A Dynamic Matching Mechanism for College Admissions: Theory and Experiment

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Market design provides managerial insights into the success and failure of various market institutions in allocating scarce resources. We investigate a dynamic matching mechanism used in real-world college admissions, where students share a common priority ranking. Theoretically, we prove that the efficient and stable matching occurs with an arbitrarily high probability, assuming sufficient revision opportunities and rationality. This predicts that the dynamic mechanism is less stable than the deferred acceptance mechanism and less efficient than the Boston mechanism. We confirm this prediction in a low-complexity lab setting. However, in a high-complexity setting, the dynamic mechanism matches the stability of the deferred acceptance and the efficiency of the Boston mechanism, as both underperform in this setting. This finding indicates that the dynamic mechanism is more resilient to increased complexity. We attribute this resilience to its belief-independent characterization of rationalizable strategies. Beyond college admissions, the dynamic mechanism has potential applications in housing assignments, job allocations, and ascending auctions.

Key words: dynamic matching, college admissions, school choice, deferred acceptance, Boston mechanism

1. Introduction

Market design has provided many managerial insights into why certain market institutions fail, and has proposed alternative mechanisms to solve known problems. For instance, soft ending rules have been proposed to solve the sniping problem in online auctions (Roth and Ockenfels 2002, Ariely et al. 2005, Ockenfels and Roth 2006); frequent batch auctions have been proposed to solve the high-frequency trading arms race in financial markets (Budish et al. 2015); team contests have been proposed to solve the low productivity problem in the ride-sharing economy (Ai et al. 2019). Matching theories have guided the allocation of scarce resources in many real-world markets, including labor market clearinghouses (Roth 1984, Roth and Peranson 1999, Echenique et al. 2016), organ allocations (Roth et al. 2004, 2005), public school assignments (Abdulkadiroğlu and Sönmez 2003, Braun et al. 2010, Abdulkadiroğlu et al. 2011, Kojima and Ünver 2014), college admissions (Balinski and Sönmez 1999, Kübler 2019, Chen and Kesten 2017), and ride-sharing platforms (Liu et al. 2019). In this paper, we examine a dynamic matching mechanism that has emerged in the field of Chinese college admissions.

In the past years, researchers have advocated for Strategy-proof mechanisms, such as the Deferred Acceptance (DA) and the Top Trading Cycles (TTC). They are theoretically appealing (Gale and Shapley 1962, Dubins and Freedman 1981, Roth 1982, Abdulkadiroğlu and Sönmez 2003). However, their complexity makes the dominant strategy (i.e., truth-telling) less obvious (Li 2017). As a result, the realized stability of DA and the realized efficiency of TTC fall well short of full stability and efficiency. Empirical and experimental studies frequently show that DA and TTC underperform their theoretical predictions (Chen and Sönmez 2006, Pais and Pintér 2008, Calsamiglia et al. 2010, Klijn et al. 2013, Chen and Kesten 2019, Hassidim et al. 2016, 2017, Rees-Jones and Skowronek 2018, Rees-Jones 2018, Shorrer and Sóvágó 2023).

In comparison, non-strategy-proof mechanisms, such as the Boston mechanism require participants to know others' preferences to best respond. With a large number of participants, the related information acquisition cost could be substantial. As a result, students often rely on luck to get into their desired schools. While having information on others' preferences might lead to welfare gains (Chen and He 2021), obtaining and providing this information could be a difficult proposition.

In recent years, technological advancements have enabled solutions to issues related to mechanism complexity and costly information acquisition. As a result, a number of modified mechanisms have emerged from the field. For example, the Wake County, North Carolina school district currently uses a dynamic truncated Boston mechanism, where students see the number of first-choice applicants for a given school and are allowed to revise their choices within two weeks (Dur et al. 2018). Similarly, the college admissions system in Brazil allows students to know each university's cutoff score and subsequently revise their school choices across four consecutive days (Bó and Hakimov 2022). A college admissions procedure in Germany (DoSV) allows students to revise their choices in the decentralized matching phrase before transitioning to a centralized phrase (Kübler 2019, Grenet et al. 2022). The French college admissions procedure, prior to 2017, used three rounds of college proposing DA where students can refine their choices in later rounds (Frys and Staat 2016, Haeringer and Iehlé 2021).

In this paper, we focus on a new dynamic mechanism implemented in college admissions in Inner Mongolia (IM), China. We refer to this mechanism as the IM Dynamic mechanism for the rest of the paper. Under this mechanism, a student submits one college choice at a time and is free to change her choice at any point before the pre-announced end time. In real-time, the system displays the remaining quota, the number of applicants, and the applicants' standardized test scores (i.e., priorities) for each college. At the end time, each college accepts students up to its quota and rejects the rest. In this paper, we first formally model the IM Dynamic mechanism. We then compare it with two well-studied mechanisms: the DA and Boston mechanisms. We use DA as the high benchmark because it is the theoretically optimal mechanism in the Chinese college admissions problem. We use Boston as the low benchmark because a truncated version of the mechanism was used in Inner Mongolia prior to its 2011 switch to the IM Dynamic mechanism.

In Chinese college admissions, students have the same priorities across different colleges. In this setting, a stable and efficient outcome can be reached by performing the Serial Dictatorship mechanism (SD) or DA over students' true preferences. Theoretically, we show that the IM Dynamic mechanism is nearly as good as DA, in that a stable and efficient outcome can be obtained almost certainly under every rationalizable strategy profile. However, unlike DA, the IM Dynamic mechanism does not have a dominant strategy. Compared to the Boston mechanism, which is efficient but not stable, the IM Dynamic mechanism has theoretical advantages in stability.

To test our theoretical predictions, we conducted a lab experiment. Lab experiments are essential to understand how people respond to the incentives provided by each mechanism, as preferences are generally unknown in the field. Our interest lies not only in the comparative performance of the three mechanisms in a specific environment but also in their resilience when confronted with more challenging environments.

We vary the strategic complexity by varying the correlations of students' preferences. As the preference correlation decreases, the challenges of determining the best response escalate disproportionately among the three mechanisms. The set of rationalizable strategies, which equals the set of Bayesian Nash equilibrium strategies, shrinks substantially under DA and Boston, leading to greater difficulty for players to reach an equilibrium. In contrast, the characterization of rationalizable strategies remains unchanged under the IM Dynamic, with the most intuitive strategy – myopic best response – being one of them.

Our experimental results validate that IM Dynamic is more robust. We observe no difference in IM Dynamic's performance, while DA and Boston's performance deteriorates as the preference correlation decreases. Specifically, in the high correlation environment (associated with low strategic complexity), IM Dynamic is less stable and less efficient than DA, while being more stable but less efficient than Boston. These findings align with our theoretical comparisons of the three mechanisms. By contrast, in the low correlation environment (associated with high strategic complexity), IM Dynamic is as stable as DA and as efficient as Boston due to the worsened performance of DA and Boston.

Our work has broad policy implications. Many real-world matching markets are strategically complex due to incomplete information, diverse preferences, and a vast number of participants. The complexity makes participants hard to best respond even under strategy-proof mechanisms. Our findings suggest IM Dynamic as an attractive alternative to DA, especially when DA is optimal but not feasible. Besides its application in college admissions, the IM Dynamic can be used in job or service assignments where one side has a single priority ranking, determined either by arrival time or a random lottery. The IM Dynamic also resembles ascending auctions, with schools acting as auctioneers and students as bidders. However, unlike typical ascending auctions, the IM Dynamic allows adjusting previous bids. This feature could be beneficial in auctions where defaulting on the winning bid is a concern.

Our paper is organized as follows. Section 2 provides background information about the Chinese college admissions process and the Inner Mongolia Dynamic mechanism. Section 3 presents our literature review. Section 4 offers our formal definitions and proves the basic theoretical properties under the IM Dynamic mechanism. Section 5 presents our experimental design. Section 6 reports the experimental results. Section 7 concludes.

2. Chinese College Admissions System and Inner Mongolia Dynamic Mechanism

In China, roughly 10 million high school seniors compete for 7 million college seats each year. The college admissions process is centralized at the province level, with each university determining a quota for each province. Each province hosts its own college entrance exam, where scores determine student priorities. Using students' reported preferences and their entrance exam scores, each province then matches students to colleges via its own centralized matching mechanism. The matching mechanisms used in China fall into three classes: sequential, parallel, and dynamic (Chen and Kesten 2017). By the year 2016, 28 out of 31 provinces had adopted some version of a parallel mechanism. Among the remaining three provinces, Qinghai and Jilin use a hybrid of parallel and sequential mechanisms, while Inner Mongolia has adopted the IM Dynamic mechanism[1].

According to Rongfei Han, Director of the Center for College Admissions in Inner Mongolia: "Our mechanism makes it easy to figure out which college to apply to based on students' scores. There is no ambiguity regarding the mapping from scores to colleges. The application and admission processes are completely transparent. Students know which college they have been admitted to by the time the system closes. Fairness is assured under this mechanism. In comparison to 2007 [when the truncated Boston mechanism was used][2], the implementation of the IM Dynamic mechanism in 2011 led to significant improvement. The percentage of students repeating their final year of high school and retaking the college entrance exam dropped from 23.4% to 7%. Additionally, the percentage of students accepting their matches increased from 91% to 99.03%."[3]

[1] Table 19 in Appendix E

[2] From the year 2008 to 2010, Inner Mongolia experimented with the IM Dynamic mechanism in its early admissions processes, which are used only for art and military colleges. The year 2007 was the last year that the truncated Boston mechanism was used in all admissions. The year 2011 was the first year that the IM Dynamic mechanism was used in all admissions.

[3] Inner Mongolia Daily, June 20th, 2013

China is not the only country where student priority in college admissions is determined by a centralized standard test. University assignments in Turkey use a similar scheme, though scores in various subjects are weighted differently for different anticipated majors (Balinski and Sönmez 1999). Hungary (Biró 2011) and South Korea (Avery et al. 2019) each use a hybrid system that considers standard test scores along with high school grades.

3. Literature Review

One of the most widely used and well-studied mechanisms is the Boston mechanism, also known as the Immediate Acceptance Mechanism. In the Boston mechanism, each student submits a ranking of all schools based on her preferences. Each school first considers students who list it as their first choice, admits these students up to its quota, and rejects the rest. If there are still slots left after this process, the school considers students who list it as their second choice if other schools have not yet admitted them, and so on. Note that the admission decision is final in each round. While the Boston mechanism is Pareto efficient if all students submit their true preferences, it has long been criticized because it is not strategy-proof. That is, students might have an incentive to misreport their preferences because they may lose their priorities if they do not rank a school highly enough. Because of the misreporting of preferences, the realized efficiency under the Boston mechanism may be low. In addition, the Boston mechanism is not stable, which leads to justified envy, and thus is considered unfair.

Given the limitations of the Boston mechanism, strategy-proof mechanisms such as DA have been advocated by scholars as alternatives (Abdulkadiroğlu and Sönmez 2003)[4]. DA, also called the Gale-Shapley mechanism, was initially employed in 1952 by the US National Intern Matching Plan to match medical school graduates with hospitals. Unaware of its real-world application, Gale and Shapley (1962) independently introduced this mechanism and demonstrated its key characteristics (Roth 1984). Unlike the Boston mechanism, allocations under DA are temporary: in each round, schools consider new applicants together with all the applicants kept from the previous rounds and reject those students with low priorities. The allocation is finalized in the round when no student is rejected. DA is both strategy-proof and stable (Gale and Shapley 1962, Dubins and Freedman 1981, Roth 1982). Although DA is generally not Pareto efficient when both sides have heterogeneous preferences, it is efficient when the priority structure is acyclical, as defined in Ergin (2002). In the context of Chinese college admissions, where colleges have an identical preference over students, DA is both stable and efficient (Balinski and Sönmez 1999, Ergin 2002).

[4] DA is only strategy-proof when only one side of the market can manipulate their preferences. In the case of college admissions, only students can be strategic. Throughout the remainder of the paper, we will use the terms "DA" and "student-proposing DA" synonymously.

A large body of research has compared the Boston and DA mechanisms theoretically, empirically, and experimentally. For example, Ergin and Sönmez (2006) prove that, with complete information, the set of Nash equilibrium outcomes of a game under the Boston mechanism equals the set of stable matchings. DA, on the other hand, yields the optimal outcome among all stable matchings, and therefore its outcome Pareto dominates Boston's Nash equilibrium outcome. In another study, Abdulkadiroğlu et al. (2006) examine data before and after a change from Boston to DA and find that unsophisticated players are exploited by sophisticated players under the Boston mechanism. Experimental studies confirm that DA is more stable and less manipulable than the Boston mechanism, and that the difference in efficiency is environment-dependent (Chen and Sönmez 2006, Pais and Pintér 2008, Calsamiglia et al. 2010, Klijn et al. 2013, Chen et al. 2018, Chen and Kesten 2019). By contrast, under incomplete information, Abdulkadiroğlu et al. (2011) find that when students have the same ordinal preference, each student is weakly better off under the Boston mechanism when symmetric tie-breaking is applied. Featherstone and Niederle (2016) further prove that in specific environments, truth-telling can be the equilibrium strategy under the Boston mechanism, and ex-ante, every student may strictly prefer the Boston mechanism to DA.

In real life, both Boston and DA can become unwieldy when there are too many schools to rank. In China, where there are more than 2,000 colleges, it is thus common to use a truncated version (also called the Parallel and Sequential mechanisms in Chen and Kesten (2017)), where the entire choice list is divided into choice bands, and students can only submit a limited number of choices for each band.

While this truncation makes the process easier to manage, it can affect both the stability and efficiency of the final allocation (Calsamiglia et al. 2010). Indeed, Pathak and Sönmez (2013) find that, in a truncated DA, the mechanism becomes more manipulable as the number of permitted choices decreases. Chen and Kesten (2017) further analyze the whole family of parallel mechanisms and prove that DA is more stable and less manipulable than any other version of the parallel mechanism. The truncation also makes it hard for students to best respond, as Rees-Jones et al. (2020) show that when preferences are truncated, students tend to ignore the correlation of being admitted to different schools and adopt a suboptimal aggressive application strategy.

Recently, the matching literature has investigated several different dynamic mechanisms, including the sequential DA mechanism (Echenique et al. 2016), the dynamic DA mechanism (Klijn et al. 2019), the iterative DA mechanism (Bó and Hakimov 2020), the continuous feedback mechanism (Stephenson 2016), a German college admissions procedure (DoSV) (Grenet et al. 2022), and a French college admissions procedure (APB) (Haeringer and Iehlé 2021). In the sequential DA mechanism, unmatched participants make simultaneous applications and are informed of temporary allocation results in each round. This mechanism is theoretically equivalent to the static

DA under some behavioral restrictions (Echenique et al. 2016). The dynamic DA mechanism of Klijn et al. (2019) is equivalent to the iterative DA (IDAM-NC) in Bó and Hakimov (2020), where students are informed of their temporary allocation results and rejected students can change their applications. In another variation of the iterative DA, students are informed of the tentative cutoff scores for acceptance at each school (IDAM) (Bó and Hakimov 2020, 2022). Though similar to our mechanism, the iterative DA (IDAM) allows only unmatched students to make new applications, whereas IM Dynamic allows tentatively matched students to make new applications as well. The IM Dynamic mechanism also differs from Stephenson (2016)'s continuous feedback mechanism in that the continuous feedback mechanism requires students to submit a complete preference list all the time. The DoSV mechanism first has a decentralized round where students can hold multiple offers and revise their preference lists, then has a centralized round where DA is implemented to clear the market (Grenet et al. 2022). The APB mechanism has three rounds of college-proposing DA and students can revise their preference lists in later rounds. In both mechanisms, students can choose between finalizing their options or moving to the next round (Haeringer and Iehlé 2021). If students choose to participate in the next round, they will not be worse off, because both mechanisms are gradually safe (Haeringer and Iehlé 2021). The IM Dynamic mechanism, on the other hand, is not gradually safe and students cannot exit the market early. Overall, the IM Dynamic mechanism stands apart from other dynamic mechanisms, due to its unique unrestricted revisions and predetermined end time. For a survey of experiments on various dynamic mechanisms, the reader is referred to Section 3.10 of Hakimov and Kübler (2021).

4. Theoretical Analysis

In this section, we formally define each of the three mechanisms before focusing on the theoretical properties of the IM Dynamic mechanism and stating our two main theorems.

4.1. Definitions and Assumptions

Before defining our mechanisms, we outline the college admissions problem. Specifically, the college admissions problem (Balinski and Sönmez 1999) can be represented as a list (I, C, q, P_I, P_C), consisting of the following: (1) a set of students $I = \{1, 2, \cdots, n\}$; (2) a set of colleges $C = \{1, 2, \cdots, m\} \bigcup \{\emptyset\}$, where $\emptyset$ denotes a student's outside option; (3) a capacity vector $q = (q_1, q_2, \cdots, q_m)$ where q_k is the capacity of college k; (4) a list of student preferences $P^I = (P^I_1, P^I_2, \cdots, P^I_n)$ where P^I_i is student i's strict preference over colleges including the no-college option; and (5) a list of student priorities $P^C = (P^C_1, P^C_2, \cdots, P^C_m)$ where P^C_k is the strict priority of a set of students for college k.

