. As a consequence, we change the admission outcomes of those students.

[8] Among the 160,936 qualified students, 24 do not apply to any school, 44 apply to only one school, 52 apply to 2 choices, 170 to 3 choices, 8,788 to 4 choices, 8,769 to 5 choices. In total 152,167 (94.55%) of the students apply to all six choices.

Table 1: Students Characteristics

		Students test score (quantiles)			
Characteristics	All	190 − 254	254 − 286	286 − 328	328 − 469
Age	16.648	17.256	16.946	16.524	15.847
Male	0.584	0.573	0.584	0.592	0.585
Regions					
Ashanti	0.233	0.150	0.222	0.281	0.282
Accra	0.255	0.156	0.195	0.255	0.418
Central	0.080	0.110	0.090	0.073	0.047
Eastern	0.099	0.119	0.111	0.095	0.072
Volta	0.063	0.089	0.073	0.058	0.032
Western	0.090	0.113	0.103	0.084	0.061

Notes: The table shows the characteristics of junior high schools students who qualify for senior high school placement. Characteristics are computed for the full sample, and by quantile of student test score. For concision, only a limited number of regions are reported.

Then, we consider the other side of the market, which consists of schools. There is a total of 641 schools, and some offer as many as 33 programs.[9] In total, there are 2,300 school-programs.[10] Table 2 reports the characteristics of schools.

[9]This includes traditional high school, and both technical and vocational training institutions.

[10]Our attempts at reducing the dimensionality of the problem have failed as there are no systematic matching patterns between individuals and schools. As such, restrictions on the set of schools or individuals considered may alter the matching outcomes, and limit the scope of any counterfactual analysis.

Table 2: School Characteristics

		School cutoffs (quantiles)			
Characteristics	All	158 – 215	215 – 240	240 – 286	286 – 433
Boarding	0.559	0.344	0.411	0.635	0.866
Colonial	0.066	0.005	0.009	0.034	0.259
Religious	0.217	0.135	0.154	0.249	0.278
Size	66.503	75.251	68.200	76.092	82.924
Gender					
Boys Only	0.034	0.002	0.004	0.018	0.136
Girls Only	0.057	0.018	0.014	0.037	0.162
Coed	0.896	0.977	0.979	0.942	0.701
Programs					
Agriculture	0.113	0.097	0.113	0.053	0.011
Business	0.122	0.167	0.165	0.120	0.093
General Arts	0.163	0.170	0.147	0.155	0.174
General Science	0.194	0.195	0.152	0.201	0.243
Home Economics	0.101	0.045	0.093	0.108	0.194
Technical	0.150	0.152	0.172	0.189	0.132
Visual Arts	0.055	0.081	0.082	0.051	0.021

Notes: The table shows the characteristics of all schools/programs. The size of the program is defined as the number of vacancy reported by the school. The gender category reports the gender exclusivity of the school. Characteristics are computed for the full sample, and by quantile of school selectivity measured by realized cutoffs in 2008. For concision, all the technical programs have been grouped into one category.

There is substantial variation across programs. Over half of the programs (55.9%) offer boarding facilities. The presence of boarding facilities implies that students may gain admission everywhere in the country. The elite schools (6.6%) were established by the British colonial administration before Ghana gained independence in 1957 (colonial), and a little more than 20% of the programs were offered in schools with a religious affiliation. The average program admits 66.5 students, with a range from 10 to 120. While co-education has been generalized over the years, 10% of schools are still single sex, with approximately two thirds of them being girls-only programs. A substantial share of the single-sex schools are also religious, and were established pre-independence.

Finally, General Sciences and General Arts are the most commonly offered programs, accounting for approximately 35% of available options. Technical and vocational education represents 15% of the choices. We now consider the same characteristics by school selectivity. In this setting, selectivity is based on realized cutoffs in 2008.[11] There is a strong correlation between school quality and the indicators for boarding, pre-independence and coed status. That is, a very large majority of high-selectivity schools offer boarding facilities (86.6%), over a quarter of them dated back to the pre-independence era, and single-sex schools are over-represented among them. We also note that although there is not a monotonic relationship between school quality and size, more selective schools appear to offer more seats. Finally, exploring selectivity levels by programs shows a consistent pattern: programs in general sciences and home economics are the most over represented among high selectivity options. On the contrary, programs in agriculture and visual arts are the least selective.

1.2 Choices and Evidence of Reverting

In this section, we study the content of individuals choices. Table 3 presents descriptive statistics on students' ranked program choices. We report the characteristics of each ranked option to determine whether there exists a consistent pattern across choices. As mentioned before students were allowed to list six choices in 2008.

[11] We have roughly the same results when using realized cutoffs in 2007.

Table 3: Characteristics of the ranked choices

	Choices					
	1	2	3	4	5	6
Colonial						
mean	0.253	0.150	0.102	0.072	0.025	0.017
sd	0.434	0.357	0.303	0.258	0.155	0.130
Religious						
mean	0.248	0.217	0.207	0.200	0.292	0.294
sd	0.432	0.412	0.405	0.400	0.454	0.455
Board						
mean	0.869	0.813	0.759	0.681	0.605	0.582
sd	0.338	0.390	0.427	0.466	0.489	0.493
Coed						
mean	0.744	0.870	0.918	0.947	0.965	0.979
sd	0.437	0.337	0.275	0.223	0.185	0.143
Cutoffs						
mean	318.359	298.838	284.470	269.438	247.247	241.697
sd	59.493	56.065	54.037	52.300	34.286	33.335
Distance						
mean	34.148	32.929	30.680	26.507	30.287	30.904
sd	47.634	45.654	43.708	41.568	28.402	28.351
Programs						
Agriculture	0.057	0.070	0.078	0.092	0.076	0.081
Business	0.196	0.213	0.202	0.187	0.181	0.170
General Arts	0.399	0.389	0.393	0.387	0.392	0.393
General Science	0.138	0.105	0.089	0.079	0.075	0.064
Home Economics	0.098	0.104	0.108	0.113	0.096	0.101
Technical	0.045	0.048	0.051	0.059	0.120	0.127
Visual Arts	0.066	0.072	0.078	0.083	0.059	0.064

Notes: Table shows the characteristics of all schools/programs by ranked choices for 6 choices. Distance is evaluated between the centroid of the junior high school and senior high school districts using GPS coordinates.

Table 3 shows that students are more likely to list a school that was established pre-independence as their first choice. That is, 25.3% of first choices are colonial schools, to be compared to 1.6% for the sixth choice. A similar pattern is observed for schools with boarding facilities, and the coed status. On the contrary, there is a gradient for religious schools only for the first 4 choices: the share of religious schools among fifth and sixth choices is even higher than among first choice. This finding is surprising given the high correlation between school selectivity and the religious status.[12]

Then, we examine the distance between a student's junior high school and selected senior high school. We do not have exact coordinates for school locations so we measure the distance between centroids of the 110 administrative districts in the country. Ghana's school choice system is truly national and some students apply to schools as far as 450 miles away (roughly the distance from Boston to Washington, DC). Preferences for distance are convex. Students' first choice programs are on average 35.1 miles away from their junior high schools and their second choice programs are 1.3 miles closer to them. Their third and fourth ranked choices are 31.4 and 27.1 miles away, but their last two choices are further away at a distance of 31.1 and 31.7 miles on average. Even though there is no clear gradient, the dispersion in distance tend to decrease over choices.

In contrast to preferences for distance, peer quality in ranked programs decreases monotonically. The average exam score of a students' first choice program is 343 but falls to 273 for the lowest ranked choice, which represents a difference of 1.2 standard deviations in the peer quality distribution. Considering preferences for distance and academic quality together, it appears that students are willing to travel for the opportunity to attend a high quality program but less willing to travel for their lower ranked, lower quality choices.

