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School Choice with Consent: An Experiment*

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Abstract

Public school choice often yields student assignments that are neither fair nor efficient. The efficiency-adjusted deferred acceptance mechanism (EADAM) allows students to consent to waive priorities that have no effect on their assignments. A burgeoning recent literature places EADAM at the center of the trade-off between efficiency and fairness in school choice. Meanwhile, the Flemish Ministry of Education has taken the first steps to implement this algorithm in Belgium. We provide the first experimental evidence on the performance of EADAM against the celebrated deferred acceptance mechanism (DA). We find that both efficiency and truth-telling rates are higher under EADAM than under DA, even though EADAM is not strategy-proof. When the priority waiver is enforced, efficiency further increases, while truth-telling rates decrease relative to the EADAM variants where students can dodge the waiver. Our results challenge the importance of strategy-proofness as a prerequisite for truth-telling and portend a new trade-off between efficiency and vulnerability to preference manipulation.

JEL Codes: C78, C92, D47, I20, K10.

Keywords: efficiency-adjusted deferred acceptance algorithm, school choice, consent, default rules, law.

1 Introduction

One of the most prominent mechanisms achieving a stable matching outcome is Gale and Shapley's student-proposing deferred acceptance algorithm (Gale and Shapley 1962), henceforth referred to as DA. Several school districts in the United States and other countries have

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adopted some version of DA, not least for its fairness virtues (Pathak and Sönmez 2013; Abdulkadiroğlu, Pathak, and Roth 2005; Abdulkadiroğlu et al. 2005).

On the one hand, DA produces stable outcomes, which means that DA completely suppresses priority violations (Gale and Shapley 1962). This implies that the assignment procedure always fully respects the criteria set by lawmakers or school authorities. By the same token, stability eliminates justified envy and thus mitigates the motives for legal action against the assignment procedure or the outcome it produces.[1] On the other hand, DA is strategy-proof, which means that it is a weakly dominant strategy for students to rank schools according to their true preferences (Dubins and Freedman 1981; Roth 1982). DA thus enhances procedural fairness and creates a level playing field, as it is impossible for sophisticated students to manipulate the outcome of the assignment procedure at the expense of less sophisticated students (Pathak and Sönmez 2008).

DA, however, comes at an important cost: it is Pareto inefficient (Balinski and Sönmez 1999). The inefficiency can be potentially quite severe (Kesten 2010) and is further exacerbated when priorities involve ties (Erdil and Ergin 2008). Empirical evidence shows that such welfare losses are a serious practical concern. Abdulkadiroğlu, Pathak, and Roth (2009) show for the New York City High School match in 2006-2007 that approximately 4300 eight-graders could have been assigned to more preferred options without hurting other students.

Kesten (2010) traced the source of the welfare loss under DA to certain priorities that have no effect on the assignment of the student holding the priority. He proposed an *efficiency-adjusted deferred acceptance mechanism* (EADAM) that allows students to waive such priorities, thereby allowing DA to recover the welfare losses. More specifically, DA is based on iterated applications of students in the order of their preferences. As further explained below, EADAM systematically "revises" the applications under DA whenever they give rise to a *rejection cycle* (see Section 2.2). Although a student's priority at a school does not affect her own final assignment, it can make other students worse off. EADAM solicits *consent* from such students to waive their priority for such a school if a situation of this type arises. A priority waiver only takes effect if the respective student consents.[2] Most importantly, incentives for consenting are not in conflict with individual welfare: a student consenting to the priority waiver causes no harm to herself but may help other students as a consequence and can thus increase the efficiency of assignments.[3]

1. Judicial review of public assignment procedures is a fundamental right in many jurisdictions. Under Art. 6 of the European Convention of Human Rights, for example, any public assignment decision can be attacked in court.

2. Through the lens of Kantian ethics, consent is an expression of autonomy that makes certain intrusions into individual interests permissible, thus serving as a legitimacy requirement. The basic variant of EADAM never "violates" priorities because each waiver is justified by way of consent. Post-allocation trades, by contrast, do "violate" priorities because a student i_1 can lose her priority to another student i_2 as a consequence of a trade between i_2 and a student i_3 without having agreed to their trade.

3. In this sense, consenting is akin to deceased organ donation where an individual donor can benefit others at no own material cost. Moreover, EADAM can be characterized as a specific type of *nested coordination game*. As in a public goods game, the more students consent, the better for them collectively. However, unlike in a standard

EADAM not only became a serious contender to DA as evidenced by a growing literature that puts it at the center of the stability and efficiency trade-off (see Section 2.1) but also sparked the interest of policy makers. In 2019, the Flemish Ministry of Education undertook the first attempt to implement EADAM in the school choice system in Flanders, which is home to more than 68% of the population of Belgium.[4] This decision was motivated by the desire to implement a set of legal rules that appeared to effectively insist on both efficiency and stability. According to statutory law:[5]

> *[...] b) a student who is favorably ranked at several schools or locations is assigned to the most preferred school or location and is removed from the less preferred schools or locations; c) after the final assignment, there can be no students who have been assigned to each other's higher choice; d) after the final ranking of the unsuccessful students, there can be no students with a higher [priority] at each other's higher choice school or location.*

This provision was conjointly adopted with other rules mandating the protection of under-represented groups, that is, typically students from vulnerable populations or socially disenfranchised families.[6] The Flemish Ministry of Education undertook several efforts to implement EADAM while currently expecting a legal reform to start implementation.