As in the Chinese college admissions, we assume that student priorities P^C_k are determined by student scores on the centralized college entrance exam, and that a student has the same priority across different colleges; therefore, $P_k^C = P_l^C$, $\forall k,l \in C$. Since student priorities are public information, they cannot be manipulated. We assume that student preferences $P^I = (P_1^I, P_2^I, \cdots, P_n^I)$ are private information, and that students have cardinal preferences over colleges. The utility of student i getting into college k is u_i^k. We consider only the welfare of students. College seats are considered as public resources to be allocated.

A matching μ is a many-to-one mapping from I to C, $\mu : I \to C$, such that $|\mu^{-1}(k)| \leq q_k, \forall k$, where $\mu^{-1}(k)$ is the set of students admitted to college k.

- A matching contains *justified envy* if there exist two students i and j, where i prefers j's assignment to her current assignment, and i has higher priority than j in j's assigned college.
- A matching is *wasteful* if there exists a student who prefers a college with an unfilled quota to her current assignment.
- A matching μ is *stable* if there does not exist any justified envy and it is not wasteful[5].
- A matching is *Pareto efficient* if there is no other matching which makes all students at least as well off and at least one student better off. We use "efficient" and "Pareto efficient" interchangeably in this paper.
- In the normal form game created by a *static* mechanism, students submit their preferences only once, and the mechanism selects a matching for each reported preference profile.
- A *static* mechanism is *strategy-proof* if truth-telling is a weakly dominant strategy.
- A *static* mechanism is Pareto efficient (stable) if the selected matching is always Pareto efficient (stable) with respect to a reported preference profile.
- In the extensive form game created by a *dynamic* mechanism. A student observes information and takes an action at each information set. The mechanism selects a matching as a function of the accumulated actions from each student.
- A *dynamic* mechanism is *strategy-proof* if myopic best response is a weakly dominant strategy.
- A *dynamic* mechanism is Pareto efficient (stable) relative to the true preference profile if the selected matching is always Pareto efficient (stable) when all players play the myopic best responding strategy.

Throughout the theoretical analysis, we assume common knowledge of rationality and that students are expected utility maximizers. We introduce some basic game theory concepts rephrased from Osborne and Rubinstein (1994) and Miller (2015), without introducing additional symbols. Note that we do not assume common knowledge of independence, meaning players' strategies can

[5] We do not need individual rationality because outside options are considered as a "college" with unlimited quota. Therefore non-wastefulness covers individual rationality. In our experimental setting, no student prefers not going to college.

be correlated (Brandenburger and Dekel 1987). Under common knowledge of independence, rationalizable strategy profiles do not equal the set of strategy profiles that survives iterated deletion of dominated strategies (Bernheim 1984, Pearce 1984).

- A strategy is strictly *dominated* if there exists another strategy such that the player is strictly better off by playing the latter strategy under any opponent strategy profiles.
- A player is *rational* if she never plays strictly dominated strategies.
- *Commom knowledge of rationality* assumes:
  — every player is rational,
  — every player knows that every player is rational,
  — every player knows that every player knows that every player is rational,
  — and so on *ad infinitum*.
- A strategy profile is *rationalizable* if, for every player, there exists a belief over opponents' strategies, such that she best responds to this belief using her strategy in this profile.
- A strategy is *rationalizable* if it belongs to a rationalizable strategy profile.
- The following are equivalent:
  — S is the set of rationalizable strategy profiles,
  — S is the set of strategy profiles that survives iterated deletion of strictly dominated strategies,
  — S is the set of strategy profiles consistent with common knowledge of rationality.

4.1.1. Boston Mechanism The Boston mechanism, formally introduced by Abdulkadiroğlu and Sönmez (2003), has been used in the US to allocate students to public schools in Boston, Cambridge, Charlotte, Denver, Minnesota, Seattle, and St. Petersburg-Tampa (Ergin and Sönmez 2006). The Boston mechanism is implemented using the following algorithm for a given problem:

- Step 1: Each college considers students who have listed it as their first choice and assigns seats to these students based on their priority orders until either there are no seats left or there are no students remaining who have listed it as their first choice. Students whose priorities are lower than the college's quota are rejected.
- Step k ($k > 1$): For the students who have been rejected after step $k-1$, only their kth choices are considered. Each college with available seats considers those students who have listed it as their kth choice and assigns the remaining seats to these students following their priority orders.
- The allocation is finalized when either there are no seats left or there are no students left who have listed a school as their kth choice.

Under complete information and heterogeneous student priorities across colleges, the Boston mechanism is efficient if everyone plays the truth-telling strategy. However, since it is not strategy-proof, it may lead to inefficient allocations. In addition, it is not stable.

Under incomplete information, full support of beliefs, and homogeneous student priorities, according to Featherstone and Niederle (2016)'s Proposition B.1., truth-telling is an ordinal Bayesian Nash equilibrium (Ehlers and Massó 2007) under the Boston mechanism. Furthermore, it is the unique Bayesian Nash equilibrium in anonymous strategies. If players play the truth-telling strategy, the allocation is always efficient ex-post. However, depending on the realization of preferences, the allocation may not be stable.

4.1.2. Deferred-Acceptance Mechanism The DA mechanism was introduced by Gale and Shapley in 1962. DA is implemented using the following algorithm for a given problem:

- Step 1: Students' applications are sent to their first-choice colleges. Colleges temporarily keep students based on students' priorities up to their enrollment capacities and reject the rest.
- Step k ($k > 1$): Each rejected student's application is sent to the next college on her reported preference list. Each college considers both students who have been temporarily kept and new applicants. It then temporarily keeps students based on their priorities, up to its enrollment capacity and rejects the rest.
- The allocation is finalized when no one gets rejected. Each student is assigned to the college in which they temporarily hold a seat.

Under heterogeneous student priorities across colleges, the DA mechanism is strategy-proof and stable, but it is not efficient.

Under homogeneous student priorities across colleges, the DA mechanism is stable, efficient, and strategy-proof. Additionally, assuming full support of beliefs over other students' preferences, rationalizable strategies under DA can be characterized as truthfully reporting to the point where the sum of reported colleges' quotas exceeds one's priority ranking. These strategies strictly dominate other strategies.

4.1.3. IM Dynamic Mechanism in Real Life The IM Dynamic mechanism was introduced by the Inner Mongolia Center of College Admissions in 2008. To our knowledge, Inner Mongolia is the only place where this mechanism is used. The IM Dynamic mechanism is implemented using the following descriptive algorithm:

- Students are divided into N groups based on a sequence of cutoff scores $s_1, s_2, \cdots, s_{N-1}$, where $s_i < s_{i-1}$, for $i = 2, \cdots, N-1$. Students with exam scores higher than s_1 comprise the first group. Students with scores between s_{i-1} and s_i comprise the ith group. Students with scores below s_{N-1} comprise the Nth group.
- All students, regardless of their group, can enter the online admission system at the same time to submit their college choices. Students can submit only one choice at a time, but they can change their choices as many times as they want within their allocated time period.

• In the online system, students can see each college's quota, the number of students applying to that college, and those students' scores, all in real-time.

• Each group i has an ending time T_i, where $T_{i-1} < T_i$, for $i = 2, \cdots, N-1$. At time T_i, the system closes for the ith group.

• For each group, by the time the system closes, each college k admits up to q_k students who are currently applying to college k. If more students are applying to college k than its quota q_k, the college admits the q_k students with the highest priorities and rejects the rest.

4.1.4. A Model of the IM Dynamic Mechanism In this subsection, we model the IM Dynamic mechanism when all students belong to one group. The grouping of students is not essential to the mechanism and does not change our theoretical results. We discuss the effect of grouping after Theorem 2.

We model the timing of the IM Dynamic mechanism as a Poisson process with parameter λ. Each student i has her Poisson recognition process R_i, which is independent of others' processes. At each arrival, the student is recognized to have a chance to revise. We use z to represent the number of arrivals, and $R_i(z)$ to represent the corresponding time of that arrival.

We choose to model the timing of this game using a Poisson process for several reasons. First, the Poisson process restricts students to act at a countable number of instances, making their history of actions tractable. Second, compared with deterministic arrivals, stochastic arrivals can capture uncertainty in real life. For example, students may not be able to update their choices when they would like, due to reasons such as network connection failures or network congestion; therefore, their total number of revision opportunities is non-deterministic. Furthermore, the Poisson process guarantees that the probability that any two students are recognized at the same instant is zero. The Poisson process is commonly used in modeling asynchronous revision games (Kamada and Kandori 2011).

We now formally define the game created by the IM Dynamic mechanism.

• At time 0: Each student i knows her own preference over colleges P_i^I, each college's quota q_k and its preference over students P_k^C, $\forall k \in C$, as well as the ending time T.

• When student i is recognized for the zth time by the Poisson process R_i, she faces a decision point at which:

—Student i observes every other student's most recent choice.

—Student i makes a choice c_i^z

If $z = 1$, meaning this arrival is student i's first arrival, student i can choose to apply to any college or not apply (empty choice), $c_i^z \in C \cup \{\emptyset\}$.

If $z > 1$, meaning student i previously had an arrival, student i can choose not to make a revision, in which case $c_i^z = c_i^{z-1}$, or she can switch to a different college $c_i^z \neq c_i^{z-1}$, where $c_i^z \in C$.

- At time T: The system closes. If a student is ranked within the quota of her applied college, she is admitted to that college. Otherwise, she is rejected.

One important note is that even though student arrivals in this game are exogenous, their revision decisions are endogenous. At each arrival, a student can always choose between acting or not. Arrivals merely provide students with chances to act. When the arrivals are frequent enough, students are able to act nearly whenever they want.

We define student i's *best college available* $\widehat{c}_i^z$ at arrival z as the highest-ranked college on student i's preference list with seats not occupied by students ranked ahead of student i. In other words, student i's *best college available* is her favorite college among all colleges in which she can temporarily have a seat at the decision point $R_i(z)$. We now define the myopic best responding strategy under the IM Dynamic mechanism.

- A player plays the *myopic best responding strategy* if $c_i^z = \widehat{c}_i^z$ for all z.

The myopic best responding strategy is commonly regarded as the truth-telling strategy in dynamic games, however, the defined myopic best responding strategy cannot be tested in our experiment due to our continuous time setting, where arrivals are unobservable. To measure players' truthfulness in the experiment, we separately introduce the truth-telling strategy. We consider a player to be *truthful* if she chooses the best college available whenever she revises. While the myopic best response requires best responding at each arrival, the truth-telling only requires best responding when players decide to revise. The defined truth-telling is experimentally testable, but it has no theoretical implications.

- A player plays the *truth-telling strategy* if there does not exist an arrival z, such that $c_i^z \neq c_i^{z-1}$, and $c_i^z \neq \widehat{c}_i^z$.

4.2. Theoretical Analysis of the IM Dynamic Mechanism

In this section, we first state our main theorems under the assumption that all students belong to one group. We then generalize the results to accommodate students divided into subgroups.

To analyze the performance of the IM Dynamic mechanism, we define player i as the player with the ith highest ranking. That is, player 1 has the highest ranking, player 2 has the second highest ranking, and so on. When students' priorities are the same across different colleges, there is a unique stable and efficient matching (Balinski and Sönmez 1999, Ergin 2002). This stable and efficient matching can be achieved by performing either DA or serial dictatorship over students' true preferences.

Given that students have sufficient revision opportunities, we find that the stable and efficient matching can be achieved almost always under the IM Dynamic mechanism. This leads us to Theorem 1.

Theorem 1. *When the Poisson parameter λ is large enough, the stable and efficient matching arises with an arbitrarily high probability under any rationalizable strategy profile.*

The proof is presented in Appendix A.1.

While the DA and IM Dynamic mechanisms yield similar outcomes in every rationalizable strategy profile, there are three differences. First, every rationalizable strategy under the IM Dynamic mechanism involves choosing the best college available once enough time has elapsed, regardless of the belief on other players' preferences. By contrast, the rationalizable strategy under DA is belief-dependent. Only when we assume the belief on others' preferences has full support, can the rationalizable strategy be characterized as: truthfully reporting to the point where the sum of reported colleges' quotas exceeds one's ranking. Second, under DA, if every player is rational, the stable and efficient outcome is a certainty; by contrast, under the IM Dynamic mechanism, there always exists a slight possibility that the allocation will not be stable and efficient. Third, strategies can be history-dependent under the IM Dynamic mechanism. This dependence makes it impossible for every player to have a weakly dominant strategy in the IM Dynamic mechanism. This is stated formally in Theorem 2.

Theorem 2. *Any player whose priority ranking exceeds the capacity of their top-choice college does not have a weakly dominant strategy.*

The proof is presented in Appendix A.2.

We now discuss the implications of dividing students into groups and assigning earlier ending times to higher score groups, as described in Section 4.1.3. When arrivals are frequent enough, dividing students into N groups and assigning earlier ending times to higher score groups is equivalent to having N sequential markets where students participate in only their corresponding market. The first market consists of students whose scores are higher than s_1 and comprises a set of all college seats. The second market consists of students whose scores are higher than s_2 but lower than s_1 and comprises the set of college seats remaining after the allocation process in the first market. The ith market consists of students whose scores are higher than s_i but lower than s_{i-1} and comprises the set of college seats remaining after the allocation process in the previous $i-1$ markets. Note that Theorems 1 still holds in each sequential market. When the outcome in each sequential market is stable and efficient, the outcome in the pooled market is also stable and efficient as later students do not have justified envy of earlier students. The benefit of dividing students into different score groups is that each market contains fewer students. Therefore, the stable and efficient outcome is more likely to arise under the same arrival frequency.

Based on Theorem 1, we expect IM Dynamic to fall between DA and Boston in terms of stability. Boston is expected to be the least stable because its Bayesian Nash equilibrium outcomes may not be ex-post stable, depending on preference realizations. Theorem 1 also predicts IM Dynamic to be less efficient than DA and Boston, because both DA and Boston have full efficiency in our context. Lastly, due to the lack of a dominant strategy (Theorem 2), IM Dynamic's truth-telling rate will be lower than DA. Our theory framework does not provide a ranking between IM Dynamic and Boston, as neither has a dominant strategy.

Our theoretical predictions are based on assumptions that may not hold in the field. For example, while we assume common knowledge of rationality, it is well documented that humans have bounded rationality (Simon 1972). In the next section, we test our theoretical predictions in a controlled lab setting, as direct testing in the field would be infeasible.

5. Experimental Design

We start with a simple setting, which captures the essential strategic components of the Chinese college admissions process. In Chinese college admissions, students know their test scores and rankings, but not others' preferences. To represent this environment, we use an incomplete information setting with correlated preferences. In each group, there are four colleges $\{A, B, C, D\}$, each of which has one seat. Correspondingly, there are four students $\{1, 2, 3, 4\}$. Students' preferences are of two different types. Each group consists of two Type I students and two Type II students. While individual preferences are private information, the composition of the group is common knowledge. Similar to reality, students also know how their score ranks among the scores of other students in the same group.

We deliberately select two environments with different levels of preference correlations, so that the difficulty of reaching a Bayesian Nash equilibrium (BNE) is different. We measure the difficulty of reaching a Bayesian Nash equilibrium in two ways. First, we measure how easily players can reach BNE by playing a random strategy. The larger the set of BNE strategy profiles, the easier it is to reach a BNE by chance. Second, we measure how many colleges a player needs to rank in order to best respond if players are not required to rank all colleges. The more colleges that players need to rank, the greater the cognitive demand for players to best respond. Consider the most extreme case, where student preferences are identical (i.e., $A \succ B \succ C \succ D$). Under all three mechanisms, when assuming rationality, students can best respond by reporting only one college. The first-ranked student chooses college A as her first choice; the second-ranked student chooses college B as her first choice; the third-ranked student chooses college C as her first choice, and the fourth-ranked student chooses college D as her first choice. In this setting, the three mechanisms are likely to perform the same, but this performance does not reflect the fundamental properties of the said mechanisms. We next consider an environment with a lower preference correlation, where two students have the preference $A \succ B \succ C \succ D$, and two students have the preference $A \succ C \succ B \succ D$. Under DA, the top two students can still best respond by reporting one college. However, the third-ranked student needs to rank colleges B and C to best respond, while the fourth-ranked student can best respond by using any strategy. Under Boston, the top two students can also best respond by reporting one college. However, in this case, the third-ranked student needs to rank colleges B, C, and D; while the fourth-ranked student needs to rank colleges C and D. Finally, under IM Dynamic, students can best respond by acting myopically. Therefore, in the latter preference setting, the difficulty of best responding is greatest under Boston, followed by DA, then by IM Dynamic. The above examples show that when we decrease the preference correlation, the complexity to best respond increases disproportionally across the three mechanisms. This difference in complexity is central to our comparison of the mechanisms.