Finally, we examine discrete program characteristics and reveals additional characteristics of aggregate choices in table 3. General arts is the most popular program track, with 39 percent of students choosing it as their first and sixth choices, which is mostly explained by the large supply of general arts programs. General science has the steepest gradient in choices. 13.8 percent of students choose a general science program as their first choice and only 6.4 percent choose one as their sixth choice. Preferences for agriculture programs show the reverse pattern, with 5.7 percent of students choosing one as their first choice and 8.1 percent choosing one as their sixth choice. The remaining programs are rela-

[12]There are two types of religious schools in our data. The first consists of colonial era schools, which are mostly single-sex, and while the second is composed of newly established schools, which provides a coranic or evangelical education. The former are very selective, while the latter are not.

tively equally represented across choices with an average of 19 percent of students choosing business programs, 10 percent choosing home economics programs, 7 percent choosing visual arts programs, and 4 percent choosing technical programs.

After reporting the aggregate characteristics in choices, we provide a deeper analysis of school selectivity in ranked choices. We discretize school selectivity by quartile, and report choices in table 4.

Table 4: School Quality in Ranked Choices

School Selectivity	Choices 1	2	3	4	5	6
(158,215]	0.038	0.058	0.083	0.131	0.151	0.184
(215,240]	0.048	0.072	0.098	0.136	0.179	0.207
(240,286]	0.194	0.261	0.300	0.322	0.457	0.442
(286,433]	0.720	0.609	0.520	0.411	0.214	0.167

Notes: Table shows the distribution of school selectivity among ranked choice. Reading: 0.038 of schools with cutoffs in $(158, 215]$ were ranked as first choice. Cutoffs are based on realization in 2008.

Table 4 shows that approximately 72.0 percent of first choices consists of the most selective schools, a ratio that decreases to 16.7 percent for sixth choices. Conversely, 3.8% of schools ranked as first choices consist of the least selective schools, while this ratio increases to 20.6% for the sixth choice. Yet, there is an odd pattern for the second quartile schools: respectively 17.9% and 20.7% of schools reported as fifth and sixth choices are made up of selective schools. Similarly, the ratio of selective schools among sixth choice may strike as high, but this could be driven by high-ability students. As a consequence, it is possible that *individuals may not be diversifying as they should*.

While instructive about aggregate patterns, the former tables do not inform us on the internal consistency of individual choices. We therefore analyze whether individuals target a specific set of characteristics in their application behavior. We aggreate schools into 5 groups of selectivity (0-20, 20-40,40-60,60-80 and 80-100), and report the number of selectivity groups reported by each student. In essence, we check whether students diversify the content of their portfolios in terms of school quality. In addition, we present these rates separately by student test-score groups to verify our previous conjecture that high test score students are driving the share of high selectivity schools among sixth ranked choices.

Table 5: Diversification in School Quality

	Number of distinct selectivity choices				
	1	2	3	4	5
Cutoffs					
All	0.0032	0.1881	0.4684	0.2922	0.0481
by test score					
0-20	0.0036	0.1085	0.4335	0.3829	0.0715
20-40	0.0029	0.1207	0.4322	0.3748	0.0695
40-60	0.0032	0.1481	0.4651	0.3266	0.057
60-80	0.0029	0.2099	0.4987	0.2562	0.0323
80-100	0.0033	0.3562	0.514	0.1173	0.0092

Notes: Table shows how many distinct school selectivity groups are reported by students, with school selectivity based on quantiles of past cutoffs. Then, the behaviour is described by student ability. Reading: 0.32% of students apply to schools within the same quantile of selectivity.

Table 5 shows that almost all students apply to at least two different school selectivity groups, with 98% of the sample ranking between 2-4 school selectivity groups. An analysis by test score group shows that as test score increases, students tend to apply to fewer groups of selectivity. These conclusions hold true considering both past and realized cutoffs.

Finally, table 6 investigates whether students apply to choices with the same set of characteristics – such as programs, schools, districts and regions. Our intuition is that individuals may target specific program characteristics and in the pursuit of these characteristics, individual choices may not reflect a thorough tradeoff. We find that only 11.8% of individuals apply to a single program throughout their entire list, which suggests that the large majority of individuals do not attach a high value to a single academic track. A larger share of the individuals apply to two and three programs (resp. 31.6% and 33.4%). With respect to schools, individuals almost exclusively apply to multiple schools, suggesting that there is no attempt to get into a particular school, and then switch to a different academic program afterwards. Finally, choices are not scattered geographically, the large majority of students apply to schools in 1 or 2 regions. The latter finding underscores the concentration of top academic tracks in a limited number of regions. This intuition is confirmed by the spread in the number of districts individuals apply to.

Table 6: Repeated Characteristics in Choices

	Number of distinct choices					
	1	2	3	4	5	6
Programs	0.118	0.316	0.334	0.184	0.044	0.004
Schools	0.000	0.004	0.020	0.077	0.231	0.668
Regions	0.557	0.318	0.106	0.017	0.001	0.000
Districts	0.042	0.154	0.297	0.336	0.170	
Colonial	0.888	0.112				
Boarding	0.885	0.115				

Notes: Table analyses whether individuals target specific program characteristics in their applications. Reading: 11.8% of students apply to a single program through out their application.

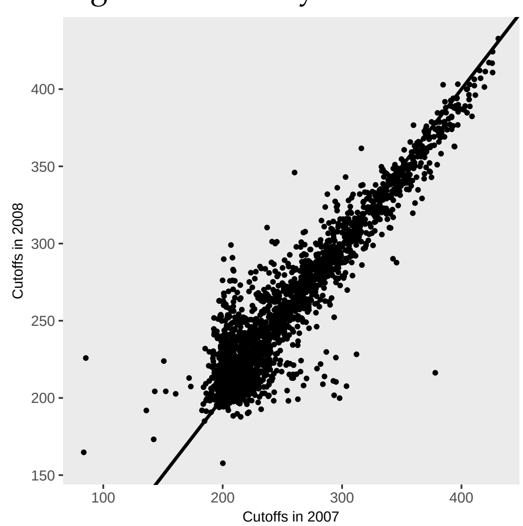
Overall these patterns suggest that students do not attach a strong value to program nor specific schools. These findings point to individuals genuinely trying to construct portfolios of schools that balance their ambitions and preferences. Yet, the fact that choices can not be characterized by a limited set of variables suggests that the portfolio construction problem may be complex, with potential substitution between multiple choices. The complexity of constructing a portfolio may lead to mistakes by individuals.

1.3 Uncertainty

In this section, we introduce the notion of uncertainty. There are two sources of uncertainty in our setting. The first, which we refer to as individual uncertainty, comes from the fact that individuals apply to schools before taking the exam that determines their ranking in the matching algorithm. The second, which we refer to as aggregate uncertainty, comes from limited information on the characteristics of other students. The problem of aggregate uncertainty is exacerbated by the fact that prior to 2008, there have been several changes in the institutional background. Since our analysis is based on administrative data, we do not have any information on an individual's prior about their test score. However, we can check whether the selectivity of schools is roughly constant across years.

Figure 1 reports a strong correlation between cutoffs across years (around 0.8). Yet, the correlation drops to less than 0.4, when we account for the schools with at least one opening. The correlation is relatively stronger for high selectivity than low selectivity schools.

Figure 1: Stability of Cutoffs



Notes: Cutoffs are defined as the test score of the last individual admitted, regardless of capacity.