In this article, we provide the first experimental evidence on the performance of EADAM and explore how EADAM affects efficiency, stability and truth-telling relative to DA. We investigate the performance of EADAM relative to DA in three markets that differ in their manipulation incentives and the number of rejection cycles. In the first market, no student can manipulate EADAM to her benefit and there are three rejection cycles. In the other two markets, some students have incentives to manipulate EADAM and the rejection cycles are zero and three, respectively.

Leveraging insights from behavioral economics, our study is also designed to understand whether consent rates under EADAM, and thus efficiency, can be increased by means of a gentle nudge. Drawing on evidence revealing a tendency to stick with the status quo (*status quo bias*), we manipulate the default rules used to legitimize the priority waiver and compare the original variant of EADAM where students can consent to a priority waiver (*opt-in default rule*) with a variant of EADAM where consent is the default and students can object to a priority waiver (*opt-out default rule*). Regardless of how a priority waiver takes effect, students always know that their decision – consenting or not objecting – will have no effect on their assignment but may help other students. Finally, we explore the effect of a variant of EADAM where the priority waiver is enforced.

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public goods game, there is no conflict between private and social interest.

4. Personal communication with Estelle Cantillon and Thomas Wouters (Flemish Ministry of Education).

5. Art. 253/16 of the Decree of 17 May 2019 (2019041360) amending the primary education decree of 25 February 1997, the Codex Secondary Education of 17 December 2010 and the Codification of certain provisions for education of 28 October 2016 regarding the right of enrollment.

6. See Art. 253/15 of the decree.

Our results are intended to contribute to the research areas of market design and behavioral economics, especially to experimental research exploring the impact of matching mechanisms on truth-telling and efficiency (see Chen and Sönmez 2006; Pais and Pintér 2008). First, we find that assignments are more efficient under all variants of EADAM than under DA. This result is not affected by whether truth-telling is an equilibrium in the specific market or not. Our analysis also suggests that the differences in efficiency do not mechanically result from the reduction of rejection cycles under EADAM. Rather, the efficiency increase observed under EADAM is in part caused by students who report their preferences truthfully, that is, the behavioral response of students to EADAM.

Second, we observe a relatively high prevalence of preference misrepresentation under DA, which is in line with existing evidence (see Hassidim et al. 2017). Interestingly, students are more likely to report their preferences truthfully under EADAM than under DA. This result holds irrespective of whether the specific market presents incentives for students to manipulate EADAM and irrespective of the number of rejection cycles.

We also observe that the students who benefit the most from EADAM in terms of individual welfare are more likely to report their preferences truthfully. Thus, the increase in truthfulness under EADAM seems to be at least partly driven by the welfare improvements it generates. Our results are in line with emerging experimental evidence showing that non-strategy-proof mechanisms may yield higher truth-telling rates than strategy-proof mechanisms. Klijn, Pais, and Vorsatz (2019), Bó and Hakimov (2020) and Hakimov and Raghavan (2020) compare DA to a dynamic version of DA where students apply for one school at a time. They find that, even though dynamic DA is not strategy-proof, it yields higher truth-telling rates than DA. Afacan et al. (2022) compare DA to the iterative deferred acceptance (IDA) mechanism with two iterations, which is not strategy-proof. They find that under IDA strategic students who play undominated strategies cannot gain at the expense of truthful students.[7] Cho, Hafalir, and Lim (2022) compare DA to the stable improvement cycle (SIC) and the choice-augmented deferred acceptance mechanism (CADA) and find no difference in truth-telling rates and higher efficiency of SIC over DA.

Our findings indicate that strategy-proofness may be far less important a design prerequisite for the optimal matching to emerge in school choice than previous literature suggests.[8] This has important implications for the protection of vulnerable students who are most likely to be harmed when failing to strategize or strategize well: our results suggest that it may be possible to relax the strategy-proofness standard at no expense to unsophisticated applicants.

Besides confirming the emerging finding that non-strategy-proof mechanisms may reduce

7. A similar result has been found in the auction literature. Subjects manipulate less under core-selecting package auctions than under the VCG mechanism, although only the latter is strategy-proof (Heczko, Thomas, and Marion 2018).

8. Budish and Cantillon (2012) raise a similar point in the context of course allocation. They use theory and field data to study the draft mechanism for allocating courses at Harvard Business School. They find that although the draft is manipulable in theory, it leads to higher welfare than its widely studied strategy-proof alternative. Unlike EADAM, however, the draft is highly manipulable and these manipulations cause significant welfare losses.

manipulations, our experiment contributes a novel perspective on the potential drivers of this finding. While non-strategy-proof mechanisms such as dynamic DA and IDA may yield higher truth-telling rates because they are easier for participants to understand, EADAM may do so because of its complexity. Being faced with a mechanism that is hard to successfully manipulate, participants may just resort to the default strategy of truthfully reporting their preferences.

Third, when comparing the variants of EADAM, we find that enforcing priority waivers generates an increase in efficiency and a decrease in truth-telling rates. We see this as evidence of a behavioral effect that points to a hitherto rarely considered trade-off between efficiency and vulnerability to preference manipulation.