To vary complexity, we include a “high correlation environment” and a “low correlation environment”. In both environments, we fix the first preference type to be $A \succ B \succ C \succ D$, and vary the second preference type. In the high correlation environment, preference Type II is $B \succ A \succ D \succ C$. In the low correlation environment, preference Type II is $B \succ D \succ C \succ A$. The two environments differ in the number of BNE strategy profiles as well as the number of colleges a player must rank in providing her best response. For simplicity, we define the “minimum strategy” as the best response with the fewest required number of college rankings. Column (2) in Table 1 reports the BNE strategies under each mechanism and environment. Note that, any combination of BNE strategies among the four players is a BNE in our game. Therefore, the numbers of BNE strategy profiles equal the numbers shown in Column (4) in Table 1. As we can see, the numbers of BNE strategy profiles under the high correlation environments are much larger than those under the low correlation environments. Column (5) in Table 1 characterizes the minimum strategy. For each player, the number of colleges in the minimum strategy in the low correlation environments is at least as large as the number of colleges under the high correlation environments. Under both measures, the complexity of the low correlation environment is higher than the complexity of the high correlation environment.

The two environments are also directly comparable. The set of BNE strategies under DA and Boston in our low correlation environment is a subset of the respective BNE strategies in our high correlation environment (Column (2) in Table 1). For a detailed proof of BNE strategies under DA and Boston, the reader is referred to Appendix A.3 and A.4.

In terms of BNE outcomes, although there are different Bayesian Nash equilibria, the equilibrium outcome is the same under each mechanism-environment combination. The BNE outcomes under DA are always stable and efficient, regardless of preference realizations. The BNE outcomes under Boston are not stable when the top two students share the same preference. A detailed

Table 1 Comparison of the Two Environments

Ranking (1)	BNE Strategies (2)	Num of Strategies (3)	Num of Profiles (4)	Minimum Strategy (5)
		DA – High Correlation		
1st	$(1,*,*,*)$	6	6912	$(1, *, *, *)$
2nd	$(1/2>3/4)$	4		$(1, 2, *, *)$ or $(2, 1, *, *)$
3rd	$(3>4)$	12		$(3, *, *, *)$
4th	any strategy	24		irrelevant
		DA – Low Correlation		
1st	$(1,*,*,*)$	6	576	$(1, *, *, *)$
2nd	$(1,2,*,*)$	2		$(1, 2, *, *)$
3rd	$(*,*,3,4)$	2		$(1, 2, 3, 4)$ or $(2, 1, 3, 4)$
4th	any strategy	24		irrelevant
		Boston – High Correlation		
1st	$(1,*,*,*)$	6	648	$(1, *, *, *)$
2nd	$(1,3>4)$	3		$(1, 3, *, *)$
3rd	$(1,3>4)$	3		$(1, 3, *, *)$
4th	$(3>4)$	12		$(3, *, *, *)$
		Boston – Low Correlation		
1st	$(1,*,*,*)$	6	24	$(1, *, *, *)$
2nd	$(1,2,3,4)$	1		$(1, 2, 3, *)$
3rd	$(1,2,3,4)$	1		$(1, 2, 3, *)$
4th	$(2>3>4)$	4		$(2, 3, *, *)$

Notes: We represent strategies using numbers and asterisks. Specifically, number a denotes a student's ath most preferred college on her preference list, and asterisks represent arbitrary colleges. For example, strategy $(1,2,*,*)$ means that the player reports her most preferred college first, followed by her second-most preferred college, while her third and fourth choices can be either her third- or fourth-most preferred college.

characterization of the Bayesian Nash equilibrium outcome under each realized preference type is provided in Table 8 in Appendix A.5.

In terms of decision time, subjects can take as much time as needed to submit their rankings under DA and Boston. Under the IM Dynamic mechanism, to mimic the real IM Dynamic mechanism, we divide the four students into two subgroups, with the top two students in the first subgroup, and the bottom two students in the second subgroup. Students in both subgroups enter the decision stage at the same time, but the decision time is 15 seconds for the first subgroup and 30 seconds for the second subgroup.[6]

The experiment lasts for 20 periods. At the start of each period, subjects are randomly assigned to be Type I or Type II and randomly re-matched to form groups of four. Their rankings rotate

[6] In our pilot sessions, we used 30 seconds of decision time for the first subgroup and 60 seconds for the second subgroup. We found that most subjects finished their choices within 20 seconds. Therefore we shortened the decision time to 15 (30) seconds for the first (second) subgroup. We found no significant difference in subject strategies and allocation outcomes between our 60-second and 30-second sessions.

every five periods. The purpose of rotating rankings is to guarantee fairness among subjects and to obtain the same subject's strategies in different ranking positions. We use a between-subjects design among different treatments.

Subjects receive 16 Yuan for getting admitted to their most preferred college, 11 for the second-most preferred college, 7 for the third-most preferred college, and 5 for the least preferred college (Table 2). This incentive scheme ensures a sufficient distinction between the monetary incentives for getting into different colleges.

Table 2 Payoffs Table

High Correlation	A	B	C	D
Payoff of Type I	16	11	7	5
Payoff of Type II	11	16	5	7
Low Correlation	**A**	**B**	**C**	**D**
Payoff of Type I	16	11	7	5
Payoff of Type II	5	16	7	11

5.1. Experimental Procedure

We conducted our experiment at Fudan University in Shanghai from October to December 2015. Subjects were students at Fudan University. After subjects arrived at the lab, we randomly assigned them seats in front of computer terminals. The experimenter first read the instructions aloud at the front of the lab. Then subjects had time to read the instructions at their own pace and ask questions. All questions were repeated and answered publicly. After all questions were addressed, subjects took a quiz consisting of 14 questions. The quiz was designed to help subjects understand the experimental setting and the corresponding mechanism. The first question asked subjects to solve an allocation problem under the corresponding mechanism. After subjects finished these questions, the experimenter solved the first allocation problem step by step on the board. The correct answers and corresponding explanations were also presented on their computer screens. Any other questions about the quiz were answered publicly.

Subjects took part in 20 periods of the college admissions game. One period out of every five periods with the same priority was randomly drawn for payment. At the end of the 20 periods, subjects filled out a demographics survey. Subjects were paid in cash privately at the end of the experiment. The quiz, matching game, and survey were programmed using z-Tree (Fischbacher 2007).

We conducted five independent sessions for each mechanism and environment combination, excluding the IM Dynamic mechanism in the low correlation environment, for which, given an unexpectedly large number of subjects showed up, we conducted one more session. This gave us a total of 31 sessions. With each session consisting of 12 subjects, we had 372 subjects in total. Detailed information on our experimental sessions is presented in Table 3. Each session under DA and Boston lasted approximately 1 hour 40 minutes, whereas each session under IM Dynamic lasted approximately 1 hour and 10 minutes. The average payment, including payment for the quiz, was 46.12 Yuan (about 7.5 US dollars, which was above the average hourly pay at Fudan University). The experimental instructions are included in Appendix D.

Table 3 Number of Subjects in Each Treatment

Environment	DA	IM Dynamic	Boston
High Correlation	5 sessions × 12 subjects	5 sessions × 12 subjects	5 sessions × 12 subjects
Low Correlation	5 sessions × 12 subjects	6 sessions × 12 subjects	5 sessions × 12 subjects

6. Experimental Results

In this section, we first discuss individual level results, such as truth-telling behavior and choice revision time. We then discuss group level results, such as stability and efficiency.

In the following discussion, we use $A > B$ to indicate that a measure under mechanism A is greater than under mechanism B at the 5% significance level, and $A \sim B$ to denote that the measured difference is not significant at the 5% level. We report the exact p-values in corresponding tables in each subsection.

6.1. Individual Behavior

We first compare truth-telling behavior across the three mechanisms among all players, then compare the truth-telling behavior among players for each priority ranking.

6.1.1. Overall Truth-telling Behavior In the DA and Boston mechanisms, the truth-telling strategy is defined as the reported preference list being the same as one's true preference. In the IM Dynamic mechanism, the truth-telling strategy is defined as selecting the best college available when a player revises.

We expect to see a higher level of truth-telling under DA than under either Boston or IM Dynamic, since truth-telling is a dominant strategy under DA.

Hypothesis 1. The proportion of truth-telling is higher under DA mechanism than under either Boston or IM Dynamic mechanism in any environment.

Our results show that the Boston mechanism indeed is more manipulable than DA, regardless of the environment. Unlike the theoretical prediction, the IM Dynamic mechanism performs as well as DA in the high correlation environment; it even performs better than DA in the low correlation environment.

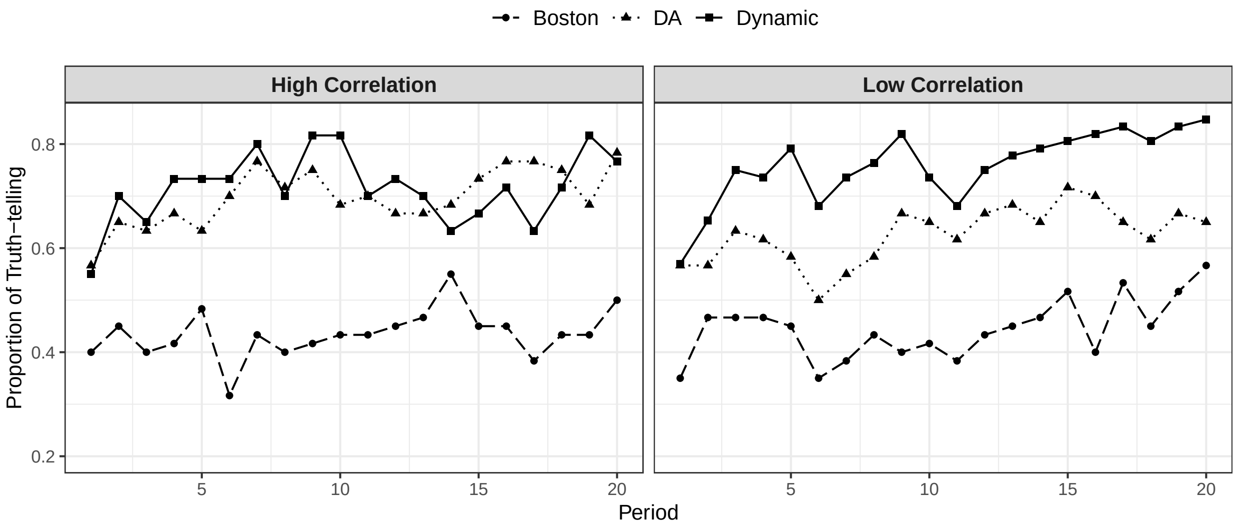

Figure 1 **Truthtelling Comparison**

Table 4 **Proportion of Truth-telling**

Mechanism (1)	Prop (High) (2)	Prop (Low) (3)	Ha (4)	p-value (5)
IM DY	0.716	0.759	High = Low	0.221
DA	0.698	0.627	High = Low	0.119
BOS	0.435	0.445	High = Low	0.786
Ha (6)	p-value (High) (7)	p-value (Low) (8)		
IM DY >DA	0.278	0.011		
DA>BOS	0.004	0.004		
IM DY = BOS	0.008	0.004		

Result 1. (Truth-telling) In the high correlation environment, truth-telling proportions are ranked as follows: IM Dynamic $\sim$ DA $>$ BOS. In the low correlation environment, it changes to IM Dynamic $>$ DA $>$ BOS. Across environments, truth-telling levels show no significant differences under each mechanism.

Support Table 4 presents the proportions of truth-telling for each treatment, along with the p-values derived from permutation tests, with each session treated as an independent observation. The proportions of truth-telling in high and low correlation environments are detailed in Columns (2) and (3), respectively. A comparison of the performance of the same mechanism across different environments is provided in Columns (4) and (5). Columns (6), (7), and (8) offer pair-wise comparisons of the three mechanisms within the same environment. The trend of truth-telling under the three mechanisms in both environments is visually represented in Figure 1.

The results in Table 4 partially support our Hypothesis 1. The predicted truth-telling comparison between DA and Boston is supported in both environments, while the predicted comparison between DA and the IM Dynamic is rejected, given that IM Dynamic performs on par with DA in the low correlation environment and outperforms DA in the high correlation environment.

Our findings of truth-telling proportions under DA and Boston align with previous studies, which report that the proportion of truth-telling is between 40% – 50% under the Boston and between 65% – 75% under DA (Pais and Pintér 2008, Calsamiglia et al. 2010, Chen and Kesten 2019).

Unlike DA and Boston, the IM Dynamic does not require students to submit a complete preference list. Thus, our previous truth-telling comparison might be unfair to DA and Boston. For example, under both DA and the Boston mechanism, students with the highest ranking have a dominant strategy to report their first choice truthfully. In this case, while manipulation of preferences from the second to the fourth choices may exist, it does not impact allocation outcomes. By contrast, we will not observe this type of manipulation under IM Dynamic, simply because the second to fourth choices are not reported. Therefore, using complete truth-telling as our measure under DA and Boston favors the IM Dynamic mechanism. To address this concern, we re-run our analyses using the first choice truth-telling as our measure. Doing so gives us the same results (see Table 9 in Appendix C). We also find similar results when we repeat our analyses using truth-telling up to one's rank for DA (see Table 10 in Appendix C).

6.1.2. Rank Effect in Truth-telling In this subsection, we break down truth-telling behavior by player's ranking. We are more interested to see how low-ranked students are affected differently under the three mechanisms since the highest-ranked students have no incentive to misreport their preferences. We find that going down one rank increases preference manipulation under all three mechanisms. However, the rank effect is most severe under the Boston mechanism, followed by DA, and then by the IM Dynamic.

Result 2. (Rank Effect in Truth-telling) Lower-ranked students are more likely to manipulate their preferences. The magnitude of manipulation, on average, has the following order: BOS $>$ DA $>$ IM Dynamic.

Support Columns (1) - (3) of Table 5 report the marginal effects period, ranking, environment, and quiz score on truth-telling for each mechanism. The marginal effects of going down one rank are 21.7%, 17.2%, and 9.4%, respectively, under the Boston, DA, and IM Dynamic mechanisms, with significant pair-wise differences (tests reported in Table 11 in Appendix C).

We also examine the effect of quiz earnings using regressions. Under Boston, while quiz earnings do not affect the likelihood of truth-telling, they do affect on participants' payoffs. Specifically, an increase of 1 Yuan in quiz earnings corresponds to a 0.305-point increase in payoffs, as shown

Table 5 Marginal Effects of Period, Ranking, Environment, and Quiz Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Truth-Telling			Justified Envy			Payoff		
	DA	Dynamic	Boston	DA	Dynamic	Boston	DA	Dynamic	Boston
Period	0.006***	0.006***	0.004	-0.002***	-0.007***	-0.004*	0.002	0.024**	0.007
	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.006)	(0.010)	(0.006)
Ranking	-0.172***	-0.094***	-0.217***	0.031***	0.031***	0.131***	-2.981***	-2.935***	-2.449***
	(0.010)	(0.010)	(0.008)	(0.011)	(0.008)	(0.007)	(0.198)	(0.172)	(0.108)
Low Corr	-0.045*	0.045	0.014	0.083***	0.040**	-0.003	1.146***	1.284***	0.960***
	(0.027)	(0.033)	(0.031)	(0.018)	(0.018)	(0.021)	(0.080)	(0.088)	(0.079)
Quiz Earn	0.139***	0.016	-0.017	-0.036***	-0.024**	-0.055**	0.215*	0.172	0.305**
	(0.036)	(0.025)	(0.034)	(0.010)	(0.011)	(0.024)	(0.109)	(0.095)	(0.125)

Notes: Columns (1) - (3) report marginal effects from Probit regressions where truth-telling is the dependent variable.
Columns (4) - (6) report marginal effects from Probit regressions where justified envy is the dependent variable.
Columns (7) - (9) report marginal effects from OLS regressions where the payoff is the dependent variable.
In OLS regressions, marginal effects are equal to the coefficients.
Standard errors in parentheses are clustered at the session level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

in Column (9) of Table 5. These findings are consistent with Basteck and Mantovani (2018), who found that low cognitive ability participants earn less than high cognitive ability participants under Boston. Under DA, quiz earnings affect the likelihood of truth-telling, but they do not significantly affect participants' payoffs at the 5% significance level. The marginal effect of 1 Yuan in quiz earnings (correctly answering four questions) increases the likelihood of truth-telling by 13.9% (Column (1) in Table 5). Under IM Dynamic, quiz earnings have no effect on either truth-telling or payoffs (Columns (2) and (8) in Table 5). These results suggest that IM Dynamic and DA are more accommodating to low cognitive ability participants if we consider quiz earnings as a proxy for cognitive ability.

6.1.3. Decision Time in the IM Dynamic In this subsection, we look at when subjects revise their choices under the IM Dynamic mechanism. In particular, we examine whether subjects submit their choices at the "last second". This behavior, also known as sniping, has been found to be prevalent in online auctions with a fixed end time (a "hard close"). Although sniping may cause lower expected revenues, it can also be a best response to incremental bidding strategies (Roth and Ockenfels 2002, Ariely et al. 2005, Ockenfels and Roth 2006).

Similar to online auctions with a hard close, sniping can also be a best response under IM Dynamic, in particular when other players play the reverse truth-telling strategy or the random strategy[7]. The following analysis examines whether participants take part in sniping in our experiment.