1.4 Reverting

The first two sections report that despite the complexity of the problem at hand, individuals seem to be reporting coherent choices. On average, cutoffs are decreasing for later ranked choices, as well as all the indicators related to school quality. Individuals are diversifying their portfolios, including different academic tracks, as well as varied schools in selectivity bandwidth.

In this section, we show that these aggregate statistics conceal several behavioural problems in individual portfolios. Specifically, we study the content of individuals, and find that a key theoretical property of portfolios is violated for very large majority of students. In order to accomplish this, we first review a theoretical background. While there is no simple strategy to construct a portfolio, the literature has provided some results about the properties of the optimal portfolio.

Proposition 1 ***Haeringer and Klijn* (*2009*).** *Let* $N_p = \mathcal{S} = \|U_n > 0\|$ *be the set of alternatives with positive utilities. Then, the optimal strategy consists of choosing* N *among* N_p*, and ranks them according to the true preference ordering.*

Proposition 1 illustrates a simple property: while finding the optimal portfolio may not be obvious, the ordering within the portfolio is. Specifically, not ranking choices according to true preferences conveys the risk of getting assigned to a less preferred option. Given our data, we can test this property.

Table 7: Reverting

			Students test score (quantiles)			
		All	1^{st}	2^{nd}	3^{rd}	4^{th}
Non-reverters	Realization	0.055	0.016	0.028	0.049	0.133
	Past	0.052	0.015	0.024	0.046	0.127

Notes: Table reports the prevalence of reverting in the panel.

An analysis using the ex-post realization of cutoffs and submitted ROLs suggests that only 5.5% of individuals report a rank-order-list where schools are properly ranked by cutoffs (non-reverting). This ratio decreases to 5.2% when considering the cutoff of the previous period. The ratio of non-reverts almost double when we consider high ability students. Further analysis shows that students who do not revert, have on average a test score of 341 to be compared to 286 for the full sample. Yet the distributions are not disjoint, suggesting that the reverting behavior can not be explained by ability alone. A regression analysis of the determinants of reverting shows it is weakly related to basic observed characteristics (age and gender). However, a junior high school fixed effect is not a significant determinant, suggesting that students are not being coached in some junior high schools. Finally, there is a strong correlation between residence in the capital region and reverting. That is, students from the region of Accra make up 38.3% of non-reverters but constitute only 25.1% of the general population.

1.5 Mismatch

We consider the outcome of students' application behavior. Table 8 reports the placement outcome of students, and shows that the large majority of students gain admission into their first three choices. That is, 27% of individuals are admitted into their first choice. Interestingly, not only high test score students are placed into their first choice, more than 15% of the low test score students are assigned to their first choice as well, which speaks to potential non diversification in the ROLs of some students.

Table 8: Placement

		Students test score (quantiles)			
Placement	All	1^{st}	2^{nd}	3^{rd}	4^{th}
1	0.272	0.150	0.218	0.273	0.453
2	0.198	0.129	0.169	0.223	0.274
3	0.184	0.159	0.192	0.216	0.168
4	0.160	0.188	0.189	0.184	0.077
5	0.023	0.055	0.024	0.010	0.003
6	0.018	0.043	0.019	0.007	0.001
Administrative	0.145	0.275	0.189	0.086	0.024

Notes: Table reports the placement of students, including administrative assignment. The placement outcome is also reported by student test score quantiles.

The value of the fifth and sixth choices appears relatively limited, as only around 4% of students get admitted to those choices. This observation is at odds with the share of students who were unassigned (administrative assignmen)t. That is, 14.5% of individuals end-up administratively assigned. As expected, administrative assignment is closely related to test score - inasmuch as 27.5% of lowest ability students are administratively assigned, while only 2.4% of the highest ability students end up unmatched. There are very few matching setting in the worlds with two digit mismatch rates. The combination of administrative assignment with the observation that fifth and sixth choices are not well utilized suggests that the aggregate trends in the data may conceal some application shortcomings. In addition, the high share of first choice admission suggests that it may be possible to improve the allocation of some of the matched students.

Table 9 shows only 55.78% of the schools end-up at capacity. Not surprising, the vacancy rate is decreasing in school selectivity. However, vacancies are not confined to low selectivity schools. That is, only 76.4% of the 25% most selective schools are at capacity, a ratio that increases to 79.5% when we consider the 5% most selective schools. While the median high selectivity school has one remaining seat, least selective schools have more vacancies.

Table 9: Vacancies

(a): Prevalence of Vacancies

			School cutoffs (quantiles)			
		All	1^{st}	2^{nd}	3^{rd}	4^{th}
Cutoffs	Share	0.442	0.669	0.638	0.174	0.236
	Seats (median).	29.000	30.000	32.000	33.000	1.000

(b): Characteristics of vacant schools

		Non vacant	Vacant
Cutoffs	mean.	267.658	230.114
	sd.	55.265	46.598
Colonial	mean.	0.104	0.039
Size	mean.	78.027	72.593
Boarding	mean	0.709	0.374

Notes: Table reports the occurence of vacancy at the school level in panel a. Panel illustrates the characteristics of vacant and non vacant schools.

In addition, we show that schools with vacancies are larger and less likely to have boarding facilities. The existence of vacancies, administrative assignment along with the high share of reverting suggest a deeper problem than application errors, which we posit to be the existence of incomplete information. Under this hypothesis, students are not aware of the characteristics of the schools but are required to engage into a costly search to acquire more precise information about school characteristics. The existence of vacancies implies that the conditional probability of being accepted in a more selective school after being rejected from a less selected school may not be zero. In essence, this implies that dominated options may be listed.

2 A Model of School Application Under Incomplete Information.

In this section, we develop an empirical model, which is consistent with the key facts presented in section 1. To that end, we introduce frictional search in the standard school application problem.[13] We formulate the school application process as a search problem, where students iteratively acquired information about schools. The search framework allows us to generate mismatch: administrative assignment for students and vacancy at the school level. In addition, the existence of search cost may compel students to consider only a subset of choices, leading to suboptimal decisions.

Framework. The school choice problem is summarized as follows. A finite set of students $\mathcal{I} = \{1, 2, \ldots, I\}$ apply to a finite set of schools $\mathcal{S} = \{1, 2, \ldots, S\}$.

Each school has positive capacity, and students can opt out of the matching system and enjoy an outside utility u_0, which is set to 0 for simplicity. A student is characterized by a set of observed attributes $\mathbf{x}$ and a test score ω which is unknown when she submit a rank order list (ROL). The latter defines individual admission priorities while the former captures his preferences. Schools have an observable set of characteristics given by $\mathbf{z}$, and a fixed capacity denoted by K. Finally and following the literature, we assume that each school has a cutoff q. Formally, letting q_j be a cutoff : the minimal test-score required for admission at school j is defined such that $\mathbb{1}\{\mathcal{D}_j(q_j)\} \leq C_j \quad \forall j \in \mathcal{J}$ where $\mathcal{D}_j()$ is the demand for that school and C_j is its capacity.

The assignment mechanism is a serial dictatorship, with student priorities determined by test scores. Students submit a rank-order list that does not have to reflect their true preferences over schools. In our current setting, students can submit up to six choices, a constraint that makes it even more likely that rank-order lists may not reflect true preferences. The payoffs depend not only on which schools are listed, but also on the order they are listed in.

[13] A recent literature provides a theoretical foundation to search as originating from endogenous consideration sets under the notion of rational inattention. Our approach is related to theoretical models that study the implications of rational inattention for choices using search technology (Masatlioglu and Nakajima, 2013; Caplin and Dean, 2011).