Fourth, we observe that more than half of the students consent to waive their priorities, both under EADAM with an option to consent (opt-in default rule) and under EADAM with consent by default (opt-out default rule). This is consistent with evidence on *costless altruism* (Güth 2010; Güth, Levati, and Ploner 2012; Ferguson et al. 2019; Fan, Li, and Zhou 2020; Engel and Van Lange 2021), that is, individual behavior that benefits others at no own material cost.[9] However, setting consent as the default option does not increase consent rates, although our data suggest that the effect of the default rule may increase over time. At least in our matching market, we see little evidence of the power of defaults – a centerpiece in behavioral economics.

Finally, our article provides novel evidence on the possibility and limits of implementing complex algorithms. EADAM is far more complex than most mechanisms usually probed in lab experiments. Understanding how far the complexity of a mechanism can be pushed without sacrificing implementability, tractability and its fairness virtues, is key not just with a view to successful market design but also to ensure compliance with the legal rules guiding the admissions procedure. More generally, our results provide important evidence for policy makers and school authorities keen on implementing a school admissions procedure that mitigates the stability and efficiency trade-off with little disruption to the compelling stability and incentive properties of DA.

An alternative way of addressing the inefficiency arising from DA is to allow students to trade the seats they have been assigned under DA once the assignment procedure is completed.[10] And indeed, several school systems allow for swaps and trades outside of the primary assignment procedure on a secondary, post-match marketplace, sometimes referred to as a *scramble* (Roth 2013; May et al. 2014).[11] Assuming transaction costs to be zero and absent

9. Those who did not consent to waive priorities may have been driven by lack of trust in the mechanism or by spite. In our view, lack of trust is a more plausible explanation than spite.

10. Alternatively, an efficient procedure such as the the top trading cycles (TTC) mechanism (Abdulkadiroğlu and Sönmez 2003) can be adopted at the expense of stability. However, such procedures have not been viewed as favorably as DA by practitioners. For example, a memo from the superintendent of Boston school district articulated how DA was chosen over TTC due to concerns over the way priorities are treated (Abdulkadiroğlu et al. 2005). Similarly, New Orleans abandoned TTC in favor of DA one year after its adoption (Abdulkadiroğlu et al. 2020).

11. A prominent example for a scramble is the Pharmacy Online Residency Centralized Application Service (PhORCAS) of the American Society of Health-System Pharmacists (ASHP) Resident Matching Program. "The

any tendency to stick with the status quo (*status quo bias*) hampering the transfer of currently assigned seats, this type of post-allocation Coasian trading would indeed produce a more efficient allocation (Coase 1960).

However, such trades face two major problems. First, by trading, students would get another chance at obtaining a preferred seat. While a trade would enable the trading students to improve their assignment, it would necessarily come at the expense of other students who cannot or do not want to trade. Trades could thus violate the priorities of students not participating in the trade. In *Association OSVO v. Municipality of Amsterdam*, the Amsterdam Court of Appeals therefore held that students are not allowed to trade seats that were assigned to them under a variant of DA with multiple tie-breaking used until 2016 (de Haan et al. 2018; de Haan 2017):[12]

> *If swapping were allowed, (...) a student with an unfavorable lottery number [lower priority] could bypass a student with a more favorable lottery number [higher priority]. Under these conditions, equal opportunities are no longer guaranteed. (...) The admissions system then no longer meets the requirements of consistency and transparency. This would be incompatible with the general interest of all students.*

Second, allowing trades encourages preference manipulations, thus eliminating the strategy-proofness of DA. As the Amsterdam Court of Appeals noted, students could apply at popular schools and attempt to obtain a highly valued seat in order to later use it as a bargaining chip in a trade:

> *If students know that swapping is allowed after the assignment, it would be optimal for them to rank popular schools (not necessarily their own preferences) high on their preferred list. If they are then assigned to one of those schools, that seat can be used in a trade. (...) Even then, the system does not work properly, because it reduces the chances of those who register in accordance with their true preferences.*[13]

Similar concerns were raised by the Boston Public Schools when redesigning the Boston school admissions system in 2005 (Abdulkadiroğlu et al. 2005) and by the Chicago Public Schools when reforming their selective high school mechanism in 2009 (Pathak and Sönmez 2013). These considerations tie in with the general finding that there is no mechanism that

Post Match (also known as "The Scramble") is the last phase of the PhORCAS application cycle. Post Match is available to applicants who did not match during Phase I, Phase II, or to new applicants who decide to apply."

12. Instantie Rechtbank Amsterdam, 30-06-2015, Zaaknummer C/13/588653 / KG ZA 15-718, paras. 4.8. and 4.9

13. A similar problem arises when Gale's top trading cycles algorithm (Shapley and Scarf 1974) is implemented once students have been assigned places under DA. Allowing a trade of priorities would not be possible without simultaneously violating the priorities of some students and thus diluting the admissions criteria (Kesten 2010). Ultimately, such a system would enable students to gain control over the admissions criteria that were initially designed in order to achieve specific policy goals (e.g. prioritizing students from walk zones, prioritizing siblings, or ensuring a diverse student body) and were therefore not intended to be at the students' disposal.

eliminates justified envy and yields a Pareto efficient matching at the same time (Roth 1982; Balinski and Sönmez 1999; Abdulkadiroğlu and Sönmez 2003).