[7] We define the reverse truth-telling strategy as selecting the least preferred college among all available colleges and adjusting to a more preferred college in subsequent arrivals based on the reverse order of the truth preference list. We define the random strategy as randomly choosing a college among all colleges at each arrival.

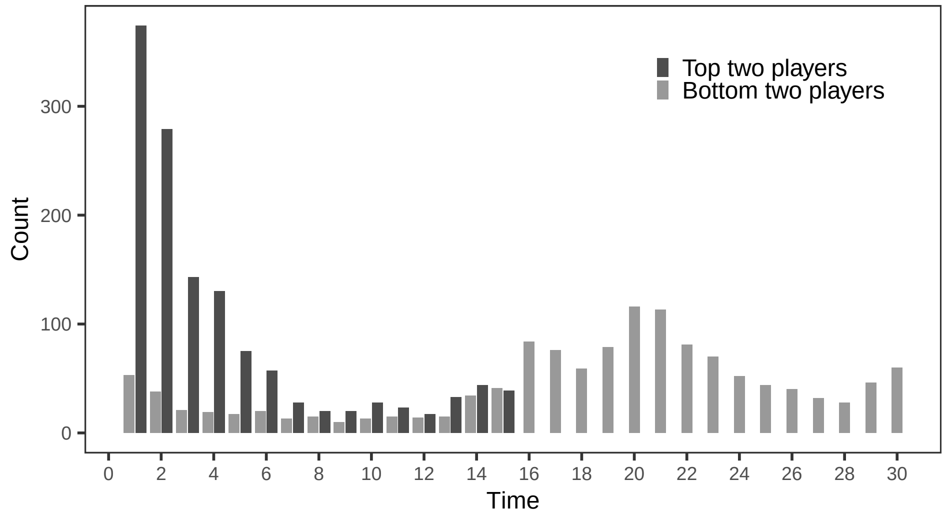

Figure 2 **Last Revision Time**

In our experiment, different subgroups have different end times. Subjects with the top two priorities have 15 seconds to make choices, while subjects with the last two priorities have 30 seconds. We define sniping behavior as revising in the last two seconds (i.e., the 14th and 15th second for the top two players, and the 29th and 30th second for the bottom two players). Figure 2 shows the number of final revisions made at each second for both the top two students and the bottom two students.

In general, we do not find prevalent sniping behavior; only 6% of last revisions are classified as such. We further investigate if sniping behavior prevents other group members from best responding. To do so, we determine whether a player's final revision is a best response to other group members' final revisions. If not, we check if any of her group members engage in sniping. If one of her group members engages in sniping, we attribute this sub-optimal final revision to a lack of time to best respond. This approach provides a maximum estimate of the number of sub-optimal final revisions caused by insufficient time to best respond. We find that 6.14% of final revisions are sub-optimal. Of these sub-optimal revisions, at most 11.11% (which represents 0.68% of all final revisions) can be attributed to the lack of time to best respond. In sum, though sniping behavior exists in our experiment, it is not the main contributor to instability and inefficiency under the IM Dynamic mechanism.

6.2. Aggregate Performance

In this subsection, we investigate the aggregate performance of the three mechanisms, using stability and efficiency as measures. In our setting, where students share a single priority ranking, stable matchings are a subset of efficient matchings. Despite this overlap, we examine stability separately because it emphasizes a mechanism's fairness – whether students have justified envy towards others.

With students having the same priority rankings, fairness becomes particularly crucial due to the straightforward comparison of priorities (scores).

6.2.1. Stability We consider an allocation to be stable when no one in the group has justified envy and it is not wasteful. We compare the performance of the three mechanisms using the proportion of stable allocations.

Based on Theorem 1, the IM Dynamic is almost as good as DA in stability under frequent revision opportunities. Therefore, we expect DA to outperform the IM Dynamic in stability. On the other hand, we expect the IM Dynamic to outperform Boston, as the BNE allocations under Boston are unstable when the top two students share the same preference (Table 8 in Appendix A.5). Accordingly, we have the following hypothesis.

Hypothesis 2. The proportion of stable allocations under the DA mechanism is higher than that under the IM Dynamic mechanism, which in turn is higher than that under the Boston mechanism in any environment.

Table 6 Proportion of Stable Allocations

Mechanism (1)	Prop (High) (2)	Prop (Low) (3)	Ha (4)	p-value (5)
IM DY	0.850	0.731	High = Low	0.056
DA	0.957	0.733	High = Low	0.008
BOS	0.543	0.490	High = Low	0.254
Ha (6)	**p-value (High) (7)**	**p-value (Low) (8)**		
IM DY<DA	0.012	0.461		
DA>BOS	0.004	0.004		
IM DY>BOS	0.004	0.004		

Result 3. (Stability) In the high correlation environment, the proportions of stable allocations are ranked as follows: DA $>$ IM Dynamic $>$ BOS. In the low correlation environment, the ranking changes to DA $\sim$ IM Dynamic $>$ BOS. Moving from the high to low correlation environment, the stability of DA drops significantly, while IM Dynamic and Boston's stability remains largely unchanged.

Support: Table 6 presents the average proportion of stable allocations for each treatment, along with the p-values derived from permutation tests, with each session treated as an independent observation. Columns (2) and (3) detail the proportions of stable allocations in the high and low correlation environments, respectively. Columns (4) and (5) reveal a 22.4% decrease in the proportion of stable allocations under DA when changing from the high to low correlation environment.

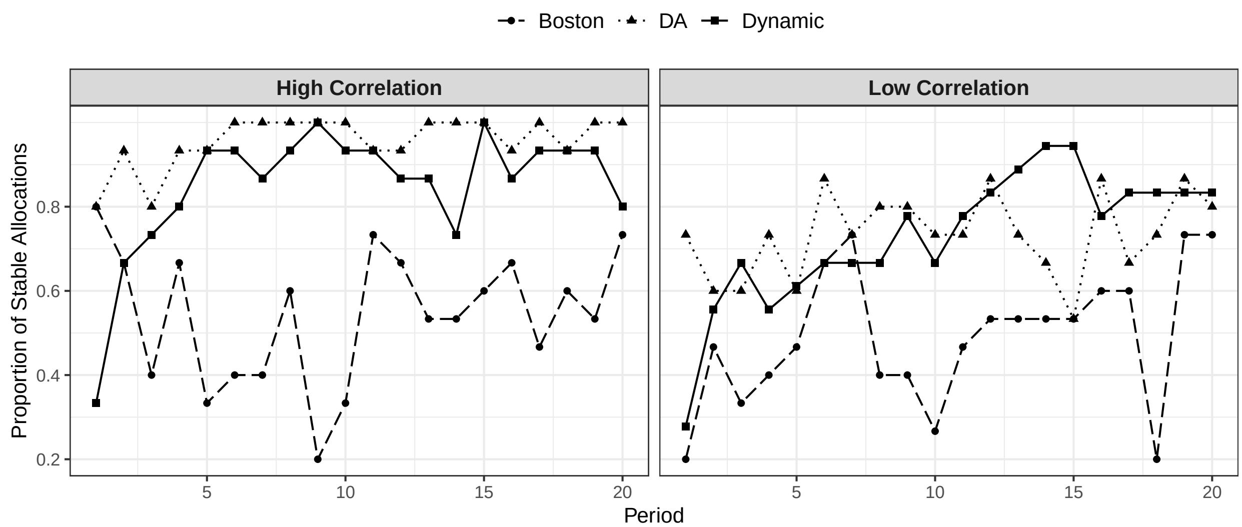

Figure 3 Stability Comparison

Columns (6) (7) and (8) present pair-wise comparisons of the three mechanisms within the same environment. Figure 3 depicts the trend of stable allocations over the 20 periods in both environments. As a robustness check, we use the proportion of justified envy as an alternative measure and find similar results, with the exception that the comparison of justified envy under IM Dynamic across the two environments is significant (see Table 14 in Appendix C).

Based on the results, we conclude that Hypothesis 2 is supported in the high correlation environment, but not in the low correlation environment, where IM Dynamic is as stable as DA. Furthermore, we find that DA suffers a stability loss when the preference correlation decreases, while Boston and IM Dynamic are resilient to environmental change.

6.2.2. Rank Effect in Justified Envy Since stability is a group-level metric, it does not show impacts on students with varied priorities. We thus use justified envy to evaluate fairness across students with different priorities. We assume that students can only be envious of their peers, not of unoccupied seats. An allocation with unoccupied seats can still be fair if no student has justified envy, but this allocation is not efficient or stable, because it is wasteful.

Result 4. (Rank Effect in Justified Envy) As student rankings increase, the proportion of justified envy increases under all three mechanisms. The order of magnitude is Boston $>$ DA $\sim$ IM Dynamic.

Support Columns (4) and (6) in Table 5 displays the marginal effects of period, ranking, environment, and quiz earnings on justified envy under each mechanism. Going down one rank increases the likelihood of having justified envy by 13.1%, 3.1%, and 3.1%, respectively, under the Boston, DA, and IM Dynamic mechanisms. Pair-wise comparisons reveal that the ranking effect of Boston significantly differs from that of DA and IM Dynamic, but no difference is observed between DA and IM Dynamic (pair-wise tests reported in Table 11 in Appendix C).

These results suggest that the DA and IM Dynamic mechanisms are more advantageous to second- and third-ranked students than the Boston mechanism. Note that the regression does not account for fourth-ranked students, as they do not have justified envy.

Lastly, we find varying magnitudes of learning effects across all three mechanisms: IM Dynamic has the strongest learning effect, followed by Boston, and then by DA. Allocations in one period later are 0.7%, 0.4%, and 0.2% less likely to contain justified envy under IM Dynamic, Boston, and DA, respectively.

6.2.3. Efficiency In our final set of analyses, we examine the efficiency of the three mechanisms. We define a matching to be efficient if there is no subset of students where at least one student is better off without making any other student worse off when allocations are switched. For robustness check, we use normalized efficiency as an alternative measure and find similar results (Table 15 in Appendix C).

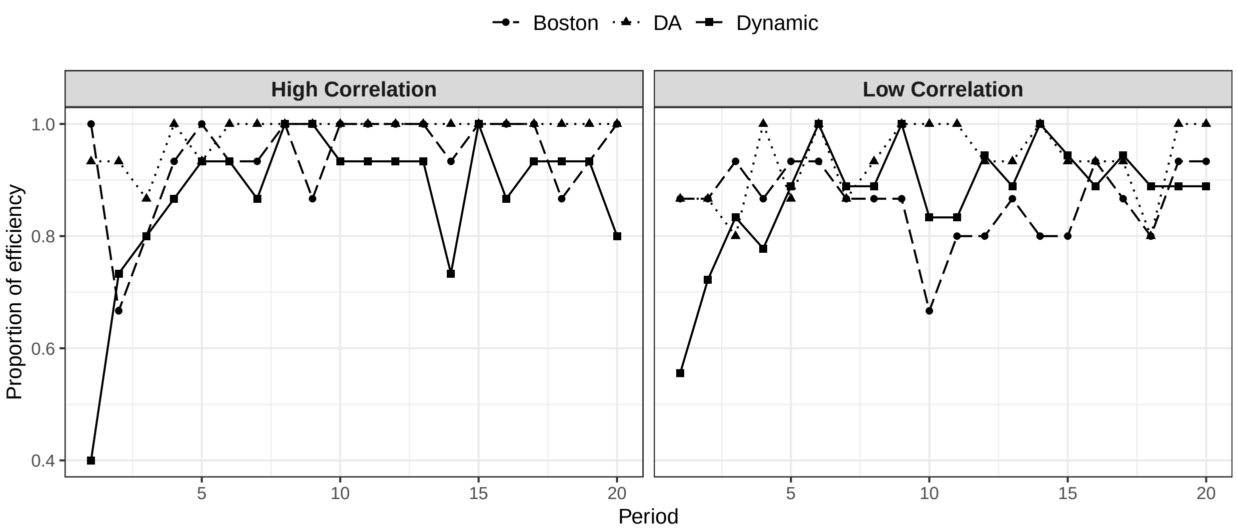

Figure 4 Efficiency comparison

Based on Theorem 1, we expect DA to outperform IM Dynamic in efficiency in both environments. Since DA and Boston yield efficient allocations in BNE, we expect that they will perform similarly in efficiency. Accordingly, we have the following hypothesis:

Hypothesis 3. The proportions of efficient allocations under the DA and Boston mechanisms are similar. Both mechanisms have higher proportions of efficient allocations than the IM Dynamic mechanism.

Result 5. (Efficiency) In the high correlation environment, the proportion of efficient allocations has the following order: DA $\sim$ BOS $>$ IM Dynamic. In the low correlation environment, the order changes to DA $>$ IM Dynamic $\sim$ BOS. Moving from the high to low correlation environment, the efficiency of DA and Boston drops significantly, while the efficiency of IM Dynamic remains largely unchanged.

Table 7 Proportion of Efficient Allocations

Mechanism (1)	Prop (High) (2)	Prop (Low) (3)	Ha (4)	p-value (5)
IM DY	0.873	0.875	High = Low	1.000
DA	0.983	0.933	High = Low	0.024
BOS	0.943	0.860	High = Low	0.032
Ha (6)	p-value (High) (7)	p-value (Low) (8)		
IM DY<DA	0.004	0.045		
DA = BOS	0.119	0.008		
IM DY<BOS	0.036	0.355		

Support: Table 7 presents the average proportion of efficient allocations in each treatment and the p-values of permutation tests, using each session as an independent observation. Columns (2) and (3) present the proportions of efficient allocations in the high and low correlation environments, respectively. Columns (4) and (5) compare the performance of the same mechanism across environments. Columns (6) (7) and (8) present pair-wise comparisons of the three mechanisms under the same environment. Figure 4 depicts the trend of efficient allocations over the 20 periods in both environments.

Based on the results, we conclude that Hypothesis 3 is supported in the high correlation environment, but not in the low correlation environment, where the IM Dynamic mechanism is as efficient as Boston. Additionally, we find that both DA and Boston suffer an efficiency loss when the preference correlation decreases, while IM Dynamic demonstrates resilience.

One drawback of the IM Dynamic mechanism is that students may not be accepted by any college at all. In fact, 60.39% of inefficient allocations in the high correlation environment, and 68.90% of inefficient allocations in the low correlation environment involve unallocated students. This is less of a concern in real life where students outnumber available college seats. Unoccupied seats from a higher score group will naturally be filled by students from a lower score group. If needed, a random re-matching among remaining students and seats can be used to improve efficiency. After a random matching, the proportion of efficient allocations goes up to 0.960 in the high correlation environment and 0.958 in the low correlation environment. This improvement makes the IM Dynamic mechanism as efficient as the Boston mechanism in the high correlation environment (p-value = 0.242 from a one-sided permutation test), and as efficient as the DA in the low correlation environment (p-value = 0.877 from a one-sided permutation test). We further investigate if the low efficiency of the IM Dynamic mechanism is caused by subjects not having enough time to best respond (i.e., that the "arrivals are frequent enough" condition in our Theorem 1 is not met); and find that this is not the case. According to Subsection 6.1.3, at most 0.68% of final revisions are sub-optimal due to not having time to best respond. This leads to at most 1.33% efficiency loss in the high correlation environment, and 2.50% efficiency loss in the low correlation environment.

We observe that subjects opt not to revise, consciously or not, when they should have revised. Our Theorem 3 in Appendix A.6 proves that as the game approaches its end, the myopic best response becomes the strictly dominant strategy. Not revising when being outranked at the end of the game is a strictly dominated strategy, and thus it cannot be a strategic choice. We further examine whether this lack of revision is caused by confusion or inattention. If participants do not revise because they are confused, we expect them to revise more in later periods when they are more familiar with the interface and the allocation rule. However, our data shows similar non-revision behavior across earlier and later periods, which indicates that non-revision behavior is due to inattention. We are uncertain as to what extent this inattention would carry out in the field setting when the stakes are much higher.

7. Conclusions

This study examines a novel market design in the context of college admissions, where students submit one choice at a time and have the ability to modify their choices before a pre-announced end time. Theoretically, we find that this dynamic mechanism performs nearly as well as DA, and it is less efficient but more stable than Boston. These theoretical predictions hold in a lab setting where student preferences are highly correlated, but not in a setting where student preferences are less correlated. As correlation decreases, the performances of DA and Boston decline, making IM Dynamic as stable as DA, and as efficient as Boston.

Our experimental results suggest that IM Dynamic performs robustly as the strategic complexity of the environment increases, while DA and Boston's performance deteriorate. This result stems from the theoretical properties of the mechanisms. In particular, the characterization of rationalizable strategies under IM Dynamic is unaffected when the preference correlation decreases, while the sets of rationalizable strategies under DA and Boston shrink substantially.

Our findings suggest that the IM Dynamic mechanism exhibits greater robustness in complex settings. In environments where DA is ideal but not feasible, the IM Dynamic mechanism could be a replacement. One such scenario is the Chinese college admissions. Other scenarios include public housing assignments, dormitory allocations, as well as job or service assignments. Based on the equivalence of college admissions problem and ascending package auctions under reasonable assumptions (Hatfield and Milgrom 2005), the IM Dynamic can also be implemented as an ascending auction that allows adjustments on previous bids.