We assume that students act as price takers, taking admission probability as given.[14] While restrictive, this assumption is likely to hold especially given the size of the market.

Preferences. The utility for an individual with characteristics $\mathbf{x}$ and test score ω matched with a school with attributes $\mathbf{z}$ is given by $u(\omega, \mathbf{z}, \mathbf{x})$. We follow Berry and Pakes (2007), and assume that the indirect utility function includes a disturbance term ϵ that is additively separable from school attributes and student characteristics:

$$u(\omega, \mathbf{z}, \mathbf{x}) = \gamma \mathbf{z} + \Gamma \mathbf{z}\mathbf{x} - d(\mathbf{z}, \mathbf{x}) + \epsilon \tag{1}$$

where the set of school attributes, $\mathbf{z}$, includes school quality as measured by the average score of students admitted the previous year, school size, and indicators for boarding facilities, pre-independence, religiosity and program track. The set of individual characteristics, $\mathbf{x}$, consists of realized individual test score, gender, age, and proxies of family background measured at the junior high school level. $d()$ provides the distance between the student and school locations. Since over 99 percent of programs are public schools, we use distance as our numeraire. As a consequence, the parameters γ measure student's willingness-to-travel for each school attributes, while Γ capture the interactions between students and school characteristics. Finally, ϵ is idiosyncratic tastes for schools. Students know their tastes, which is unobservable to the econometrician. The error term ϵ is iid and follows a distribution $\mathcal{N}(0, \varsigma)$.

Beliefs about admission chances. At the time of submitting lists, priorities and cutoffs are not known. Priorities are based on individual test score obtained from a national exam that will take place 4 months later. In the next section, we describe in more detail how students learn about cutoffs. For now, we state that students do not know cutoffs, but may learn about them through search q_j.

We assume that before the exam, each student has a prior about his test score, which is private information τ, not observed to the econometrician. We assume that agents form beliefs about realized test score following $t_i = \tau_i + \epsilon_i$ with the

[14] see for example Azevedo and Leshno (2016); Agarwal and Somaini (2018) among others for a similar assumption.

cdf of ϵ given $F_\epsilon(\cdot)$, with the variance of ϵ being a population-wide parameter. Given q_j, a student with t_i can form admission probability as $Pr(t_i > q_j)$.

Finally, we model the effect of uncertainty. As reported by figure 1, cutoffs may be not stable over years, which implies that the ranking of schools may not either. The introduction of an error term was designed to capture this effect on admission chance. However, uncertainty will also affect the conditional probability of being rejected from a seemingly least selective school and being admitted to a seemingly more selective school. We posit when considering two schools with cutoffs q_l and q_n, this conditional probability is denoted by $\sigma(q_l, q_n)$.[15]

Search. In order to acquire information about school characteristics, students engage in a sequential and costly search among the alternatives.[16] One could imagine a process where students visit schools and gather information at the same time. As a consequence, we view frictions as emerging from the existence of a large number of options.

Since our analysis of application, presented in section 1, did not reveal any systematic pattern on search directedness, we assume that search is random. While this assumption may be strong for high ability students, the technology of directed search may be extremely hard (if not impossible) to identify given our data.

In order to describe the search problem, we resort to the notion of consideration set, which allows us to dissociate the search process from the construction of a ranked order list. Through search, agents build and expand a consideration set, denoted by $\mathbf{c} \subset \mathcal{S}$. The existence of incomplete information gives rise to the notion of a consideration set, whereby only a subset of available alternatives will be considered for choice.

A draw is a school characteristics $\mathbf{z}$, and a cutoff q. One element of the consideration set is a couple $(\mathbf{z}, q)$. At the beginning of time, the consideration set is

[15]This assumption is not necessary to generate reverting in our setting. We provide additional details in the estimation section.

[16]There is a literature that studies the nature of search in environment characterized by costly acquisition of information. While most applications are in consumer search, the theoretical foundations explores questions related to sequential versus non sequential search, and the impact of recall on consumer choices Morgan and Manning (1985); Morgan (1983). The main difference with our current setting is that individuals search in order to construct an optimal portfolio.

empty $\mathbf{c} = \emptyset$.[17]

Individuals search through available options, at cost $c(n)$, where $n = \|\mathbf{c}\|$, the number of elements. Furthermore, we assume that $c(n)$ is positive and given by $c(n) = c \times n$. In our empirical application, we include a stochastic shock in the cost of application, which helps generating heterogeneity in the size of ROLs.

The value of search to a student with consideration set $\mathbf{c}$ is given by $\mathcal{V}(\mathbf{c})$:

$$\mathcal{V}(\mathbf{c}) = \iint u(\mathcal{B}(\mathbf{c}')) \,\mathrm{d}g(\mathbf{z}', q') - c(n') \tag{2}$$

where $\iint$ is a convenient abuse of notation (set of schools are finite). $\mathbf{c}' = \mathbf{c} \bigcup (\mathbf{z}', q')$, $n' = \|\mathbf{c}\|'$ and $u(\mathcal{B}(\mathbf{c}))$ is the highest utility portfolio attainable from the consideration set $\mathbf{c}$.

The search problem has an optimal stopping structure: individuals will keep searching as long as the marginal value of search exceeds the cost of searching:

$$c(n') = \mathcal{V}(\mathbf{c}') - \mathcal{V}(\mathbf{c}) \tag{3}$$

where $\mathbf{c}'$ is the expected consideration set.

Portfolio construction. Finally, we consider how individuals can construct the best set of schools $\mathcal{B}(\mathbf{c}')$ given $\mathbf{c}'$. Since individuals use the same test score to evaluate her admission chance throughout the search process, choices are inter-dependent. Explained differently, rejection in the first choice conveys additional information on one's test score and the expected distribution of cutoffs. Recently, Shorrer (2019); Calsamglia et al. (2018) have proposed methods to construct the best set of schools in that setting. In our case, it turns out that consideration sets are relatively small, and as a consequence, we can compute all the combinations and pick the one that yields the highest utility as in He (2012).

[17] The assumption that initial consideration sets are empty is arguably strong. One could imagine that students may acquire information about a number of schools from parents, friends and school teachers. However, an analysis of the applications does not reveal that students from the same junior high-schools apply to the same set of schools, and we do not have any information about the information set of parents. As a consequence, we opt for this strategy.

3 Estimation

Our final sample consists of the 169,097 individuals who complete the BECE exam. Although the individuals who do not pass the exam could provide additional information about test score uncertainty, we opt against this strategy since their test scores are reported as missing. In order to limit the number of available schooling options, we do not consider schools that were not subscribed at all, which leaves us with 2,182 choices. We estimate the model by Simulated Method of Moments. That is, we match the empirical characteristics of student ranked choices to their theoretical counterparts generated by the model. Formally, let us denote by Θ the set of parameters to be estimated. The criterion function is given by:

$$\mathcal{L}(\Theta) = -\frac{1}{2}\big(\widehat{m} - m(\Theta)\big)^T \widehat{W}^{-1}\big(\widehat{m} - m(\Theta)\big) \tag{4}$$

where $\widehat{m}$ is a set of empirical moments, and $\widehat{W}$ is the weighting matrix.[18]

In the rest of this section, we provide identification argument for the parameters for preferences, beliefs about admission chances and search cost. Then, we describe our moments.

3.1 Identification

This section studies the identification of our model. The standard identification result in the job search literature relies on wages and duration. Since we have access to choice data, we use discrete choice theory with limited attention (Barseghyan et al., 2019).[19] Formally, we show that application data along with some functional form assumptions is enough to identify separately individual preferences, admission chances probabilities, and consideration set parameters.