The remainder of this article proceeds as follows. Section 2 discusses the theoretical properties of EADAM and illustrates how it operates through an example. Section 3 presents the experimental design and the hypotheses. Section 4 presents the results of the experiment. Section 5 concludes.

2 EADAM

2.1 Properties

A burgeoning theoretical literature has highlighted a number of attractive properties of EADAM. One strand of literature shows that when the objective is efficiency, EADAM is *the* central mechanism to achieve several natural axioms of fairness such as *legality* (Ehlers and Morrill 2020), *essential stability* (Troyan, Delacrétaz, and Kloosterman 2020), *weak stability* (Tang and Zhang 2021),[14] *α-equity* (Alcalde and Romero-Medina 2017), *sticky stability* (Afacan, Aliogullari, and Barlo 2017), and *priority neutrality* (Reny 2022). Tang and Yu (2014) propose an efficient and simpler version of EADAM.[15] EADAM is the unique minimally stable among efficient mechanisms in both an ordinal sense (Kwon and Shorrer 2020; Tang and Zhang 2021) and a cardinal sense (Doğan and Ehlers 2021).

EADAM has also been advocated as a useful tool for restoring welfare losses under weak priorities (Kesten 2010), finding a strictly strong Nash equilibrium outcome of DA and the optimal von Neumann-Morgenstern stable matching in a one-to-one matching market (Bando 2014), affirmative action in school choice (Doğan 2016), organ allocation, that is, settings with both social and private endowments (Kwon and Shorrer 2020), and under substitutable choice functions (Ehlers and Morrill 2020).

EADAM, however, is not strategy-proof. This entails that the desirable features of EADAM cannot be guaranteed unless students are truthful. Strategy-proofness is not always an effective enabler of truth-telling. Recent experimental evidence documents a widespread prevalence of preference misrepresentation even when truth-telling is a weakly dominant strategy (see Hakimov and Kübler 2021; Featherstone, Mayefsky, and Sullivan 2021). Even under mechanisms based on DA, incentives to report preferences truthfully do not seem to effectively mitigate attempts to game the system among medical students applying under the National Resident Matching Program (Rees-Jones 2018; Rees-Jones and Skowronek 2018) nor among students applying to graduate programs in psychology in Israel (Hassidim, Romm, and Shorrer

14. Tang and Zhang (2021) also show that EADAM is *self-constrained optimal* at each problem in the sense that its outcome Pareto dominates any other assignment that is more stable.

15. From a computational perspective, Faenza and Zhang (2022) introduce a fast algorithm and show that EADAM can be run with similar time complexity as Gale and Shapley's deferred acceptance algorithm.

2021).[16]

While not being strategy-proof, EADAM has nonetheless good incentive properties: it is *not obviously manipulable* under complete information (Troyan and Morrill 2020) and harder to manipulate than well-known mechanisms (Decerf and Van der Linden 2021). Moreover, truth-telling is a weakly dominant strategy under low information (Ehlers and Morrill 2020). In this vein, Reny (2022) shows that truth-telling is an ordinal equilibrium and offers participants explicit advice to be truthful under EADAM. When incentives to consent are built into the mechanism design problem, within a large class of *consent-proof* mechanisms (that is, a consenting student is never hurt by her decision), EADAM is the unique constrained efficient mechanism that is consent-proof (Dur, Gitmez, and Yılmaz 2019). EADAM is also *regret-free truth-telling* (Chen and Möller 2021), a weaker incentive property than strategy-proofness introduced by Fernandez (2020). Finally, Shirakawa (2023) characterizes EADAM based on an immunity to collective misreports of students: no group of students can gain by trimming their preferences from above (e.g., dropping top choices) or below (e.g., truncation). This gives further support to EADAM's good incentives properties.

2.2 A Simple Example

Let $I \equiv \{i_1, ..., i_n\}$ denote a finite set of students and $S \equiv \{s_1, ..., s_m\}$ denote a finite set of schools. Each student i has strict preferences over schools, denoted by P_i, and each school has strict priorities over students, denoted by $\succ_s$. We assume that each school has a finite number of available seats, q_s, where the number of students n does not exceed the number of available seats, $n \leq \sum_{s \in S} q_s$. A school choice problem is a pair $((\succ_s)_{s \in S}, (P_i)_{i \in I})$ consisting of a collection of priority orders and preference profiles.

A school choice *mechanism* φ is a systematic procedure designed to solve a school choice problem by producing a *matching* μ of students and schools at which each student is assigned to one school and the number of students assigned to a school does not exceed the number of available seats at that school.

With respect to the matching outcome, there are two core properties a mechanism can be designed to satisfy: stability and Pareto-efficiency. A matching μ that assigns a student j at a school s is *stable* if there is no student i who prefers school s over the school she is currently assigned to while having higher priority than student j at school s. A matching μ is *Pareto-efficient* if there is no alternative matching that can improve at least one student's assignment without making any other student worse off.

With respect to the mechanism, the core property is strategy-proofness. A mechanism φ is

16. An alternative method to increase truth-telling rates is to implement *obviously strategy-proof* (Li 2017), *one-step simple* or *strongly obviously strategy-proof* mechanisms (Pycia and Troyan, forthcoming) that facilitate optimal choices for non-sophisticated individuals. However, since obvious strategy-proofness is more demanding than strategy-proofness, such a pursuit only adds new challenges to the existing incentive-efficiency-fairness trade-off: there is no obviously strategy-proof mechanism achieving stable outcomes (Ashlagi and Gonczarowski 2018).

strategy-proof if it is a dominant strategy for each student to report her preferences truthfully, that is, if no student can ever benefit from misreporting her preferences for schools.