Finally, our study suggests certain practices to improve the efficiency and stability of the IM Dynamic. One such practice is to conduct practice rounds before the actual matching process, as our data reveals a strong learning effect under the IM Dynamic. Another suggested practice is to carry out matching among unfilled seats and unallocated students to improve efficiency.

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Appendix A: Proof

A.1. Proof for Theorem 1

Proof We first characterize the rationalizable strategy profiles. To do so, we define an exogenous time sequence $t_0, t_1, t_2, \cdots, t_n$, where $t_0 = 0$, $t_i = \epsilon i$, $\epsilon > 0$; $\forall i \in I$. We also define ρ to be the largest utility ratio between a less preferred college and a more preferred college among all students.

$$\rho = \max_i \{\max_{k \neq l} \{\frac{u_i^k}{u_i^l}\}\}; \forall k, l \in C, \text{such that } u_i^k < u_i^l; \forall i \in I.$$

We prove that when $\lambda > -\frac{ln(1-\rho^{\frac{1}{n-1}})}{\epsilon}$, player i's undominated strategies satisfy the following conditions: at player i's first arrival within $(t_{i-1}, t_i]$, conditional on seeing players ranked ahead of her have obtained seats at their current choices, player i chooses the best college available; for all subsequent arrivals, if players ranked ahead of her do not change their choices, she also does not make any changes. This is obviously true for player 1, since player 1 has a strictly dominant strategy to choose her most-preferred college at her first arrival within time $(0, \epsilon]$, and not to make any changes for all subsequent arrivals. A strategy that chooses any other college at some arrival is dominated because there is a chance that player 1 will not have another arrival after choosing a less-preferred college. For player 2, seeing player 1 has made a choice means that player 1 has already picked her favorite college and will not make a change during subsequent arrivals. At player 2's first arrival within $(t_1, t_2]$, conditional on seeing player 1 has made a choice, player 2 should choose his best college available and make no change during future arrivals. For player 3, seeing player 1 and player 2 have obtained seats in their current choices does not mean that player 1 and player 2 have had arrivals in sequence. Player 2's choice could have been made before player 1's choice. Therefore, player 3 needs to consider the possibility of being outranked by player 2 during future arrivals. At player 3's first arrival within $(t_2, t_3]$, she compares the expected utility between choosing the best college available and choosing another college based on the following possibilities:

1. Player 3 has future arrivals. This happens with a greater than $1 - e^{-\lambda(T-3\epsilon)}$ probability.
2. Player 3 does not have future arrivals. This happens with a less than $e^{-\lambda(T-3\epsilon)}$ probability.

2A. Player 1 had at least one arrival in $(t_0, t_1]$ and player 2 had at least one arrival in $(t_1, t_2]$. This happens with a $(1 - e^{-\lambda\epsilon})^2$ probability.

2B. Either player 1 did not have an arrival in $(t_0, t_1]$, or player 2 did not have an arrival in $(t_1, t_2]$. This happens with a $1 - (1 - e^{-\lambda\epsilon})^2$ probability.

In Case 1, where player 3 has future arrivals, player 3's choice at this arrival does not matter as her current choice will be superseded by her future choice. Therefore, the expected utility of choosing the best college available and choosing a different college at this arrival is the same. Hence, we only need to focus on Case 2, where player 3 does not have future arrivals. We assume player 3's utility of getting into the best college available is u_3^*, and the maximum utility of getting into any other college is u_3'.

If player 3 chooses the best college available, she will get u_3^* under Case 2A. Under Case 2B, the worst-case scenario would be ending up unmatched. Hence, the expected utility of choosing the best college available under Case 2 is:

$$U(\text{best college available}) \geq (1-e^{-\lambda\epsilon})^2 \times u_3^* + [1-(1-e^{-\lambda\epsilon})^2] \times 0. \tag{1}$$

Alternatively, if player 3 chooses another college, she will receive u_3' under Case 2A. Under Case 2B, her best-case scenario is not being outranked and receiving the same college match. Hence, the expected utility of choosing another college under Case 2 is:

$$U(\text{another college}) \leq u_3' \tag{2}$$

When $\lambda > -\frac{ln[1-\rho^{\frac{1}{2}}]}{\epsilon}$, $(1-e^{-\lambda\epsilon})^2 \times u_3^* + [1-(1-e^{-\lambda\epsilon})^2] \times 0 > u_3'$. Thus, choosing the best college available strictly dominates choosing another college.

Note that, if neither player 1 and player 2 have made a change, player 3 has no incentive to make a change during future arrivals.

For any player i ranked below player 3, her decision process is similar to player 3. Specifically, player i faces the following possibilities:

1. Player i has future arrivals. This happens with a greater than $1-e^{-\lambda(T-i\epsilon)}$ probability.
2. Player i does not have future arrivals. This happens with a less than $e^{-\lambda(T-i\epsilon)}$ probability.

2A. All players ranked ahead of player i have had at least one arrival in their designated time interval. This happens with a $(1-e^{-\lambda\epsilon})^{(i-1)}$ probability.

2B. At least one player ranked ahead of player i has not had an arrival in their designated time interval. This happens with a $1-(1-e^{-\lambda\epsilon})^{(i-1)}$ probability.

Assume player i's utility of getting into her best college available is u_i^*, and the maximum utility of her getting into any other college is u_i'. Thus, the expected utility of player i choosing the best college available under Case 2 is:

$$U(\text{best college available}) > (1-e^{-\lambda\epsilon})^{(i-1)} \times u_i^* + [1-(1-e^{-\lambda\epsilon})^{(i-1)}] \times 0. \tag{3}$$

The expected utility of choosing another college under Case 2 is:

$$U(\text{another college}) \leq u_i' \tag{4}$$

When $\lambda > -\frac{ln[1-\rho^{\frac{1}{i-1}}]}{\epsilon}$, $(1-e^{-\lambda\epsilon})^{i-1} \times u_i^* + [1-(1-e^{-\lambda\epsilon})^{i-1}] \times 0 > u_i'$. Hence, choosing the best college available dominates choosing another college. As long as players ranked ahead of player i have not made any changes, player i does not have an incentive to change her choice for all subsequent arrivals.

When $\lambda > -\frac{ln[1-\rho^{\frac{1}{n-1}}]}{\epsilon}$, the above argument is true for all players.

Under any rationalizable strategy profile, players reach the stable and efficient outcome if each player i has at least one arrivals within their designated time period $(t_{i-1}, t_i]$, which happens with the probability $(1-e^{-\lambda\epsilon})^n$. When $\lambda \to \infty$, $(1-e^{-\lambda\epsilon})^n \to 1$. Thus, the stable and efficient matching can be reached with an arbitrarily high probability. □

A.2. Proof for Theorem 2

proof For our proof, we first consider a two-player two-college example. In this example, player i has higher priority than player j at both colleges. With probability α, player i and player j have the same preference, and with probability $1-\alpha$, they have the opposite preferences. Suppose player i's strategy is to wait until player j makes a choice and then to choose whichever college player j has chosen, and remains at that college. In this case, player j's best response is to choose her less preferred college at her first arrival and then switch to her favorite college at her second arrival (referred to as Strategy I in this proof). Any other strategies are strictly dominated. Alternatively, if player i uses the myopic best responding strategy, that is, player i chooses her favorite college at her first arrival and does not change during subsequent arrivals, then player j's previous best response - Strategy I - is strictly dominated by the myopic best responding strategy (referred to as Strategy II in this proof). This is because when player i and player j have the same preference, player j will get into her less preferred school by playing Strategy II given sufficient arrivals, whereas she will end up unallocated by playing Strategy I.

To prove this, we denote the utility for player j of getting into her favorite college as $\bar{u}$ and the utility for player j of getting into her less preferred college as $\underline{u}$. If player j players strategy II, her expected payoff U_{II} satisfies the following:

$$U_{II} > \text{P(player } i \text{ and player } j \text{ have arrivals in sequence)} \times [\alpha\underline{u} + (1-\alpha)\bar{u}], \tag{5}$$

where P(player i and player j have arrivals in sequence) equals $(1-e^{-\lambda T}-\lambda T e^{-\lambda T})$. Therefore,

$$U_{II} > (1-e^{-\lambda T}-\lambda T e^{-\lambda T})[\alpha\underline{u} + (1-\alpha)\bar{u}]. \tag{6}$$

Note that the expected payoff is greater because player j still has a positive expected payoff even if player i and j do not have arrivals in sequence. One such scenario is when player j has arrivals, and player i does not.

On the other hand, If player j plays Strategy I, she faces four possibilities:

Case I: Player i has at least one arrival and player j has at least two arrivals. This happens with probability $(1-e^{-\lambda T})(1-e^{-\lambda T}-\lambda T e^{-\lambda T})$. The expected payoff for player j under Case I is $(1-\alpha)\bar{u}$.

Case II: Player i has at least one arrival, and player j has one arrival. This happens with probability $(1-e^{-\lambda T})\lambda T e^{-\lambda T}$. The expected payoff under Case II is $\alpha\underline{u}$.

Case III: Player i has zero arrivals, and player j has one arrival. This happens with probability $\lambda T e^{-2\lambda T}$. The expected payoff under Case III is $\underline{u}$.

Case IV: Player i has zero arrivals and player j has at least two arrivals. This happens with probability $e^{-\lambda T}(1-e^{-\lambda T}-\lambda T e^{-\lambda T})$. The expected payoff under case IV is $\bar{u}$.

Combining payoffs across all four cases, player j's expected payoff U_I of playing Strategy I satisfies the following:

$$\begin{aligned} U_I =& (1-e^{-\lambda T})(1-e^{-\lambda T}-\lambda T e^{-\lambda T})(1-\alpha)\bar{u} + (1-e^{-\lambda T})\lambda T e^{-\lambda T}\alpha\underline{u} \\ &+ \lambda T e^{-2\lambda T}\underline{u} + e^{-\lambda T}(1-e^{-\lambda T}-\lambda T e^{-\lambda T})\bar{u} \end{aligned} \tag{7}$$

The difference between U_{II} and U_I satisfies the following:

$$\begin{aligned}
U_{II} - U_I > &(1 - e^{-\lambda T} - \lambda T e^{-\lambda T})[\alpha \underline{u} + (1-\alpha)\bar{u}] \\
&- (1 - e^{-\lambda T})(1 - e^{-\lambda T} - \lambda T e^{-\lambda T})(1-\alpha)\bar{u} - (1 - e^{-\lambda T})\lambda T e^{-\lambda T}\alpha \underline{u} \\
&- \lambda T e^{-2\lambda T}\underline{u} - e^{-\lambda T}(1 - e^{-\lambda T} - \lambda T e^{-\lambda T})\bar{u} \\
> &(1 - e^{-\lambda T} - \lambda T e^{-\lambda T})\alpha \underline{u} - (1 - e^{-\lambda T})\lambda T e^{-\lambda T}\alpha \underline{u} \\
&- \lambda T e^{-2\lambda T}\underline{u} - e^{-\lambda T}(1 - e^{-\lambda T} - \lambda T e^{-\lambda T})\bar{u} \\
= &\alpha \underline{u} - e^{-\lambda T}(\alpha \underline{u} + 2\lambda T \alpha \underline{u} + \bar{u}) + e^{-2\lambda T}(\bar{u} + \lambda T \bar{u} + \lambda T \alpha \underline{u} - \lambda T \underline{u})
\end{aligned} \tag{8}$$

In Equation (8), the first term, $\alpha \underline{u}$, is a constant. Since the second and the third terms can be arbitrarily small when λ increases, $U_{II} - U_I > 0$ when λ is large enough. Hence, for player j, Strategy I is strictly dominated by Strategy II when player i plays the myopic best responding strategy. Therefore, player j does not have a weakly dominant strategy.

We next consider the case with more than two players and two colleges. In this case, for any player k whose priority ranking exceeds the quota of her favorite college (denoted as q), we can always find q players who rank ahead of her. If these q players play the two strategies used by player i in the previous example, we can show that player k does not have a weakly dominant strategy, following the same proof as for player j in the previous example. □

A.3. Bayesian Nash equilibrium under DA

Here, we prove that any combination of strategies listed in Table 1 is indeed a Bayesian Nash equilibrium under the DA mechanism. Furthermore, we prove that these are the only Bayesian Nash equilibria. We know that in the college admissions problem, the allocation outcome under the DA mechanism equals the allocation outcome under the serial dictatorship mechanism. In other words, students need to care about only those other students who have a higher score rank than they do. We use this property to prove that the strategies listed in Table 1 are Bayesian Nash equilibrium strategies and are the only Bayesian Nash equilibrium strategies. There are six different preference type realizations in our experiment; each of them happens with probability $\frac{1}{6}$. The six realizations are listed below:

Case 1: The 1st student and 2nd student have preference Type I, and the 3rd student and 4th student have preference Type II.

Case 2: The 1st student and 2nd student have preference Type II, and the 3rd student and 4th student have preference Type I.

Case 3: The 1st student and 3rd student have preference Type I, and the 2nd student and 4th student have preference Type II.

Case 4: The 1st student and 3rd student have preference type II, and the 2nd student and 4th student have preference type I.

Case 5: The 1st student and 4th student have preference type I, and the 2nd student and 3rd student have preference type II.

Case 6: The 1st student and 4th student have preference Type II, and the 2nd student and 3rd student have preference Type I.

We first examine the high correlation environment. Recall that, in the high correlation environment, preference Type I is $A \succ B \succ C \succ D$, while preference Type II is $B \succ A \succ D \succ C$.

- For the 1st student, her dominant strategy is to report her first choice truthfully, regardless of her own and others' preferences.

- For the 2nd student, she needs to consider the realization of different preference types. When she has the same preference as the 1st student (cases 1 and 2), the best she can do is to get into her second most preferred college. She can obtain this allocation by reporting her second most preferred college ahead of her third and fourth most preferred colleges. Since her most preferred college is already occupied by the 1st student, the reported position of her most preferred college does not matter. Hence, her best response in cases 1 and 2 is $(2 > 3/4)$. When she has a different preference from the 1st student (cases 3 through 6), she can get into her most preferred college by either playing either $(1, 2, *, *)$ or $(2, 1, *, *)$. When playing the latter strategy, since her second most preferred college has been occupied by the 1st student, she will be kicked out and sent to her most preferred college. Therefore, her best response in cases 3 through 6 is $(1/2 > 3/4)$. Since, ex-ante, the 2nd student does not know the realization of the preference type, only strategies that are best responses in all six cases will be Bayesian Nash equilibrium strategies. These strategies are $(1/2 > 3/4)$.

- For the 3rd student, regardless of the realization of different preference types, the best she can do in equilibrium is to get into her third most preferred choice. She can do so by reporting her third most preferred choice ahead of her fourth most preferred choice $(3 > 4)$.

- For the 4th student, any strategy is a best response because she can do nothing but accept what is left.

Together, this proves that any combination of strategies in Table 1 in the high correlation environment under DA is a Bayesian Nash equilibrium strategy. Furthermore, these strategies are the only Bayesian Nash equilibrium strategies, since any other strategies are strictly dominated.

We next examine the low correlation environment. The preference Type II is $B \succ D \succ C \succ A$

- For the 1st student, her dominant strategy is to report her first choice truthfully, regardless of her own and others' preferences.

- For the 2nd student, she needs to consider the realization of different preference types. When she has the same preference as the 1st student (cases 1 and 2), the best she can do is to get into her second most preferred college. She can obtain this allocation by reporting her second most preferred college ahead of her third and fourth most preferred colleges. Since her most preferred college will be occupied by the 1st student, the reported position of her most preferred college does not matter. Hence, her best response in cases 1 and 2 is $(2 > 3/4)$. When she has a different preference from the 1st student, and the 1st student has preference Type I (cases 3 and 5), she can get into her most preferred college by playing $(1 > 2/3)$. The ranking of her least preferred college does not matter because it will be occupied by the 1st student. When she has a different preference from the 1st student, and the 1st student has preference Type II (cases 4 and 6), she can get into her most preferred college by playing $(1 > 3/4)$. The ranking of her second-most preferred college does not matter because it will be occupied by the 1st student. Since, ex-ante, the 2nd student does not know the realization of the preference type, the only strategies that are best responses in all six cases will be Bayesian Nash equilibrium strategies. These strategies are $(1, 2, *, *)$.

- For the 3rd student, in cases 1, 4, and 5, she can get into her second most preferred college by playing $(2 > 3)$. The rankings of her first and fourth-most preferred colleges do not matter because they will be occupied by the top two students. In case 2, she can get into her most preferred college by playing $(1 > 3)$. In cases 3 and 6, she can get into her third-most preferred college by playing $(3 > 4)$. The intersection of the three strategy sets is $(*, *, 3, 4)$, which is her Bayesian Nash equilibrium strategy.
- For the 4th student, any strategy is a best response because she can do nothing but accept what is left.

Together, this proves that any combination of strategies in Table 1 in the low correlation environment under DA is a Bayesian Nash equilibrium strategy. Furthermore, these are the only Bayesian Nash equilibrium strategies, since any other strategies are strictly dominated.