[18]We use a diagonal weighting matrix, with the elements set equal to the inverse of the diagonal variance-covariance matrix of the empirical moments. Since we have discrete dependents, approximation of the gradient vector are sensitive to the chosen step size. We therefore calculate the derivative by first approximating the function by a low-order polynomial function as we vary each parameter locally.

[19]Formally, identification hinges on the single crossing property of the utility function, a consideration set formation mechanism, independence between consideration sets and preferences and the large support assumption (one observed characteristics allow to trace the key parameter throughout its support). Our framework differs in two aspects: choices are also driven by beliefs about admission chances, and consideration sets are endogenous.

Let us assume that the set of parameters may be partitioned: $\Theta = (\Theta_u, \Theta_q, \Theta_c)$. In addition, it is useful to redefine the identification problem as separating the utility u, the admission probability q and the size of the consideration set c_s. Since there are J schools, we have C_6^J potential portfolios, and data on school applications allows us to identify C_6^J moments. Under random search, the theoretical counterpart of these probabilities can be written the likelihood of the full consideration model can be derived.[20] We now study our problem.

Proposition 2 *Assume*

1 *Random search (consideration sets are random)*

2 *Large support ()*

3 *Independence between unobserved heterogeneity in u,q,c_s conditional on observed characteristics.*

then consideration set parameters Θ_c are identified.

Proposition 3, which is an application of Theorem 2 in Barseghyan et al. (2019), shows that the parameters that drive individual consideration sets are identified. Intuitively, as consideration sets are random, there is a simple way to construct the probability of being considered, shifts in choices will be informative about which schools are being considered by the individual. More specifically, when individuals with the same observed characteristics choose different schools, this allows us to learn about which schools are being considered. We can now study the identification of preferences and belief about admission chances.

Proposition 3 *Θ_u and Θ_q are identified.*

Given Θ_c, the standard identification result based on revealed preferences applies, which allows us to identify the expect utility of each ROLs. The main challenge consists of separating preferences from beliefs about admission chances. We use a generic property of ROLs under correlated admission chance, that is, the expected value is a nonlinear function of elements that depends on admission chances and preferences parameters.

[20]In practice, many empirical probabilities will be zeros, and (Barseghyan et al., 2019) provides a strategy to derive the choice probability without computing all the combinations.

Finally, we should note that our initial monte-carlo studies suggest that the parameter $\sigma(q_m, q_n)$, which is the conditional probability that one may be accepted in a more selective school after being rejected in a more selective school is not identified. Intuitively, this non-identification may be explained by the fact that the mechanism of reverting does not operate through the conditional probability but hinges on the existence of dominated options. Formally, school m dominates school n if $u_m > u_n$ (utilities) and $q_m > q_n$. As soon as $\sigma(q_m, q_n) > 0$, the individual will list dominated option. As the value of $\sigma(q_m, q_n)$ is uncorrelated with the search technology, this parameter can not be identified.

As a consequence, after several tests, we set this probability to 0.02, which corresponds to the value to minimizes the moment criterion. The value of this parameter does not have any impact on preference parameters but does appear to have a very modest effect on the scale of the uncertainty parameter.

3.2 Moments

We construct empirical analogs that capture the identification content provided by the data. That is, consistent with our identification strategy, we use empirical choice probabilities conditional on observed characteristics. First, we use the characteristics of ROLs, calculated separately across individuals and then averaged across rank-order list. For any simulated portfolio, $\mathcal{S} = \{\mathcal{S}_n\}_1^6$, the set of moments is given by:

1. Expectation of schools' observable characteristics by ranked choice

$$\mathbb{E}\left(Z_{ij}(\mathcal{S}_{i,n}))\right) \tag{5}$$

2. Conditional expectation between students' and schools' observable characteristics

$$\mathbb{E}\left(Z_{ij}(\mathcal{S}_{i,n})|X_i\right) \tag{6}$$

3. Conditional expectation between students' and schools' observable characteristics

4. Share of monotonically ranked portfolios, share of ROLs with less than 6 choices and the correlation between past and realized cutoffs.

Our moments use the characteristics of ranked ordered lists, which are supposed to identify the parameters of the utility functions. The intuition is similar to standard discrete choice analysis, where demand is identified from moments conditional on demographics. The constraints in the length of the ROLs are likely to impend the identification argument only admission probabilities. As a consequence, we use additional moments on the share of monotonically ranked portfolios, the share of individuals reporting less than 6 choices in their ROLs, and the correlation between past and realized cutoffs.

Given the set of school characteristics and the number of characteristics, the model is over-identified. We use this opportunity to target a limited number of characteristics, and jauge the out-of-the sample validity of our model using moments that are not included in the estimation. Notably, we omit the distance variable, and many school programs.

Since some of the moments depend on the matching outcomes, we solve the search problem for all individuals in our sample, then solve for the matching allocation to compute the moments. Luckily, the most intensive part of the problem (solving for the search problem) can be parallelized. The stochastic components are integrated-out through simulations. In our final specification, we have 163 moments and 27 parameters. We estimate the model using POUNDERS (TAO implementation), which is a Derivative-free model-based algorithm for nonlinear least squares.

4 Results

4.1 Parameter Estimates

Table 10 presents the estimated parameters governing student's preference. Our final specification includes several school characteristics, which are then interacted with key individual characteristics.[21] Estimates for school characteristics

[21]Boarding is an indicator variable for the existence of boarding facilities at the school, while Colonial, Religious, Coed, are indicator variables for the creation of the school prior to Ghana independence, religious school, and mixed gender education. G. Science, G. Arts, and Technical are program indicators for General Sciences, General Arts and Technical. Score is the standardized test score obtained at the BECE, which is rescaled between 0-1 for the estimation. Quality is measured as the average test score of students admitted in the program the previous year. Finally, J.Quality and J.Rate are demographic characteristics at the junior high school level capturing

are consistent with qualitative evidence, presented in section 1.

Table 10: Estimation results (utilities)

Variables	Est.	Std.
Boarding	2.737	0.215
Colonial	2.065	0.415
Religious	-0.211	0.264
Coed	0.833	0.543
G. Science	1.881	0.119
G. Arts	0.163	0.118
Technical	- 1.142	0.311
Quality	0.502	0.091
Score × Colonial	1.093	0.321
Score × Boarding	0.379	0.283
Score × Quality	0.399	0.483
Male × Colonial	0.644	0.281
Male × Boarding	-0.222	0.371
Male × Quality	0.589	0.329
J. Quality × Colonial	0.148	0.141
J. Quality × Boarding	0.251	0.46
J. Quality × Quality	0.729	0.198
J. Rate × Colonial	1.093	0.117
J. Rate × Boarding	0.326	0.231
J. Rate × Quality	0.895	0.482
Score × G.Science	0.205	0.091
Score × G.Arts	-1.319	0.377
Score × Technical	-5.638	0.356

Notes: The table shows parameter estimates under our preferred and parsimonious specification. A description of the variables in provided in the footnote 21.

On average, students prefer boarding schools, and older schools established before Ghana gained independence. Religious and single-sex schools appear to impact negatively students utility although the effect is not significant. Students

respectively the average score and the passing rate at the BECE.