To illustrate EADAM and the welfare gains it entails, we present a simple example provided by Kesten (2010).[17] Let $I \equiv \{i_1, i_2, i_3\}$ and $S \equiv \{s_1, s_2, s_3\}$, where each school has only one seat. The priorities for the schools and the preferences of the students are given as follows:

$\succ_{s_1}$	$\succ_{s_2}$	$\succ_{s_3}$
i_3	i_1	$\vdots$
i_1	i_2	
i_2	i_3	

P_{i_1}	P_{i_2}	P_{i_3}
s_1	s_1	s_2
s_2	s_2	s_1
s_3	s_3	s_3

The EADAM algorithm proceeds as follows:

Round 0: Run the DA algorithm. At each step, students apply to their most-preferred schools from which they are not yet rejected and schools tentatively admit students with the highest priority up to the number of available seats. The steps are illustrated below. Students tentatively admitted at a school are inserted in a box.

Step	s_1	s_2	s_3
1	$\boxed{i_1}, i_2$	$\boxed{i_3}$	
2	$\boxed{i_1}$	$i_3, \boxed{i_2}$	
3	$i_1, \boxed{i_3}$	$\boxed{i_2}$	
4	$\boxed{i_3}$	$i_2, \boxed{i_1}$	
5	$\boxed{i_3}$	$\boxed{i_1}$	$\boxed{i_2}$

The matching produced by DA in Step 5 is stable but Pareto-inefficient. The efficiency loss is caused by students whom we refer to as *interrupters*. An interrupter is a student who applies to a school causing another student to be rejected, while she eventually gets rejected from that school. For example, student i_1 is an interrupter because starting at Step 1, she applies to school s_1 kicking out student i_2 who then applies to school s_2 kicking out student i_3 who in turn applies to school s_1 kicking out i_1. It is easy to see the welfare loss due to the application of i_1 to s_1. While this does not secure i_1 the seat at s_1, it displaces i_2 and i_3 who would otherwise get into their top choices. A similar situation occurs due to the application of i_2 to s_2 in Step 2.

Formally, if a student i is tentatively accepted at a school s in Step t and rejected in a later Step t', and if at least one other student j is rejected at that school in a Step l such that $t \leq l \leq t'$, student i is an *interrupter* at school s and the pair (i, s) is an *interrupting pair* of Step t'. An interruption implies that an application at a school in Step t does not benefit the student but initiates a rejection chain that hurts other students. The interrupter causes an inefficient assignment at

17. Appendix B.1 and B.2 present and explain the markets we investigate in the experiment.

no gain to herself. In our example there are two interrupting pairs: (i_1, s_1) (student i_2 was rejected while student i_1 was tentatively placed at school s_1) and (i_2, s_2) (student i_3 was rejected while student i_2 was tentatively placed at school s_1). Any efficiency loss caused by an interrupting pair can be recovered without any harm by soliciting consent (actively, passively, or forcibly) from the associated interrupter to remove the corresponding school from her rank-order preference list. In particular, we proceed according to the following rules:

Round 1: Find the last step of the DA algorithm run in Round 0 in which a consenting interrupter is rejected from the school for which she is an interrupter. Identify all interrupting pairs of that step, each of which contains a consenting interrupter. If there are no interrupting pairs, then stop. For each identified interrupting pair (i, s), remove school s from the rank-order preference list of student i without changing the relative order of the remaining schools. The rank-order preference lists of the other students remain unchanged. Rerun DA with the updated rank-order preference lists.

Round k: Find the last step of the DA algorithm run in Round $k-1$ in which a consenting interrupter is rejected from the school for which she is an interrupter. Identify all interrupting pairs of that step, each of which contains a consenting interrupter. If there are no interrupting pairs, then stop. For each identified interrupting pair (i, s), remove school s from the rank-order preference list of student i without changing the relative order of the remaining schools. The rank-order preference lists of the other students remain unchanged. Rerun DA with the updated rank-order preference lists.

End: The algorithm ends when there are no more interrupting pairs. Admissions now become final.

We first identify the last interrupting pair, which is (i_2, s_2) in our example. If consent is acquired, then school s_2 is removed from the rank-order preference list of student i_2. Then we rerun DA. There is no interrupting pair and we obtain a Pareto-efficient matching at Step 2. Each student is assigned to her top choice.

Step	s_1	s_2	s_3
1	$\boxed{i_1}, i_2$	$\boxed{i_3}$	
2	$\boxed{i_1}$	$\boxed{i_3}$	$\boxed{i_2}$

3 Experimental Design

In this section, we present our experimental design and our hypotheses. Our experiment is designed to assess the performance of EADAM relative to DA. Both DA and EADAM are implemented in a non-manipulable market (Section 3.1) and in two manipulable markets (Section 3.2). The non-manipulable market has a key advantage: it enables us to compare DA and EADAM in a setting where, despite their intrinsically different incentive properties, neither of the mechanisms can be manipulated. This is, in a sense, the most rigorous test, as it allows for a comparison of truth-telling behavior across different mechanisms while keeping the mechanisms' actual manipulability constant. However, the non-manipulability of the market might affect truth-telling rates. To address this concern, we also analyze two manipulable markets. The first manipulable market (Market 1) has no interrupters, while the second manipulable market (Market 2) has three interrupters like our non-manipulable market. This allows us to evaluate the impact of the market's manipulability on truth-telling rates, as well as the impact of the number of interrupters on truth-telling and efficiency.