A.4. Bayesian Nash Equilibrium under Boston

In this subsection, we show that any combination of strategies listed in Table 1 is a Bayesian Nash equilibrium under the Boston mechanism. We further show that they are the only Bayesian Nash equilibria. Truth-telling is one Bayesian Nash equilibrium strategy.

First, we examine the high correlation environment, where a Type I player has the preference $A \succ B \succ C \succ D$, and a Type II player has the preference $B \succ A \succ D \succ C$. There are six different realizations of preference combinations, similar to DA, with each combination occurring with probability $\frac{1}{6}$:

- For the 1st student, she has a dominant strategy, which is to truthfully report her first choice $(1, *, *, *)$.
- For the 2nd student, there is a $\frac{1}{3}$ of probability that she has the same preference as the 1st student (cases 1 and 2), and a $\frac{2}{3}$ probability that she has a different preference from the 1st student (cases 3 through 6). Assuming the 1st student is rational, ex-ante, she has an incentive to report her first choice truthfully, because, with probability $\frac{2}{3}$, she will receive a placement at that school. Any untruthful first choice will make her strictly worse off. When the 2nd student has the same preference as the 1st student, she will not get into her first choice. The worst case would be if the 3rd student is truthful and gets into the 2nd student's second-most preferred college. In this case, the 2nd student would have unpreventable justified envy toward the 3rd student. The 2nd player also has an incentive to rank her third most preferred college ahead of her fourth most preferred college, otherwise, she will be admitted to her fourth most preferred college if she gets rejected from her first choice. Hence, for the 2nd student, her best response is $(1, 3 > 4)$. The ranking of her second most preferred college does not matter, because, in equilibrium, she will not get into it.
- Given the 1st and the 2nd students are rational, the 3rd student's best response is to truthfully report her first choice as well. When the 1st and the 2nd student have the same preference type, which happens with probability $\frac{1}{3}$ (cases 1 and 2), the 3rd student will be able to get into her first choice. In all the other cases (cases 3 through 6), her first and second most preferred colleges will already be claimed by the 1st and the 2nd students, so the best she can get is her third most preferred college; therefore, her best response is $(1, 3 > 4)$.
- Given the first three students are rational, the 4th student can best respond by reporting her third most preferred college ahead of her fourth most preferred college $(3 > 4)$, because the best she can get into under each of the six cases is her third most preferred college.

Next, we look at the low correlation environment, where a Type I player has the preference $A \succ B \succ C \succ D$, and a Type II player has the preference $B \succ D \succ C \succ A$. Similar to the high correlation environment, there are six different realizations of preference types, and each occurs with the probability of $\frac{1}{6}$.

- For the 1st student, her dominant strategy is to truthfully report her first choice $(1,*,*,*)$.
- Given the 1st student is rational. When the 1st and the 2nd students have different preferences (cases 3 through 6), the 2nd student can get into her most preferred college by reporting her first choice truthfully $(1,*,*,*)$. In the case where the 1st and 2nd students have preference type II (case 2), the 2nd student can best respond by listing her second most preferred college ahead of her third and fourth most preferred college $(2>3,4)$. When the 1st and 2nd students have preference Type I (case 1), at most, the 2nd student can get her third-most preferred college by listing her third-most preferred college ahead of her fourth-most preferred college $(3>4)$. The only strategy that is the best response in all six cases is the complete truth-telling $(1,2,3,4)$. Thus, truth-telling is the only Bayesian Nash equilibrium strategy for the 2rd student.
- Given the top two students are rational, the only Bayesian Nash equilibrium strategy for the 3rd student is also complete truth-telling. When the top two students have the same preference (cases 1 and 2), she can get into her most preferred college by truthfully reporting her first choice $(1,*,*,*)$. When the 1st and 3rd students have preference Type II (case 4), or the 1st and the 4th students have preference Type I (case 6), she can get into her second-most preferred college by listing her second-most preferred college ahead of her third and fourth most preferred college $(2>3,4)$. In the rest two cases (cases 3 and 5), the 3rd student can get into her third-most preferred college by listing her third-most preferred college ahead of her fourth-most preferred college $(3>4)$. Hence, complete truth-telling is the only best response in all six cases.
- Given the top three students are rational, when the 4th student has the preference Type II (cases 1, 3, and 6), she can get into her second most preferred school by listing her second most preferred school ahead of her third and fourth most preferred school $(2>3,4)$. When the 4th student has a preference Type I (cases 2, 4, and 5), she can get into her third most preferred school by listing her third most preferred school ahead of her fourth most preferred school $(3>4)$. Thus the 4th student can best respond by truthfully reporting the order of her last three choices $(2>3>4)$ under all six cases.

A.5. Bayesian Nash Equilibrium Outcomes under DA and Boston

Table 8 shows the BNE allocation in each case. The capital letters represent the college that a student is assigned to. The numbers in the parentheses represent the corresponding payoffs. In the high correlation environment, under Boston, the allocations in case 1 and case 2 are not stable; in the low correlation environment, the allocation in case 1 is not stable. The BNE allocations under DA are always efficient and stable.

A.6. The Dominant Strategy under IM Dynamic

Our Theorem 3 establishes that dominant strategies generally do not exist under IM Dynamic. However, as the end time approaches, the myopic best responding strategy emerges as the strictly dominant strategy, as stated in our Theorem 3.

Theorem 3. *There exists an η, such that within the period $[T-\eta, T]$, the myopic best responding strategy strictly dominates all the other strategies.*

Table 8 Bayesian Nash Equilibrium Outcomes under DA and Boston

	Boston											
	High Correlation						Low Correlation					
Ranking	Case1	Case2	Case3	Case4	Case5	Case6	Case1	Case2	Case3	Case4	Case5	Case6
1st	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)
2nd	C(7)	D(7)	B(16)	A(16)	B(16)	A(16)	C(7)	D(11)	B(16)	A(16)	B(16)	A(16)
3rd	B(16)	A(16)	C(7)	D(7)	D(7)	C(7)	B(16)	A(16)	C(7)	D(11)	D(11)	C(7)
4th	D(7)	C(7)	D(7)	C(7)	C(7)	D(7)	D(11)	C(7)	D(11)	C(7)	C(7)	D(11)
Efficient	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stable	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
	DA											
	High Correlation						Low Correlation					
Ranking	Case1	Case2	Case3	Case4	Case5	Case6	Case1	Case2	Case3	Case4	Case5	Case6
1st	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)	A(16)	B(16)
2nd	B(11)	A(11)	B(16)	A(16)	B(16)	A(16)	B(11)	D(11)	B(16)	A(16)	B(16)	A(16)
3rd	D(7)	C(7)	C(7)	D(7)	D(7)	C(7)	D(11)	A(16)	C(7)	D(11)	D(11)	C(7)
4th	C(5)	D(5)	D(7)	C(7)	C(7)	D(7)	C(7)	C(7)	D(11)	C(7)	C(7)	D(11)
Efficient	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Proof Consider the expected utility for a player i when choosing between the best available college and any other college, given a small remaining time interval η. Let the payoff for getting into the best available college be denoted as u_i^* and for any other college as $u_i^{'}$, where $u_i^* > u_i^{'}$. We will focus on the scenario where player i does not have future arrivals, as the expected payoff only varies in this case. If player i does have future arrivals, her choice at this arrival is inconsequential, since any future arrival will override her current choice.

At time $T-\eta$, the probability that any players ranked ahead of player i have a future arrival is $1-e^{-\lambda\eta(i-1)}$. If player i chooses the best college available, in the worst case, she could get outranked by a higher-ranked player. This happens with a probability of $(1-e^{-\lambda\eta(i-1)})$. Therefore, her expected utility will be greater than $u_i^* \times e^{-\lambda\eta(i-1)} + 0 \times (1-e^{-\lambda\eta(i-1)})$. However, should player i choose any other college, her expected utility will not be greater than $u_i^{'}$. As $\eta \to 0$, $e^{-\lambda\eta(i-1)} \to 1$. There exists a sufficiently small η such that $u_i^* \times e^{-\lambda\eta(i-1)} > u_i^{'}$. Consequently, choosing the best college available is the strictly dominant strategy for player i within the period $[T-\eta, T]$. □

Appendix B: Generalizing the IM Dynamic mechanism to heterogeneous student priorities.

One key assumption in this paper is that students have homogeneous priorities across different colleges. In this section, we generalize our main theoretical result to a special case of heterogeneous student priorities. Note that our results cannot be generalized to general heterogeneous student priorities.

According to Theorem 1, when arrivals are frequent enough, the stable and efficient outcome arises with arbitrarily high probability under the IM Dynamic mechanism. However, under heterogeneous student priorities, a stable and efficient outcome does not exist. Thus, the question becomes whether students can reach the same stable outcome as under student-proposing DA. Inspired by Example 2 in Ashlagi and Gonczarowski

(2018), our Lemma 1 proves that when there are only two students and two colleges, the stable outcome arises with an arbitrarily high probability under any rationalizable strategy profile.

LEMMA 1. *When the Poisson parameter λ is large enough, if there are two students and two colleges, each with one respective seat, the stable outcome arises with an arbitrarily high probability under any rationalizable strategy profile.*

Proof Suppose we have two students i and j, and two colleges a and b. If both colleges prefer one student, either $i \succ j$ or $j \succ i$, Theorem 1 applies. Therefore, the stable outcome arises with an arbitrarily high probability. When the two colleges prefer different students, without losing generality, assume $i \succ_a j$ and $j \succ_b i$. If either student has a higher priority at her most preferred college, without losing generality, assume $a \succ_i b$, then student i has a dominant strategy which is to choose her most preferred school at her first arrival. Conditional on seeing student i has a seat at the college where she has a higher priority, the only rationalizable strategy for student j is to choose the remaining school at her next arrival. In this case, the two students will reach the stable outcome as long as student j has an arrival after student i. If neither student has a higher priority at her most preferred school, which is $b \succ_i a$ and $a \succ_j b$. Assuming rationality, if student j sees student i choose college b, then student j knows that i's preference must be $b \succ_i a$; otherwise, if student i's preference is $a \succ_i b$, then student i has a dominant strategy to choose college a at her first arrival. Conditional on seeing student i choose college b, the only rationalizable strategy for student j is to choose college a at her next arrival. Knowing this, student i should truthfully report her preference – choosing college b – at her first arrival. The same is also true *vice versa*. In this case, the two students will reach the stable outcome as long as each of them has an arrival. Combining the two cases, the two students will reach the stable outcome as long as there exist three arrivals in the sequence $i > j > i$ (or $j > i > j$), which happens with arbitrarily high probability when λ is large enough. □

DEFINITION 1 (ERGIN (2002) ACYCLICALITY). Student priorities are said to be acyclical if there does not exist three students i, j, k and two colleges a, b such that $i \succ_a j \succ_a k \succ_b i$.
We can now state Theorem 4, as follows:

THEOREM 4. *When the Poisson parameter λ is large enough, if student priorities are acyclical, the stable outcome arises with an arbitrarily high probability under any rationalizable strategy profile.*

proof By acyclicality, there are at most two students who have the highest priority at some colleges. If only one such student exists, then she has the highest priority at all colleges. In this case, the student has a dominant strategy. Otherwise, there are exactly two students who rank first or second place in all colleges. Denote these two students as i and j. Using Lemma 1, we know that these two students will reach a stable outcome between themselves as long as there exist three arrivals in the sequence $i > j > i$ (or $j > i > j$). For simplicity, we call arrivals in the sequence of $i > j > i$ (or $j > i > j$) "mixed arrivals". Again by acyclicality, there exists a third-ranked student or a student-pair, such that all colleges prefer them over the remaining students. Conditional on seeing the top student or student-pair receiving a seat at her current choice, the rationalizable strategy profiles of the third-ranked student or student-pair are characterized by Lemma 1, and they will reach a stable outcome between themselves as long as there exist three mixed arrivals. The same logic applies to lower-ranked students or student pairs. Since a lower-ranked group cannot have justified envy over a higher-ranked group, the entire allocation outcome is also stable. Using the technique of proving Theorem 1, we can assign a small time interval to each rank group. As long as there is one arrival within the time interval for each one-student rank group and three mixed arrivals within the time interval for each two-student rank group, students will reach the stable outcome under any rationalizable strategy profile. With a sufficiently large λ, the desired arrival sequence happens with an arbitrarily high probability. □

Note that our proof borrowed the technique from the proof of Theorem 2 in Ashlagi and Gonczarowski (2018).

Appendix C: Tables and Regressions

Table 9 presents the proportion of first choice truth-telling under each mechanism. Table 10 presents the proportion of truth-telling under each mechanism, where truth-telling under DA is defined as truthfully reporting one's preferences up to one's ranking. Table 12 (Table 13) presents the proportion of truth-telling (first choice truth-telling) by each score rank under each mechanism. Table 14 compares the stability of the three mechanisms using the proportion of justified envy as the measure. Table 15 compares the efficiency of the three mechanisms using normalized efficiency as the measure. Table 16 presents session level averages of the respective proportions of truth-telling, justified envy, and efficient allocation, as well as the standard deviations at the treatment level.

Table 9 Proportion of First Choice Truth-telling

Mechanism	Proportion	Ha	p-value
	High Correlation		
IM DY	0.763	IM DY >DA	0.317
DA	0.746	DA>BOS	0.008
BOS	0.611	IM DY = BOS	0.008
	Low Correlation		
IM DY	0.801	IM DY >DA	0.002
DA	0.664	DA>BOS	0.012
BOS	0.611	IM DY= BOS	0.004

Table 11 columns (1) - (3) report the pair-wise comparisons of marginal effects of the period, ranking, changing to the low correlation environment, and quiz earnings on truth-telling. Column (1), labeled "DA − Dyn," illustrates the difference between the marginal effect under DA and the marginal effect under IM Dynamic. For example, the value -0.078 (Ranking) is the marginal effect of ranking under DA minus the marginal effect of ranking under IM Dynamic. The number 0.014 in parentheses below represents the standard error of the estimate. Similarly, column (2), "BOS − Dyn," displays the difference in marginal effects under Boston and IM Dynamic, while column (3), "BOS − DA," shows the difference in marginal effects under Boston and DA. Columns (4) - (6) report the pair-wise comparisons of marginal effects on justified envy, and Columns (7) - (9) provide the pair-wise comparisons of marginal effects on payoff.

Table 10 Proportion of Truth-telling (DA Truth-telling Up-to-rank)

High Correlation			
Mechanism	Proportion	Ha	p-value
IM DY	0.716	IM DY >DA	0.444
DA	0.712	DA>BOS	0.004
BOS	0.435	IM DY = BOS	0.008
Low Correlation			
Mechanism	Proportion	Ha	p-value
IM DY	0.759	IM DY >DA	0.011
DA	0.632	DA>BOS	0.004
BOS	0.445	IM DY= BOS	0.004

Table 11 Pair-wise Marginal Effect Comparisons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Truth-Telling			Justified Envy			Payoff	
	DA − Dyn	BOS−Dyn	BOS−DA	DA − Dyn	BOS − Dyn	BOS − DA	DA − Dyn	BOS− Dyn	BOS − DA
Period	0.000	-0.002	-0.002	0.004***	0.003	-0.002	-0.022*	-0.017	0.004
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.011)	(0.011)	(0.008)
Ranking	-0.078***	-0.123***	-0.044***	0.000	0.100***	0.100***	-0.046	0.486**	0.532**
	(0.014)	(0.012)	(0.012)	(0.013)	(0.011)	(0.013)	(0.253)	(0.196)	(0.217)
Low Corr−High Corr	-0.090**	-0.032	0.059	0.036*	-0.042	-0.078***	-0.138	-0.324***	-0.186*
	(0.041)	(0.044)	(0.040)	(0.021)	(0.026)	(0.024)	(0.115)	(0.114)	(0.109)
Quiz Earnings	0.124***	-0.033	-0.157***	-0.011	-0.031	-0.019	0.043	0.133	0.090
	(0.042)	(0.041)	(0.048)	(0.014)	(0.026)	(0.025)	(0.140)	(0.152)	(0.160)

Standard errors in parentheses are clustered at the session level.
*** p<0.01, ** p<0.05, * p<0.1

Table 12 Truth-telling by Rank

High Correlation									
Rank	IM DY	DA	BOS	Ha	p-value	Ha.1	p-value.1	Ha.2	p-value.2
1st	0.907	0.947	0.900	IM DY<DA	0.091	DA>BOS	0.151	IM DY>BOS	0.464
2nd	0.837	0.830	0.513	IM DY<DA	0.595	DA>BOS	0.004	IM DY>BOS	0.004
3rd	0.500	0.567	0.177	IM DY<DA	0.123	DA>BOS	0.004	IM DY>BOS	0.004
4th	0.620	0.450	0.150	IM DY>DA	0.020	DA>BOS	0.004	IM DY>BOS	0.004
Low Correlation									
Rank	IM DY	DA	BOS	Ha	p-value	Ha.1	p-value.1	Ha.2	p-value.2
1st	0.925	0.967	0.927	IM DY<DA	0.024	DA>BOS	0.103	IM DY>BOS	0.563
2nd	0.742	0.683	0.430	IM DY>DA	0.175	DA>BOS	0.004	IM DY>BOS	0.002
3rd	0.653	0.437	0.230	IM DY>DA	0.015	DA>BOS	0.016	IM DY>BOS	0.002
4th	0.717	0.420	0.193	IM DY>DA	0.002	DA>BOS	0.008	IM DY>BOS	0.002

As a robustness check, we repeat our analysis using normalized efficiency as the measure. We define normalized efficiency as:

$$\text{Normalized Efficiency} = \frac{\text{maximum group rank} - \text{actual group rank}}{\text{maximum group rank} - \text{minimal group rank}},$$

where group rank is the sum of the ranks of each assigned college in everyone's preference list.