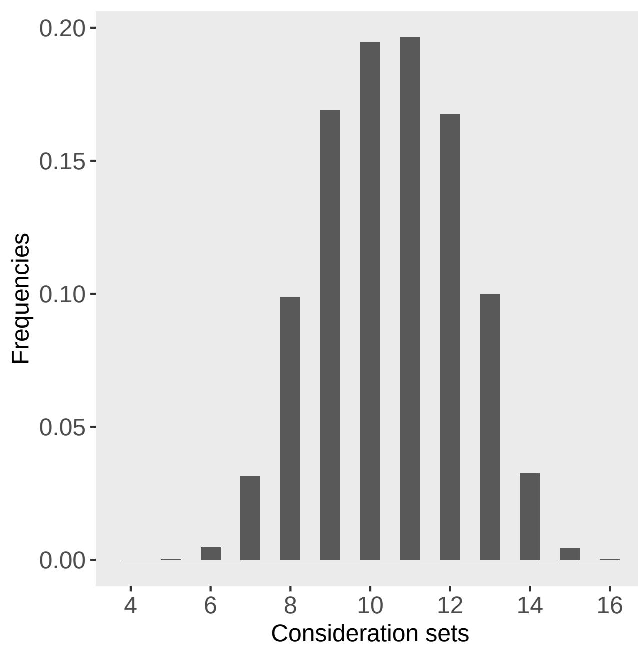
have a significant preference for general sciences and general arts programs and a strong negative taste for technical programs.

Compared to these average preferences, students with higher test scores place more emphasis on programs in general sciences and in pre-independence schools. Male students have a stronger preference for school quality and value less older schools relative to females, with a significantly weaker preference for boarding schools.

Students from higher-performing junior high schools place relatively more value on school quality and value less boarding facilities, but have a weaker preference for older schools.

Then, we quantify the role of search cost. The parametrization allows us to interpret c as a marginal cost. Our estimate is approximately 0.073 to be compared to the average (resp. median) utility of a program of 2.2 (resp. 1.88). The main implications of these costs are related to consideration sets. Figure 2 shows the distribution of implied consideration sets under our model. Students consider between 7 to 35 choices.

Figure 2: Size of consideration sets



Notes: Distribution of the size of consideration set in the estimation.

As reported by Figure 2, the very large majority of students (90%) consider between 7 to 13 schools. The remaining 10% consider between 15 to 35 choices, and consist almost exclusively of the very high ability students. The remainder of our comments focus on the 90% of students. The consideration set of the median student contains 10 schools, which is negligible when compared to the choice set of 1,182 choices. Yet, the total search cost is almost 5% of the average school utility. One would have expected that consideration sets may have been larger under random search to generate the choices of high ability students. This is not the case because essentially there are too many choices, and as students are not able to direct their search toward specific schools, the value of an additional school in the consideration appear limited. In all this is consistent with our data as it is essentially this feature that allows us to generate the high share of reversion in the data. If students were to consider a larger set of schools, it would be possible to find a ROL which is monotonically ranked by admission probability.

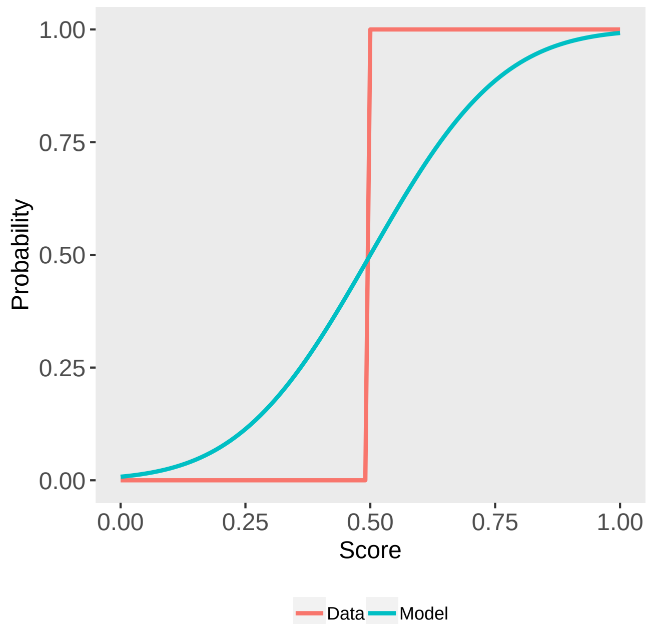
Table 11: Estimation results (cost and shocks)

Variables	Est.	Std.
c	0.073	0.026
σ_q	0.207	0.045
σ_c	0.013	0.002
σ_u	0.195	0.027

Notes: The table shows estimates of the marginal cost of search, and the shock parameters.

Finally, we consider the parameters that characterize students beliefs about admission chances, and the shock parameters (preference and search cost). First, σ_q captures the level of uncertainty in the matching process, whose effect is report in Figure 3.

Figure 3: Beliefs and Realized Admission Probabilities



Notes: Admission probability for a school with a cutoff of 0.5 for a grid of test score ranging from 0 to 1.

Figure 3 report beliefs about admission chance to a school with a cutoff of 0.5 for a grid of test score ranging from 0 to 1. Under the normal error assumption, admission chances are smoothed on the support of the admission scale. As such, the admission probabilities of lower ability students are over-estimated, while those of high ability students are under-estimated.

4.2 Goodness of Fit

Since we are interested in counterfactual simulations, we present evidence on how well our model fits the data. We use our model to simulate ROLs and and compare them to the real data.

Figure 4: Fit

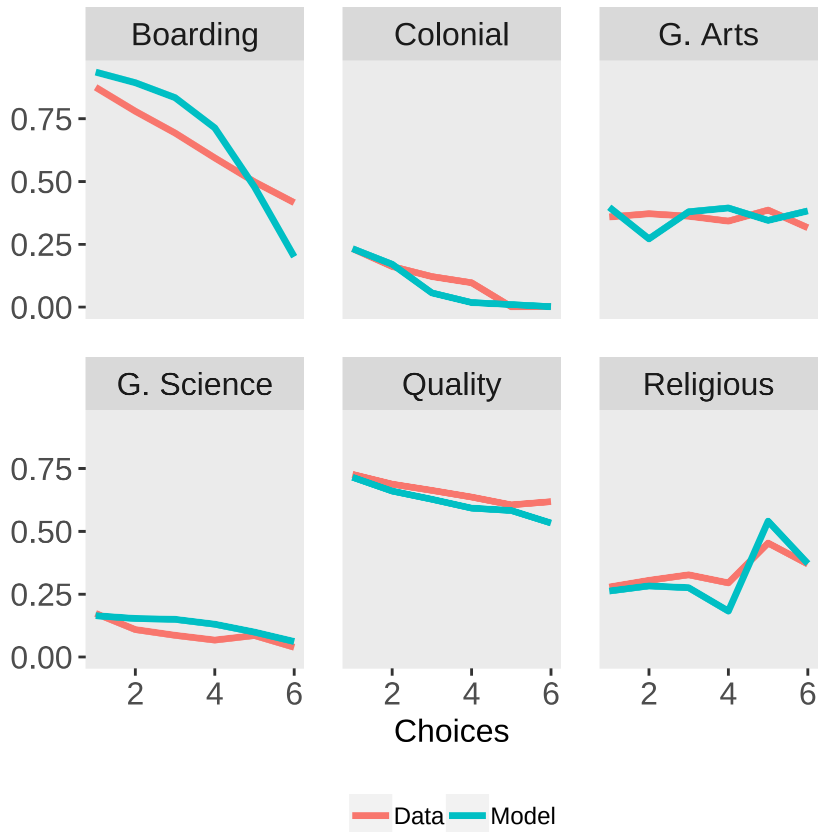
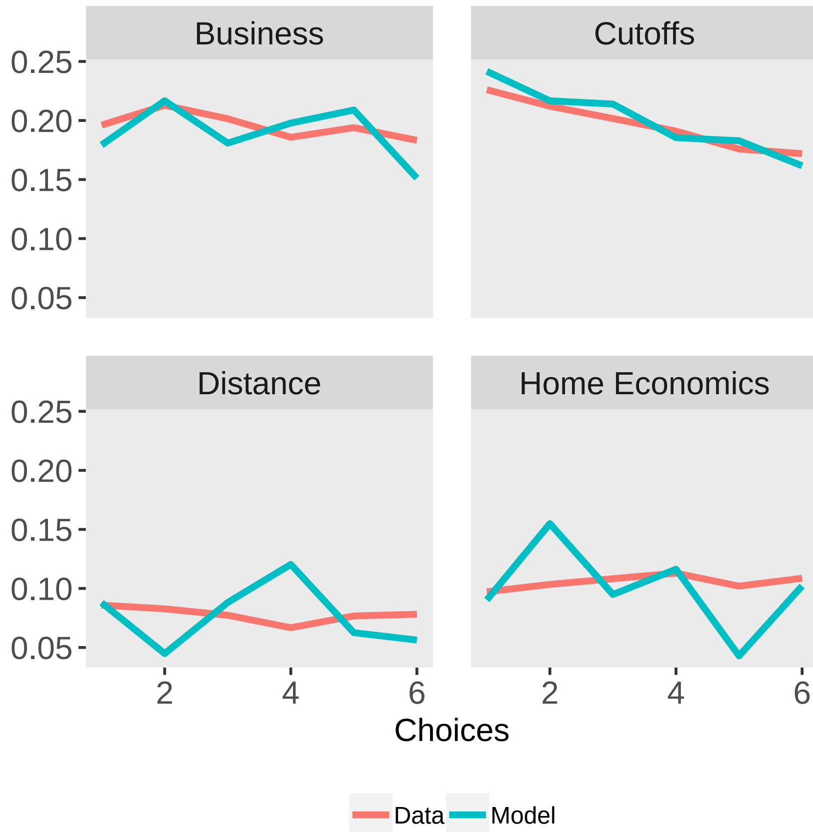