3.1 Non-Manipulable Market

We begin by exploring a non-manipulable market with three interrupters (see Appendix B.1). We deliberately opted for a matching market with a sufficient number of interruptions in order to generate enough potential for efficiency adjustments under EADAM and thus make the comparison between DA and EADAM meaningful. There are five schools, s_1, s_2, s_3, s_4, s_5, where each school has only one seat, and five student types, i_1, i_2, i_3, i_4, i_5. Preferences and priorities are given as follows.

Points	P_{i_1}	P_{i_2}	P_{i_3}	P_{i_4}	P_{i_5}
25	s_1	s_2	s_4	s_3	s_3
18	s_3	s_4	s_1	s_1	s_2
12	s_4	s_1	s_2	s_2	s_1
7	s_2	s_5	s_3	s_5	s_4
3	s_5	s_3	s_5	s_4	s_5

	$\succ_{s_1}$	$\succ_{s_2}$	$\succ_{s_3}$	$\succ_{s_4}$	$\succ_{s_5}$
1^{st}	i_2	i_4	i_3	i_4	i_1
2^{nd}	i_4	i_1	i_2	i_5	i_3
3^{rd}	i_1	i_2	i_4	i_3	i_2
4^{th}	i_5	i_3	i_5	i_2	i_5
5^{th}	i_3	i_5	i_1	i_1	i_4

The payoffs for students and the priorities of schools are presented above. Payoffs range from 25 points to 3 points, the conversion rate being 1 point = 0.25 Euros. Preferences and priorities are exogenous and heterogeneous by design: each student has different preferences for schools, and each school has different priorities over students.

Students have complete information and therefore know the payoff table, the priority table, the availability of seats, and the exact modus operandi of the respective mechanism before submitting their rank-order preference lists.

To facilitate learning and test for convergence to predicted behavior, the experiment runs over 20 periods. Each participant is assigned a student type before the first period and keeps that student type throughout the experiment. This design feature is intended to prevent the risk of confusion associated with reassigning a new student type in each period and facilitates learning. Moreover, each participant is assigned to a matching group composed of 10 participants before the first period. At the beginning of each period, each participant is randomly assigned to a different group of 5 students randomly drawn from the matching group (each matching group contains two participants from each type).[18] This design feature is crucial to mitigate the dependence problem resulting from the repeated interaction of students. With 500 participants taking part in our experiment, we are able to generate 50 matching groups and thus 50 independent observations: 14 independent observations for EADAM Consent and 12 independent observations for each of the other three treatments.

Students submit a complete rank-order preference list for schools. Neither can students include the same school more than once nor are they allowed to truncate their rank-order preference list, as this may have created further incentives to misrepresent their preferences under DA (see Calsamiglia, Haeringer, and Klijn 2010) – our baseline treatment. In the EADAM treatment, participants are asked whether they consent to waive their priorities. Interrupting pairs are only eliminated if interrupting students *consent* (active choice). This corresponds to the initial version of EADAM as proposed by Kesten (2010), and we refer to it as EADAM Consent. We also test the performance of two variants of EADAM. Our four treatments are described below.

DA: Students submit their rank-order preference lists under the student-proposing version of DA. This treatment serves as our baseline.

EADAM Consent: Students submit their rank-order preference lists under EADAM. In each period, all students are offered the option to consent to waive their priorities before submitting their rank-order preference lists. If they consent, all schools at which they turn out to be interrupters are removed from their rank-order preference lists. Otherwise, no school is removed. Efficiency-adjustments are therefore only possible if interrupting students make the active choice to consent. This is our core treatment and tests the mechanism developed by Kesten (2010).

EADAM Object: Students submit their rank-order preference lists under a variant of EADAM. In each period, all students are offered the option to object to waive their priorities before submitting their rank-order preference lists. If they do not object, all schools at which they turn out to be interrupters are removed from their rank-order preference lists. Otherwise, no school is removed. Efficiency-adjustments are therefore only possible

18. We opted for groups of 5 because with smaller size groups we would not have observed enough interruptions to infer anything meaningful from the comparison between DA and EADAM.

if interrupting students remain passive and decide not to object. This treatment is motivated by the extensive evidence on status quo bias: if students have a preference for the default option, making consent the default will increase the efficiency gains of EADAM over DA in a simple and costless way.

EADAM Enforced: Students submit their rank-order preference lists under a variant of EADAM. All schools at which they turn out to be interrupters are automatically removed from their rank-order preference lists. Students have no option to prevent the removal. This variant of EADAM is relevant as it would be the easiest to implement in practice and the one that may offer the highest efficiency gains relative to DA.