Table 17 presents the average earnings by rank under each environment and each mechanism. Columns (5), (6), (7), (12), (13), and (14) present the respective corresponding p-values from two-sided permutation

Table 13 First Choice Truth-telling by Rank

				High Correlation					
Rank	IM DY	DA	BOS	Ha	p-value	Ha.1	p-value.1	Ha.2	p-value.2
1st	0.943	0.983	0.980	IM DY<DA	0.016	DA>BOS	0.500	IM DY<BOS	0.036
2nd	0.850	0.847	0.637	IM DY<DA	0.563	DA>BOS	0.008	IM DY>BOS	0.004
3rd	0.607	0.637	0.460	IM DY<DA	0.313	DA>BOS	0.016	IM DY>BOS	0.012
4th	0.653	0.517	0.367	IM DY>DA	0.083	DA>BOS	0.044	IM DY>BOS	0.004
				Low Correlation					
Rank	IM DY	DA	BOS	Ha	p-value	Ha.1	p-value.1	Ha.2	p-value.2
1st	0.944	0.977	0.987	IM DY<DA	0.063	DA<BOS	0.278	IM DY<BOS	0.035
2nd	0.767	0.713	0.490	IM DY>DA	0.182	DA>BOS	0.004	IM DY>BOS	0.002
3rd	0.750	0.490	0.390	IM DY>DA	0.002	DA>BOS	0.095	IM DY>BOS	0.002
4th	0.744	0.477	0.277	IM DY>DA	0.002	DA>BOS	0.020	IM DY>BOS	0.002

Table 14 Proportion of Justified Envy

Mechanism (1)	Prop (High) (2)	Prop (Low) (3)	Ha (4)	p-value (5)
IM DY	0.033	0.066	High = Low	0.022
DA	0.011	0.073	High = Low	0.008
BOS	0.154	0.152	High = Low	0.960
Ha (6)	**p-value (High) (7)**	**p-value (Low) (8)**		
IM DY>DA	0.022	0.701		
DA<BOS	0.004	0.004		
IM DY<BOS	0.004	0.002		

Table 15 Normalized Efficiency Comparison

	High Correlation		
Mechanism	Proportion	Ha	p-value
IM DY	0.776	IM DY<DA	0.020
DA	0.847	DA = BOS	0.722
BOS	0.860	IM DY <BOS	0.004
	Low Correlation		
Mechanism	Proportion	Ha	p-value
IM DY	0.913	IM DY<DA	0.130
DA	0.932	DA = BOS	0.167
BOS	0.914	IM DY <BOS	0.5t35

tests. We see that the earnings of the 1st ranked student are not significantly different across environments or mechanisms. The 2nd ranked student consistently earns less, whereas the 4th ranked student consistently earns more under the Boston mechanism compared to the other two mechanisms. Comparing IM Dynamic and DA, we find that in the high correlation environment, the 3rd ranked student earns slightly more under

Table 16 Session Average and Standard Deviation

				High Correlation				
Measure	Mechanism	Session1	Session2	Session3	Session4	Session5	Session6	SD
Truth-telling	IM DY	0.733	0.675	0.738	0.704	0.729		0.026
	DA	0.771	0.725	0.713	0.629	0.654		0.057
	Boston	0.408	0.483	0.442	0.458	0.383		0.040
Justified envy	IM DY	0.046	0.033	0.050	0.025	0.054		0.012
	DA	0.008	0.004	0.004	0.004	0.033		0.013
	Boston	0.171	0.158	0.121	0.146	0.175		0.022
Efficiency	IM DY	0.817	0.883	0.833	0.933	0.900		0.048
	DA	0.983	0.983	1.000	1.000	0.950		0.020
	Boston	0.950	0.983	0.967	0.950	0.867		0.045
				Low Correlation				
Measure	Mechanism	Session1	Session2	Session3	Session4	Session5	Session6	SD
Truth-telling	IM DY	0.679	0.846	0.758	0.817	0.750	0.704	0.064
	DA	0.562	0.558	0.621	0.713	0.679		0.069
	Boston	0.392	0.379	0.442	0.525	0.487		0.062
Justified envy	IM DY	0.050	0.033	0.100	0.079	0.062	0.108	0.029
	DA	0.083	0.100	0.092	0.050	0.042		0.026
	Boston	0.138	0.188	0.117	0.179	0.142		0.030
Efficiency	IM DY	0.933	0.950	0.783	0.883	0.850	0.850	0.061
	DA	0.917	0.917	0.917	0.950	0.967		0.024
	Boston	0.900	0.850	0.900	0.783	0.867		0.048

the IM Dynamic as these students have the highest priority in their score group, whereas in the low correlation environment, there is no difference between the two mechanisms.

Table 17 Average Earnings by Rank

				High Correlation		
Ranking	IM DY	DA	Boston	IM DY $\neq$ DA	IM DY $\neq$ Boston	DA $\neq$ Boston
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	79.050	79.583	79.500	0.516	0.659	1.000
2	67.717	71.900	59.767	0.095	0.016	0.008
3	36.967	35.300	42.117	0.048	0.008	0.008
4	30.767	32.233	39.467	0.063	0.008	0.008
				Low Correlation		
Ranking	IM DY	DA	Boston	IM DY $\neq$ DA	IM DY $\neq$ Boston	DA $\neq$ Boston
(8)	(9)	(10)	(11)	(12)	(13)	(14)
1	79.417	79.217	79.567	0.762	0.870	0.357
2	65.250	66.167	61.667	0.636	0.082	0.008
3	51.625	51.667	51.800	0.987	0.857	0.937
4	43.056	44.233	47.133	0.377	0.013	0.008

Table 18 reports the distribution of the first choices of third-ranked students under the IM Dynamic mechanism. To see if students choose schools based on where they think they can get in, regardless of their true preference, we focus on the behavior of third-ranked students because their allocation outcome differs the most across different environments. In a high correlation environment, we find that the third-ranked students always prefer school A or B, even though the best they can get is either C or D, depending on their preference types. If students choose only practical schools, we would observe few students choosing school A or B as their first choice. By contrast, if students always choose their most preferred schools even when these schools are not practical, we would observe few students choosing school C or D as their first choice. In fact, we find that the third-ranked students choose the four schools almost equally likely as their first choice, with a slightly higher frequency of choosing school A. From these findings, we conclude that students show a blend of practicality and idealism in choosing their schools. A similar behavior pattern is observed in the low correlation environment. Despite students having zero chance of getting into school B, we find that 39% of the third-ranked students' first choices are school B because school B is the most preferred college for 50% of students. Students still choose college C or D even though these two colleges are not their favorite, simply because these colleges are practical.

Table 18 Distribution of the 3rd-ranked Students' First Choices

	High Correlation			
	A	B	C	D
Best can get	0	0	50%	50%
Most preferred	50.00%	50.00%	0	0
Actual	29.33%	24.67%	24.67%	21.00%
	Low Correlation			
	A	B	C	D
Best can get	16.67%	0	33.33%	50.00%
Most preferred	50.00%	50.00%	0	0
Actual	28.67%	39.00%	27.00%	25.33%

Appendix D: Experimental Instructions

The following instructions are translated from the original Chinese version. Instructions for the IM Dynamic mechanism high correlation environment are presented first. Instructions for the Boston mechanism and the DA mechanism are identical except for the subsection of allocation methods and for Review Questions #1, #9, #10, #11; thus, only these subsections are presented. Instructions for the low correlation environments are identical except for preference type II; hence they are omitted. The Chinese version of the instructions and the instructions for the low correlation environment is available from the authors upon request.

D.1. Instructions for the IM Dynamic Mechanism, High Correlation Environment

Instructions

Please turn off your cell phone. Thank you!

This is an experiment about decision making. In this experiment, you will participate in a game of submitting college applications, and you will earn income based on your decisions. The amount of money you earn will depend upon the decisions you make and on the decisions other people make. Please read the procedure, payment rules, and allocation method carefully.

We kindly ask you not to communicate with each other during the experiment. If you have questions at any point during the experiment, please raise your hand and the experimenter will help you.

Procedure

• The experiment consists of 20 periods. Participants will be divided into several groups, and each group has 4 participants.

• Every group has 4 colleges. Each college has 1 seat. You will submit college applications to get into your desired college which gives you the highest payoff.

• In each group, there are 2 Type I participants, and 2 Type II participants.

—Payoff amounts of type I are outlined in the following table.

Seat received at college	A	B	C	D
Payoff to Type I	16	11	7	5

For Type I participants, the table reads as follows:

* You will be paid 16 points if you receive a seat of college A at the end of a period.
* You will be paid 11 points if you receive a seat of college B at the end of a period.
* You will be paid 7 points if you receive a seat of college C at the end of a period.
* You will be paid 5 points if you receive a seat of college D at the end of a period.

—Payoff amounts of Type II are outlined in the following table.

Seat received at college	A	B	C	D
Payoff to Type II	11	16	5	7

For Type II participants, the table reads as follows:

* You will be paid 11 points if you receive a seat of college A at the end of a period.
* You will be paid 16 points if you receive a seat of college B at the end of a period.
* You will be paid 5 points if you receive a seat of college C at the end of a period.
* You will be paid 7 points if you receive a seat of college D at the end of a period.

In each period, you will be randomly assigned to be Type I or Type II

• At the beginning of each period, You will be randomly matched into groups of 4. In other words, the group composition is not fixed.

- Your priority of getting into colleges will change every five periods. The participant who ranks first has the highest priority in any colleges; the participant who ranks second has the second highest priority in any colleges; the participant who ranks third has the third highest priority in any colleges; and the participant who ranks fourth has the fourth highest priority in any colleges.
- Note that your allocation in one period is independent of your allocations in other periods.
- In addition, the upper left corner of the screen will show the current period number. The upper right corner of the screen will show the remaining time in this period. When a new period starts, you will see a history of your submissions, rankings, and payoffs in previous periods.

Payment Rule

- At the end of the experiment, we will randomly select 1 out of every 5 periods for payment. This is to make sure we pay you for every ranking position. In total, 4 out of 20 periods will be selected for payment.
- Your total payment will be the sum of payments from the allocation game and your payment from the review questions.
- You will get 1 Yuan for every 1 point you earned from the allocation game, and 0.25 Yuan for every review question answered correctly.
- You will be paid in cash privately at the end of the experiment, and you are under no obligation to tell others how much you earn.

Allocation Method

- All participants enter an online system to apply for colleges at the same time. Each participant can apply for one college at a time and see other group members' real-time applications. Before the system closes, you can change your application as many times as you want.
- The system will be open for half a minute (30 seconds) in each period.
- The system has different closing times for students with different rankings. At 15 seconds, the system will close for the 1st- and 2nd-ranked students. These students will log out automatically. After 15 seconds, the 3rd- and 4th-ranked students can still change their applications. At 30 seconds, the system will close to the 3rd- and 4th- students.
- If a college receives more than 1 applicant by the time the system closes, the applicant with the highest priority will be admitted, and the remaining applicants will not be admitted to any colleges.

Below is the interface of the system. The upper left corner of the screen shows the current period. Below that are your ranking in the group, your group id, and your id. The left side of the screen shows your payoffs of getting into different colleges. The right side of the screen displays everyone's application at the moment. As shown, the student who ranks first applies for college A, the student who ranks second applies for college B, the student who ranks third applies for college C, and the student who ranks fourth applies for college D. If you want to change your application, just click the "Apply" button behind the college you want to apply to, and the system will update automatically. The upper right corner of the screen displays the remaining time in this period. The bottom of the screen shows your submissions and results of all previous periods.

Example

In this example, there are 4 students and 4 schools, each school has 1 seat. By the time the system closes, the application status is the following:

Student	Application at the deadline
Student 1	B
Student 2	C
Student 3	D
Student 4	C

Priority: student 1 has the highest priority, student 2 has the second highest priority, student 3 has the third highest priority, and student 4 has the fourth highest priority. Please allocate these students into school based on the allocation method above.

This example will be Review Question #1. Please fill your answer into the computer. We will go through this example after you submit your answer.

Please go over the instructions carefully at your own pace. Feel free to ask any questions. If you don't have any questions, you can click the "continue" button on the screen. After everyone clicks the "continue" button, the experiment will start.

Review Questions

Feel free to refer to the experimental instructions before you answer any questions. Each correct answer is worth 0.25 Yuan, and will be added to your total payoff. You can earn up to 4.25 Yuan for the Review Questions.

1. In this example, there are four students, 1, 2, 3, and 4; and four colleges, A, B, C, and D. The priorities of students are: student 1 $\succ$ student 2 $\succ$ student 3 $\succ$ student 4. By the time the system closes, students' applications are as follows:

Student	Application at the deadline
Student 1	B
Student 2	C
Student 3	D
Student 4	C

Please fill in student 1, 2, 3, 4 into the college that admits them. If a college did not admit any students, fill in 0.

College	A	B	C	D
Student				

Review Questions 2-14

2. How many participants are there in your group including you?
3. True or False: You will be matched with the same three participants in every period.
4. How many different preference types are there?
5. True or False: Your priority is determined by your ranking.
6. True or False: Your ranking is fixed for the entire 20 periods.
7. True or False: The participant who ranks the first has the highest priority.
8. True or False: Other things being equal, a lower ranking number is better than a higher ranking number.
9. True or False: You are only allowed to revise your application up to a certain number of times.
10. True or False: You can't change your application once the system closes.
11. True or False: By the time the system closes, if the college you apply to has another applicant whose priority is higher than you, you will not be admitted by any colleges.
12. How many participants are there in a group with the preference type A$\succ$B$\succ$C$\succ$D?
13. How many participants are there in a group with the preference type B$\succ$A$\succ$D$\succ$C?
14. True or False: Your preference of colleges is fixed for all 20 periods.

Answers to Review Questions

1. Answers:

College	A	B	C	D
Student	0	1	2	3

Explanation:

By the time the system closes, each school receives applications as follows:

College	A	B	C	D
Student		1	2,4	3

- School A does not receive any applications, therefore, no one is allocated to school A
- School B receives one application from student 1. Student 1 is allocated to school B.
- School C has two applicants, which exceeds its quota. Because student 2 has higher priority than student 4, college C accepts student 2 and rejects student 4. Therefore, student 2 is allocated to school C and student 4 is unallocated.
- School D receives one application from student 3. Student 3 is allocated to school D

The final allocation result is as follows:

College	A	B	C	D
Student	0	1	2	3

2. Answer: 4.

Explanation: There are 4 participants in your group including you.

3. Answer: False.

Explanation: Your group composition changes every period.

4. Answer: 2.

Explanation: There are 2 preference types.

5. Answer: True.

Explanation: Your priority is determined by your ranking

6. Answer: False.

Explanation: Your ranking rotates every 5 periods.

7. Answer: True.

Explanation: The participant who ranks the first has the highest priority.

8. Answer: True.

Explanation: Other things being equal, a lower ranking number is better than a higher ranking number.

9. Answer: False.

Explanation: You can revise your application as many times as you want.

10. Answer: True.

Explanation: You cannot change your application once the system closes.

11. Answer: True.

Explanation: By the time the system closes, if the college you apply to has another applicant whose priority is higher than you, you will not be admitted by any colleges.

12. Answer: 2.

Explanation: There are 2 participants in a group with preference type A$\succ$B$\succ$C$\succ$D.

13. Answer: 2.

Explanation: There are 2 participants in a group with preference type B$\succ$A$\succ$D$\succ$C.

14. Answer: False.

Explanation: Your preference is randomly assigned in each period.