Figure 4 presents the fit for a subset of moments targeted in the estimation. For concision we focus on a limited number of moments although all moments fit very well.[22] Our model fits the distribution of school characteristics for each chosen school very well. The model captures the sharp decline in school quality over ranked choices. The actual and predicted school profiles (namely availability of boarding facilities, the creation of the school prior to independence, and religiosity) are very close. We predict well the patterns of academic program choices as well. General arts is more popular than general science in both cases. In all cases, not only, do we match the patterns across choices, but also the value of the variables. Figure 5 presents additional evidence on out-of-sample fit, using data on moments non targeted in the estimation.

[22]The complete fit is available upon request.

Figure 5: Non targeted Moments



Notes: Out of the Sample Validation. Cutoffs has been divided by 3 to produce variables that are on the same scale.

The main patterns observed in the targeted moments largely hold with the non-targeted moments. However, when variations across ranked choices are not monotonic, the model produces changes that appear to be sharper across choices. Yet, even for the distance variable which does not appear to be fitting very well, there is never a difference of more than 0.05 between true and estimated moments. To sum up, for a model, which is over-identified (163 moments vs 27 parameters), the out-of-sample fit is very good, suggesting that the model fits the patterns observed in the data both quantitatively and qualitatively. As such, we are confident that we can use the framework to perform counterfactual simulations.

5 Efficiency

In this section, we analyze the efficiency content of our model. Given individual preferences, and technological constraints on vacancies, we analyze whether the planner can achieve a better allocation. Inefficiency results from the discrepancy between private and social values of search which arises because of the standard "overcrowding" among students: when an extra person lists a school, it reduces the availability of vacancies for other students. An externality that students are not likely to internalize.[23]

Efficiency, or its lackoff is clearly reflected in the existence of vacancies, administrative assignment, and potential mismatches among matched students. Our findings in section 1 suggest that a substantial share of students could have been admitted to a more selective school by changing the ordering of schools. There are two sources of inefficiencies namely search frictions, and uncertainty.

We quantify the respective importance of these features on individual welfare. We consider three settings. Frictional Application is our benchmark case. Then, the problem of the Constrained Planner (CP), who maximizes total welfare subject to preference and technology constraint. Since matching is centralized, we assume that the planner can alleviate the frictional nature of matching. As such, the planner is not affected neither by search frictions nor uncertainty.

Finally, we quantify the importance of the two sources of inefficiency. We evaluate welfare assuming there is no frictions, such that individuals can construct Optimal Portfolios (OP). In OP, individuals observe perfectly the characteristics of all choices, and hence can optimally select the best portfolio. Recently Shorrer (2019); Calsamglia et al. (2018) have proposed a method to recover such a portfolio. The idea is to use dynamic programming to account for the inter-dependence in admission chances across choices. We implement this strategy. In doing so, one potential problem is related to the fact that it is likely that cutoffs may be affected by how students construct portfolios. As a consequence, we solve for the Bayesian Nash Equilibrium. That is, given set of initial cutoffs denoted by q^0, and preferences estimated in our setting summarized by u, we solve for the following algorithm.

1 Individuals select the rank-order list that maximizes her expected utility.

[23] See Abdulkadiroglu et al. (2015) for a theoretical analysis of this problem in school choice.

2 Given submitted lists, students get admitted to schools, and realized matchings determine the new distribution of cutoffs.

3 Repeat until cutoffs converge.

Table 12 reports the results.

Table 12: Efficiency

	Benchmark	Constrained Planner (CP)	Optimal Portfolios (OP)
Utilities	100	397.5	233.4
Cost	100	-	31.3
Admin Assignment	0.16	-	0.09
Vacancies	0.52	0.11	0.47

Notes: Under CP, the planner learns of individual preferences, and assign under them to school using realized test scores as priorities. Under OP, individuals submit optimal ROLs, which are used as input in the matching. Benchmark is normalized to 100.

We show that the constrained planner achieves approximately 4 times more welfare than our benchmark. The gap between the frictional application and the allocation achieved under the constrained planner highlights the importance of inefficiencies. Interesting, we find that eliminating search frictions would multiply welfare by 2.3.[24] As a consequence, we can conclude that 58.7% of the welfare loss can be imputed to the existence of frictions, while the remaining 41.3% are due to uncertainty (test score and coordination frictions).

6 Choice Paradigm and Welfare

School choice is based on the premise that students (or parents) are better positioned to know which school to attend. The standard paradigm in choice theory, *the more options the better*, reinforces the notion that expanding the horizon of choices beyond an assigned neighborhood improves the allocation.

However, when school decisions are made without the full examination of all available options, students may be worst off. Furthermore, as the number of

[24]Which still implies that students are still able to construct optimal portfolios.

choices increases, it becomes almost impossible for decision makers to know all choices. In this section, we analyze whether, restricting choice could be welfare improving.

In the first experiment, we let the planner assign students under the assumption that individuals value only school quality. The second experiment considers also preferences for programs. That is, we let the planner assign a student to a less selective program, if the program is more popular and the difference in cutoffs between the two choices is less than 20 points.[25] The intuition for doing so is that many high achieving girls apply to home economics programs. Using programs in the assignment allows us to assign less high achieving boys to those programs, without taking any stance on the "value of home economics". We measure the popularity of programs using an over-supply index among first ranked choices. Results are described in Table 13

Table 13: Restricting Choices and Welfare

	Benchmark	Quality	Quality + Program
Utilities	100	172.2	213.4
Vacancies	0.52	0.29	0.27

Notes: Under quality, the planner reduces individual utility to school quality alone, and assigns the best student to the most selective school. Under quality + program, the planner still assigns the best student to the most option, but is allowed to make a trade-off between school quality and program popularity.