Given that there is no way of telling who is an interrupter and who is not prior to the admissions procedure, any decision about whether to consent or object to a priority waiver needs to be made prospectively before running the algorithm. This implies that students have to decide whether to consent or object when submitting their rank-order preference lists in each period, without knowing whether their application will actually entail an interruption. Each student is told that consenting, not objecting or being subject to an enforced removal of schools at which she turns out to be an interrupter will never affect her assignment but may improve the assignment of other students.

One feature of our design is that we did not provide students with guidance about whether they would be better off by stating their preferences truthfully in any of our treatments. This choice was motivated by the following reasons.

First, while a recent strand of literature is focusing on the effect of advice about optimal strategies on truth-telling (for a survey, see Hakimov and Kübler 2021), the provision of advice is not standard in school choice experiments (for an experiment on advice under TTC, see Guillen and Hakimov 2018). Given that our experiment is the first to explore the performance of EADAM relative to DA, we deliberately opted for a design enabling us to isolate the effect of the mechanisms' actual properties rather than students' responses to advice.

Second, while participants could have been told that truth-telling will always make them better off in the non-manipulable market, this piece of advice would not have been true in our two manipulable markets. We were keen on avoiding inconsistencies or varying the content of advice across markets. Moreover, evidence suggests that participants tend to interpret information hinting at the possibility of beneficial manipulations as an invitation to manipulate their preferences (Hermstrüwer 2019; Guillen and Hing 2014).

Third, while comprehensive advice is offered under some assignment procedures such as the NRMP (Rees-Jones and Skowronek 2018), several administrative bodies around the world refrain from giving advice. Even if school authorities do offer advice, there is no consistent evidence on the effectiveness of advice in practice.

To ensure that our participants understood all the rules and features of our experiment, we slowly walked them through explanations and examples (see Appendix C). In order to start the actual experiment, all participants had to provide correct answers to each of our nine control questions. Our data show that very few of the answers provided were incorrect. Participants were also allowed to ask questions, but very few did.[19]

Hypotheses As discussed in Section 1 and Section 2, if at least one interrupting student consents to waive her priorities, EADAM will produce an assignment that is pareto-superior to the DA matching (Hypothesis 1). The efficiency gain increases with the number of consenting students. Due to status quo bias, we expect consent rates to be higher under EADAM Object than under EADAM Consent (Hypothesis 4). Against this background and given that priority waivers are enforced under EADAM Enforced, we expect efficiency to be higher under EADAM Enforced than under EADAM Object, and under EADAM Object than under EADAM Consent (Hypothesis 2). EADAM is expected to maintain the stability properties of DA (Hypothesis 3). Finally, given that the market is non-manipulable, truth-telling is not expected to differ between EADAM and DA (Hypothesis 5).

Hypothesis 1 (Efficiency DA-EADAM)**.** *Assignments are more efficient under EADAM than under DA.*

Hypothesis 2 (Efficiency under EADAM)**.** *Assignments are more efficient under EADAM Enforced than under EADAM Object, and more efficient under EADAM Object than under EADAM Consent.*

Hypothesis 3 (Stability)**.** *The proportion of stable assignments does not differ between EADAM and DA.*[20]

Hypothesis 4 (Consent)**.** *Students are more likely to consent to a waiver under EADAM Object than under EADAM Consent.*

Hypothesis 5 (Truth-telling DA-EADAM)**.** *Truth-telling rates do not differ between EADAM and DA.*

3.2 Manipulable Markets

We explore two markets in which truth-telling is not an equilibrium under EADAM: a manipulable market without interrupters (Market 1) and a manipulable market with three interrupters (Market 2), that is a market with the same number of interrupters as our non-manipulable market (see Appendix B.2). The comparison between Market 2 and the non-manipulable market

19. Regarding the consent decision, for example, only one participant mentioned that she found it difficult to understand the instructions. The large majority of participants offered clear motivations for their decision to object, telling us (i) that they had forgotten to check the box, (ii) that they wanted to test whether their assignment really remained unaffected by the consent decision, or (iii) that they were willing to reciprocate the perceived reluctance of other group members to consent.

20. As further explained in Section 4.1.2, our definition of stability under EADAM is subject to students waiving their priorities.

allows us to study the role of manipulation incentives; the comparison between Market 1 and Market 2 allows us to study the role of the number of interrupters.

In Market 1, preferences and priorities are given as follows.

Points	P_{i_1}	P_{i_2}	P_{i_3}	P_{i_4}	P_{i_5}
25	s_4	s_5	s_4	s_4	s_4
18	s_1	s_1	s_3	s_2	s_5
12	s_2	s_2	s_5	s_3	s_3
7	s_5	s_4	s_1	s_1	s_2
3	s_3	s_3	s_2	s_5	s_1

	$\succ_{s_1}$	$\succ_{s_2}$	$\succ_{s_3}$	$\succ_{s_4}$	$\succ_{s_5}$
1^{st}	i_5	i_4	i_4	i_2	i_1
2^{nd}	i_3	i_1	i_5	i_4	i_4
3^{rd}	i_4	i_2	i_1	i_5	i_5
4^{th}	i_1	i_3	i_2	i_3	i_2
5^{th}	i_2	i_5	i_3	i_1	i_3

In Market 2, preferences and priorities are given as follows.