D.2. Instructions for the Boston Mechanism, High Correlation Environment

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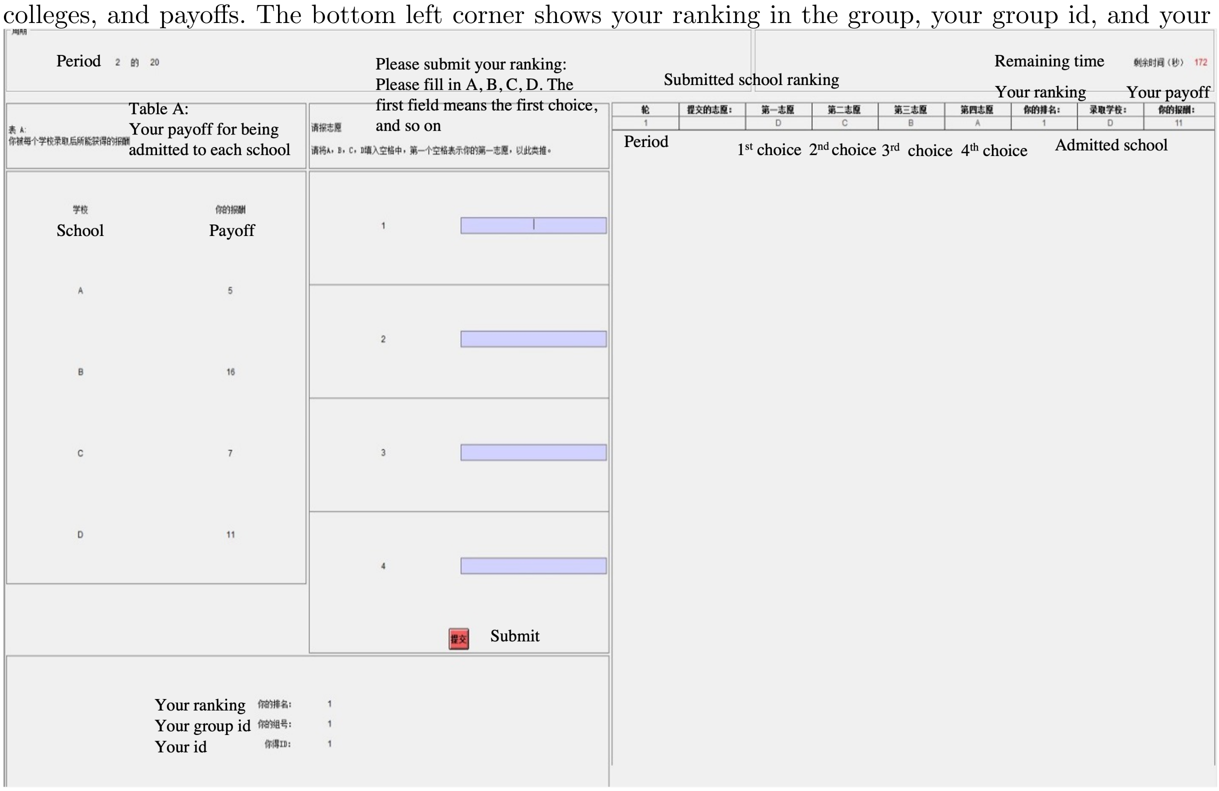
In each period, you will submit a complete ranking of the 4 colleges. The first ranked college is your first choice, the second ranked college is your second choice, the third ranked college is your third choice, and the fourth ranked college is your fourth (last) choice. After all members in your group submit their college rankings, you will be allocated to a college according to the following allocation method.

Allocation Method

- Step 1. An application to the first ranked school is sent for each participant. Each college accepts the student with the highest priority in that college. These students and their assignments are removed from the system. The remaining applications for each respective college are rejected.
- Step 2. The rejected applicants are sent to their second choice. If a college is still vacant, then it accepts the student with the highest priority and rejects the remaining applications.
- Step 3. The rejected applicants from the previous step are sent to their third choice. If a college is still vacant, then it accepts the student with the highest priority and rejects the remaining applications.
- Step 4. Each remaining participant is assigned a seat at his/her last choice.

Note that the allocation is final in each step.

Below is the interface of the system. The upper left corner of the screen shows the current period. The left side of the screen shows your payoffs of getting into different colleges. The middle section is where you submit your college ranking. The right side of the screen shows the history of your previous college rankings, admitted colleges, and payoffs. The bottom left corner shows your ranking in the group, your group id, and your id.



Example

In this example, there are 4 students and 4 schools, each school has 1 seat. The students submit the following college rankings:

	1st Choice	2nd Choice	3rd Choice	4th Choice
Student 1	D	A	C	B
Student 2	D	A	B	C
Student 3	A	B	C	D
Student 4	A	D	B	C

Priority: student 1 has the highest priority, student 2 has the second highest priority, student 3 has the third highest priority, and student 4 has the fourth highest priority. Please allocate these students into school based on the allocation method above.

This example will be Review Question #1. Please fill your answer into the computer. We will go through this example after you submit your answer.

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Review Questions

1. In this example, there are four students, 1, 2, 3, and 4; and four colleges, A, B, C and D. The priority of students is: student 1 $\succ$ student 2 $\succ$ student 3 $\succ$ student 4. The students submit the following college rankings:

	1st Choice	2nd Choice	3rd Choice	4th Choice
Student 1	D	A	C	B
Student 2	D	A	B	C
Student 3	A	B	C	D
Student 4	A	D	B	C

Please fill student 1, 2, 3, 4 into the college that admits them. If a college did not admit any students, fill in 0.

College	A	B	C	D
Student				

9. True or False: If you are accepted by a college at a step, the colleges ranked below are irrelevant.

10. True or False: If you are not rejected at a step, then you are accepted into the college you apply to at that step.

11. True or False: The allocation is final at each step.

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Answers to Review Questions

1. Answer:

College	A	B	C	D
Student	3	2	4	1

Explanation:

- Step 1. An application to the first ranked school is sent for each participant as follows:

College	A	B	C	D
Admitted				
New Applicants	3,4			1,2

College A accepts student 3 because student 3 has higher priority than student 4. College D accept student 1 because student 1 has higher priority than student 2. Student 2 and 4 are rejected

College	A	B	C	D
Admitted	3			1
New Applicants	~~4~~			~~2~~

- Step 2. The rejected applicants are sent to their second choice. Student 2 is sent to his/her second choice (college A). Student 4 is sent to his/her second choice (college D).

College	A	B	C	D
Admitted	3			1
New Applicants	2			4

Because college A and D are already full, student 2 and 4 are rejected.

College	A	B	C	D
Admitted	3			1
New Applicants	~~2~~			~~4~~

- Step 3. Student 2 is sent his/her third choice (college B). Student 4 is sent to his/her third choice (college B).

College	A	B	C	D
Admitted	3			1
New Applicants		2,4		

College B still has a seat. Because student 2 has higher priority than student 4, college B accepts student 2 and rejects student 4.

College	A	B	C	D
Admitted	3	2		1
New Applicants		~~4~~		

- Step 4. Student 4 is assigned a seat at his/her last choice (college C).

College	A	B	C	D
Admitted	3	2	4	1
New Applicants				

9. Answer: True.

Explanation: If you are accepted by a college at a step, the colleges ranked below are irrelevant.

10. Answer: True.

Explanation: If you are not rejected at a step, then you are accepted into the college you apply at that step.

11. Answer: True.

Explanation: The allocation is final at each step.

D.3. Instructions for the DA mechanism, High Correlation Environment

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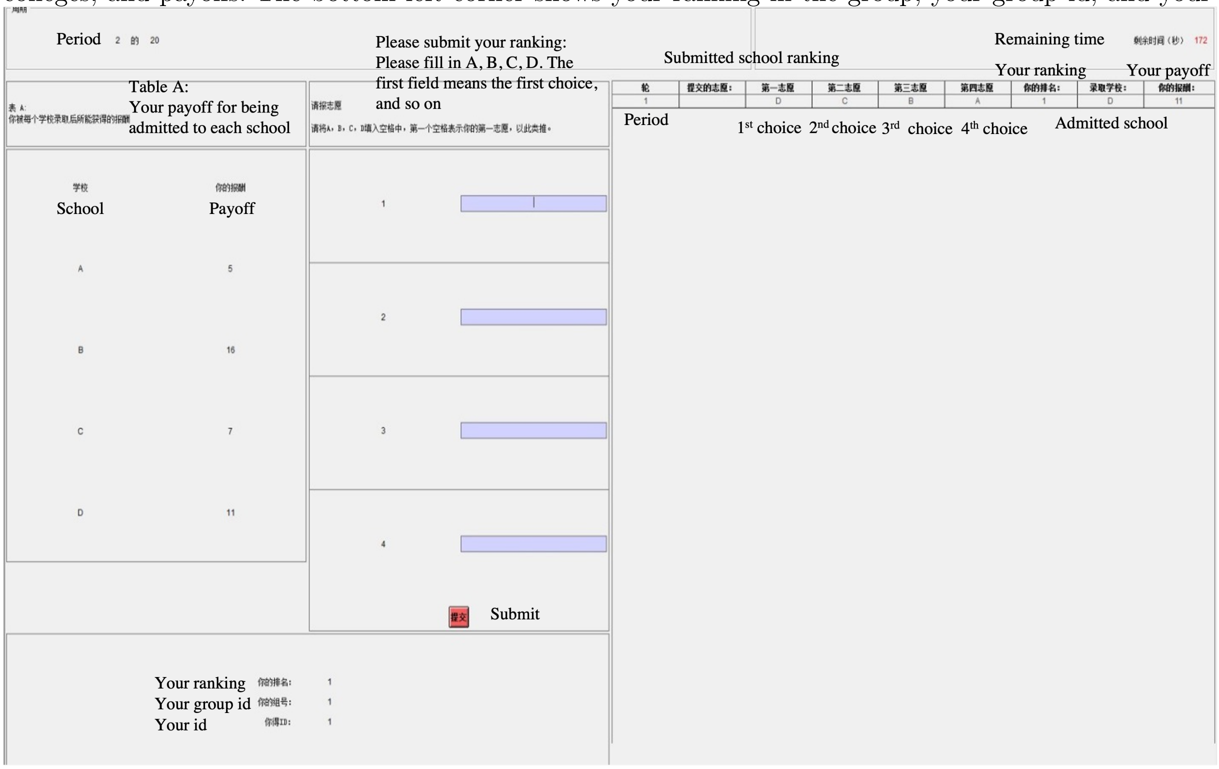
In each period, you will submit a complete ranking of the 4 colleges. The first ranked college is your first choice, the second ranked college is your second choice, the third ranked college is your third choice, and the fourth ranked college is your fourth (last) choice. After all members in your group submit their college rankings, you will be allocated to a college according to the following allocation method.

Allocation Method

- An application to the first ranked college is sent for each participant. If a college receives more than 1 application, then it temporarily retains the student with the highest priority and rejects the remaining students.
- Whenever an applicant is rejected at a college, his or her application is sent to the next highest ranked college.
- Whenever a college receives new applications, these applications are considered together with the retained application for that college. Among the retained and new applications, the one with the highest priority is temporarily held.
- The allocation is finalized when no more applications can be rejected. Each participant is assigned a seat at the college that holds his/her application at the end of the process.

Note that the allocation is temporary in each step until no one gets rejected.

Below is the interface of the system. The upper left corner of the screen shows the current period. The left side of the screen shows your payoffs of getting into different colleges. The middle section is where you submit your college ranking. The right side of the screen shows the history of your previous college rankings, admitted colleges, and payoffs. The bottom left corner shows your ranking in the group, your group id, and your id.



Example

In this example, there are 4 students and 4 schools, each school has 1 seat. The students submit the following college rankings:

	1st Choice	2nd Choice	3rd Choice	4th Choice
Student 1	D	A	C	B
Student 2	D	A	B	C
Student 3	A	B	C	D
Student 4	A	D	B	C

Priority: student 1 has the highest priority, student 2 has the second highest priority, student 3 has the third highest priority, and student 4 has the fourth highest priority. Please allocate these students into school based on the allocation method above.

This example will be Review Question #1. Please fill your answer into the computer. We will go through this example after you submit your answer.

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Review Questions

1. In this example, there are four students, 1, 2, 3, and 4; and four colleges, A, B, C and D. The priority of students is: student 1 $\succ$ student 2 $\succ$ student 3 $\succ$ student 4. The students submit the following college rankings:

	1st Choice	2nd Choice	3rd Choice	4th Choice
Student 1	D	A	C	B
Student 2	D	A	B	C
Student 3	A	B	C	D
Student 4	A	D	B	C

Please fill student 1, 2, 3, 4 into the college that admits them. If a college did not admit any students, fill in 0.

College	A	B	C	D
Student				

9. True or False: If you are temporarily retained by a college, the colleges ranked below are irrelevant.

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Answers to Review Questions

1. Answers:

College	A	B	C	D
Student	2	3	4	1

Explanation:

- An application to the first ranked college is sent for each participant.

College	A	B	C	D
Temporarily retain				
New Applicants	3,4			1,2

Because colleges A and D receive more than 1 application, they temporarily retain the student with the highest priority and reject the remaining students. College A temporarily retains student 3. College D temporarily retains student 1. Students 2 and 4 are rejected.

College	A	B	C	D
Temporarily retain	3			1
New Applicants	$\cancel{4}$			$\cancel{2}$

- Student 2 and 4's applications are sent to their 2nd choice college (college A and college D, respectively).

College	A	B	C	D
Temporarily retain	3			1
New Applicants	2			4

- College A receives new application from student 2. Student 2's application is considered together with student 3's application. Because student 2 has higher priority than student 3, college A temporarily retains student 2. Student 3 is rejected. College D receives new applicant from student 4. Student 4's application is considered together with student 1. Because student 1 has higher priority than student 4. College D temporarily retains student 1. Student 4 is rejected.

College	A	B	C	D
Temporarily retain	2, $\cancel{3}$			1
New Applicants				$\cancel{4}$

- Student 3's application is sent to his/her 2nd choice college (college B). Student 4's application is sent to his/her 3rd choice college (college B).

College	A	B	C	D
Temporarily retain	2			1
New Applicants		3,4		

- College B receives applications from students 3 and 4. Because student 3 has higher priority, college B temporarily retains student 3. Student 4 is rejected.

College	A	B	C	D
Temporarily retain	2	3		1
New Applicants		$\cancel{4}$		

- Student 4's application is sent to his/her 4th choice college (college C).

College	A	B	C	D
Temporarily retain	2	3		1
New Applicants			4	

- College C receives the application from student 4. Because this is the only application, college C temporarily retains student 4.

College	A	B	C	D
Temporarily retain	2	3	4	1
New Applicants				

- At this time, no more applicants can be rejected. The allocation is finalized. Each participant is assigned a seat at the college that holds his/her application at the end of the process.

College	A	B	C	D
Admitted	2	3	4	1

9. Answer: False.

Explanation: If you are temporarily retained by a college, you might be rejected later and sent to the next college on your list.

10. Answer: False.

Explanation: If you are not rejected at a step, you might be rejected later and sent to the next college on your list.

11. Answer: False.

Explanation: The allocation is temporary in each step until no one get rejected.

Appendix E: Chinese College Admissions Mechanism

In this table, we present the mechanisms used across different provinces in China. These mechanisms do not include tier 0, ethnic minority, military, art, PE students, or students who qualify for the national anti-poverty program. All numbers listed below are for four-year college admissions; two-year college admissions are omitted. Semicolons are used to separate different tiers. Commas are used to separate different groups within each tier. Some provinces have three tiers, while others have two tiers.

Table 19 Chinese College Admission Mechanism by Province in 2016

Province	Mechanism Type	Sequence	No. of Applications in 2016
Beijing	symmetric parallel	$(6;6;6;\cdots)$	61200
Tianjin	symmetric parallel	$(9,9;9,9;9;\cdots)$	60000
Jiangsu	symmetric parallel	$(5;5;5;\cdots)$	360400
Zhejiang	symmetric parallel	$(5;5;5;\cdots)$	307400
Shandong	symmetric parallel	$(6;6;\cdots)$	710000
Henan	symmetric parallel	$(6;6;6;\cdots)$	820000
Hubei	symmetric parallel	$(9;9;\cdots)$	361000
Hunan	symmetric parallel	$(5;5;5\cdots)$	401600
Guangxi	symmetric parallel	$(6;6;\cdots)$	330000
Hainan	symmetric parallel	$(6;6;6;\cdots)$	60400
Chongqing	symmetric parallel	$(6;6;\cdots)$	249000
Sichuan	symmetric parallel	$(6;6;\cdots)$	570000
Yunnan	symmetric parallel	$(5;5;5;\cdots)$	281100
Tibet	symmetric parallel	$(10;10;10;\cdots)$	23976
Shǎnxi	symmetric parallel	$(6;6;6;\cdots)$	328000
Gansu	symmetric parallel	$(6;6;6;\cdots)$	296000
Ningxia	symmetric parallel	$(4;4;4;\cdots)$	69100
Shanghai	asymmetric parallel	(1(peking U or Tsinghua U); $10;\cdots)$	51000
Anhui	asymmetric parallel	$(6;6;4;\cdots)$	509900
Fujian	asymmetric parallel	$(6;10;\cdots)$	175000
Jiangxi	asymmetric parallel	$(6;8;\cdots)$	360600
Guangdong	asymmetric parallel	$(7,4;7,4;\cdots)$	733000
Guizhou	asymmetric parallel	$(6;8;8;\cdots)$	373800
Hebei	asymmetric parallel	$(5;10;\cdots)$	423100
Shanxi	asymmetric parallel	$(5,5,5;8,5,5;\cdots)$	330000
Liaoning	asymmetric parallel	$(7;9;\cdots)$	218200
Heilongjiang	asymmetric parallel	$(5,1;5,1;5,1;\cdots)$	197000
Xinjiang	asymmetric parallel	$(6;6;1;\cdots)$	166100
Jilin	parallel&sequential	(5, 2(sequential); $1,7,1,3;1,6;\cdots)$	148000
Qinghai	parallel&sequential	(2(sequential); 2(sequential); $5;\cdots)$	44600
Inner Mongolia	dynamic adjustment		201100