We find that a planner who is only interested in assigning the best student to the most selective schools increases welfare by 72%. The fact that we produce such a level of welfare gain after reducing the utility function to a single component is yet another sign for the level of inefficiency in our setting. In addition, restricting choices is likely to help lower ability students since they are the group that are the most affected by inefficiencies. Yet, we are still very for the efficient allocation. We

[25]This represents a very rough approximation of the importance of programs in individual utility.

also find that welfare more than doubles when the planner allows for substitution between school quality and programs.

7 Discussion and conclusions

In this paper, we propose a model to understand and estimate individual preferences for schools in a large matching market. Our framework allows us to understand how mismatch between students and schools emerges in a centralized allocation system.

Our application in Ghana shows that indeed search cost are high, which implies a great deal of inefficiency. An analysis of welfare shows that students achieve approximately a quarter of the efficient allocation. Further computation shows that 58.7% of the welfare loss can be attributed to the inability of students to gather information about all alternatives, while the remaining 41.3% is due to uncertainty (test score and coordination frictions). Finally, we show that a policy that would restrict choice in that setting would be welfare increasing – a planner who is only interested in assigning the best student to the most selective school increases welfare by 72%.

Obviously, many of our findings are driven by the small consideration set. In order to see the real impact of consideration sets, we have estimated various models where we imposed a fixed size consideration set. Under a consideration set of thirty (30) choices, we find that restricting choice increases welfare by 69% to be compared to 65% when we impose a consideration set of fifty (50) schools. Interestingly when consideration sets increase, we are unable to generate reverting. Finally, we find that eliminating welfare gains associated with restricting choices, requires consideration sets to be as large as six hundreds (600) choices.

The second key assumption is related to random search in large matching markets, which results in limited gain from search. Unfortunately, the technology of directed search can not be identified given our data. We estimate an alternative model, where for each individual, we group schools into 3 categories: reach, match and safety schools following Avery et al. (2014). Then, we iteratively let a student choose an optimal type of school, upon which she receives a draw of a specific school/program. Under this model, we find that consideration sets are even smaller and restricting choices leads to 71% welfare gain.[26] Given these estimates, we are confident that our model provides a good characterization of welfare losses in the current setting.

Our findings raise new questions about school choice in large matching markets. Given the number of choices, some students are likely to not be aware of all schooling opportunities. The size of the choice set imposes several challenges on low ability students. The first is related to the lack of social ties that allows to collect easily information about schools. The second is related to the potential existence of liquidity constraints when faced with search cost. Finally, the expected gain from search is relatively small for lower ability students, which decreases their value to search.[27] Restricting choice in large markets can help mitigate some of the inefficiencies, but clearly not all of them. Future works could speak to the optimal size of a matching market.

The methods used in this paper provide several avenues for future research. Although our analysis focuses on key features of the education system in Ghana, the potential behavioural implications can be extended to many countries, as well large school districts in the US. One key extension would be to augment these types of administrative dataset with surveys to get a better understanding of the nature of search. These extensions are left for future work.

[26]Several unattractive normalizations are required in order to estimate the model.

[27]Unfortunately, our data does not allow us to quantify the respective importance of these channels.

References

Abdulkadiroglu, A., Agarwal, N., and Pathak, P. A. (2017). The welfare effects of coordinated assignment: Evidence from the new york city high school match. *American Economic Review*, 107(12):3635–89.

Abdulkadiroglu, A., Che, Y.-K., and Yasuda, Y. (2011). Resolving Conflicting Preferences in School Choice: The Boston Mechanism Reconsidered. *American Economic Review*, 101(1):399–410.

Abdulkadiroglu, A., Che, Y.-K., and Yasuda, Y. (2015). Expanding "Choice" in School Choice. *American Economic Journal: Microeconomics*, 7(1):1–42.

Abdulkadiroglu, A. and Sonmez, T. (2003). School Choice: A Mechanism Design Approach. *American Economic Review*, 93(3):729–747.

Abdulkadiro?lu, A., Pathak, P. A., and Roth, A. E. (2005). The new york city high school match. *American Economic Review*, 95(2):364–367.

Agarwal, N. and Somaini, P. (2018). Demand analysis using strategic reports: An application to a school choice mechanism. *Econometrica*, 86(2):391–444.

Avery, C., Howell, J. S., and Page, L. (2014). A review of the role of counseling, coaching, and mentoring in students? postsecondary outcomes. *College Board Research Brief*.

Azevedo, E. M. and Leshno, J. D. (2016). A Supply and Demand Framework for Two-Sided Matching Markets. *Journal of Political Economy*, 124(5):1235–1268.

Barseghyan, L., Coughlin, M., Molinari, F., and Teitelbaum, J. C. (2019). Heterogeneous Choice Sets and Preferences. Papers 1907.02337, arXiv.org.

Berry, S. and Pakes, A. (2007). The Pure Characteristics Demand Model. *International Economic Review*, 48(4):1193–1225.

Calsamglia, C., Fu, C., and Güell, M. (2018). Structural Estimation of a Model of School Choices: the Boston Mechanism vs. Its Alternatives. NBER Working Papers 24588, National Bureau of Economic Research, Inc.

Caplin, A. and Dean, M. (2011). Search, choice, and revealed preference. *Theoretical Economics*, 6(1).

Dinerstein, M., Einav, L., Levin, J., and Sundaresan, N. (2018). Consumer price search and platform design in internet commerce. *American Economic Review*, 108(7):1820–59.

Duflo, E., Dupas, P., and Kremer, M. (2017). The Impact of Free Secondary Education: Experimental Evidence from Ghana. Working paper, Stanford University.

Fack, G., Grenet, J., and He, Y. (2019). Beyond truth-telling: Preference estimation with centralized school choice and college admissions. *American Economic Review*, 109(4):1486–1529.

Goeree, M. S. (2008). Limited information and advertising in the u.s. personal computer industry. *Econometrica*, 76(5):1017–1074.

Haeringer, G. and Klijn, F. (2009). Constrained School Choice. *Journal of Economic Theory*, 144(5):1921–1947.

Hastings, J. S. and Weinstein, J. M. (2008). Information, School Choice, and Academic Achievement: Evidence from Two Experiments*. *The Quarterly Journal of Economics*, 123(4):1373–1414.

He, Y. (2012). Gaming the Boston School Choice Mechanism in Beijing. TSE Working Papers 12-345, Toulouse School of Economics (TSE).

Honka, E., Hortaçsu, A., and Vitorino, M. A. (2017). Advertising, consumer awareness, and choice: evidence from the u.s. banking industry. *The RAND Journal of Economics*, 48(3):611–646.

Hoxby, C. M. and Turner, S. (2015). What high-achieving low-income students know about college. *American Economic Review*, 105(5):514–17.

Kapor, A., Neilson, C. A., and Zimmerman, S. D. (2018). Heterogeneous beliefs and school choice mechanisms. Working Paper 25096, National Bureau of Economic Research.

Masatlioglu, Y. and Nakajima, D. (2013). Choice by iterative search. *Theoretical Economics*, 8(3).

Morgan, P. and Manning, R. (1985). Optimal search. *Econometrica*, 53(4):923–944.

Morgan, P. B. (1983). Search and optimal sample sizes. *The Review of Economic Studies*, 50(4):659–675.

Pallais, A. (2015). Small differences that matter: Mistakes in applying to college. *Journal of Labor Economics*, 33(2):493–520.

Shorrer, R. I. (2019). Simultaneous search: Beyond independent successes.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3):665–690.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy*, 69(3):213–225.

Walters, C. R. (2018). The demand for effective charter schools. *Journal of Political Economy*, 126(6):2179–2223.