Points	P_{i_1}	P_{i_2}	P_{i_3}	P_{i_4}	P_{i_5}
25	s_2	s_1	s_2	s_2	s_3
18	s_3	s_2	s_3	s_3	s_4
12	s_1	s_3	s_4	s_1	s_1
7	s_5	s_4	s_5	s_5	s_5
3	s_4	s_5	s_1	s_4	s_2

	$\succ_{s_1}$	$\succ_{s_2}$	$\succ_{s_3}$	$\succ_{s_4}$	$\succ_{s_5}$
1^{st}	i_5	i_5	i_2	i_4	i_1
2^{nd}	i_4	i_2	i_3	i_1	i_3
3^{rd}	i_1	i_3	i_4	i_3	i_2
4^{th}	i_2	i_4	i_5	i_5	i_5
5^{th}	i_3	i_1	i_1	i_2	i_4

Note that we only implement DA and EADAM Consent in these markets, the main reason being that EADAM Consent corresponds to the initial version of EADAM.

Incentive analysis As shown in Appendix B.2, in Market 1, i_2 has an incentive to manipulate by swapping s_2 and s_3. If i_1 anticipates this manipulation, she has an incentive to counter-manipulate by swapping s_2 and s_3 too. In Market 2, i_1 has an incentive to manipulate by swapping s_5 and s_4, and i_5 has an incentive to manipulate by reporting s_2 as second choice.[21]

We do not exhaustively calculate the full set of Nash equilibria in our manipulable markets due to the large strategy space; each student has $5! = 120$ possible reports, which makes a brute force calculation virtually impossible.[22] Instead, we focus our equilibrium analysis on an equilibrium refinement called "truthful equilibrium" which allows us to identify any focal equilibria that students may be able to coordinate on if they play equilibrium at all. The refinement idea is based on allowing students to choose truth-telling "as much as possible". That is, for a given student, holding others' reports fixed, if truth-telling is a best response, then we only consider the truth-telling strategy as being part of the equilibrium play. In other words, if a student can use truth-telling as a best response strategy in equilibrium, she always chooses it over any other best response she may have.

21. For the sake of uniformity and to keep everything as constant as possible, the payoff tables and the priority tables are kept as in the manipulable market whenever the specific order of schools or students is irrelevant.

22. Moreover, there is no known theoretical characterization of the full set of Nash equilibria under EADAM. Even under DA, while a dominant strategy equilibrium always exists, we are not aware of a paper that calculates the full set of equilibria.

Formally, let P be the true preference profile. Then a profile report Q is a *truthful equilibrium* if

(i) it is a Nash equilibrium under the true preferences, and

(ii) if Q_i is different than P_i for any student i, then (P_i, Q_{-i}) is not a Nash equilibrium.

We believe that this is a natural refinement, and truthful equilibria are the most likely focal equilibrium candidates that students can be expected to coordinate on—if they are to coordinate on any equilibrium at all. What helps with coordination is that when strategizing, the truth-telling profile is the common departure point. One checks for unilateral profitable deviations from this profile and keeps iterating until an equilibrium is reached. In our manipulable markets, since few student types have an incentive to misreport, we expect the truthful equilibrium profiles as the most likely Nash equilibrium candidates to be actually played. Nevertheless, we find that students never play these equilibria under EADAM, as discussed in Section 4.2.1. This suggests that other non-truthful Nash equilibria are even more unlikely to be played.

Hypotheses Because EADAM is not strategy-proof and because it is manipulable for some students in both markets, truth-telling is expected to be higher under DA than under EADAM (Hypothesis 6). While EADAM should leave efficiency levels unaffected in the market without interrupters, it should yield more efficient assignments in the market with interrupters (Hypothesis 7).

Hypothesis 6 (Truth-telling)**.** *Students are more likely to report their preferences truthfully under DA than under EADAM.*

Hypothesis 7 (Efficiency)**.** *In markets without interrupters (Market 1), EADAM Consent and DA yield the same efficiency levels. In markets with interrupters (Market 2), assignments are more efficient under EADAM Consent than under DA.*

3.3 Procedure

The experiment was programmed using the experimental software *o-Tree* (Chen, Schonger, and Wickens 2016). Sessions for the non-manipulable market were conducted online in September and October 2020, while sessions for the manipulable markets were conducted online in March and April 2023. All participants were recruited via ORSEE (Greiner 2015) from the common participant pool of the University of Bonn and the Max Planck Institute for Research on Collective Goods. We ran 9 independent sessions for the non-manipulable market (500 participants) and 13 independent sessions for the manipulable markets (470 participants), with each session being embedded in a Zoom or BigBlueButton webinar that allowed participants to privately ask questions to the experimenter, but kept complete anonymity among participants.[23] Each session was scheduled to take approximately 75 minutes, with most groups finishing the experiment after 50 to 60 minutes. The experiment ended with a demographics questionnaire to control for gender, age, and subject studied. At the end of the experiment, participants received the sum of their earnings, including a participation fee of 4 Euros in the non-manipulable market and of 2 Euros in the manipulable markets. On average, participants earned 11.49 Euros in the non-manipulable market and 10.10 Euros in the manipulable markets.

4 Results

In this section, we present the results of the experiment. We begin with the analysis of the non-manipulable market (Section 4.1). Within this market, we first examine the effect of EADAM on efficiency relative to DA and how efficiency varies across the three variants of EADAM (Section 4.1.1). We then present results on stability (Section 4.1.2), truth-telling (Section 4.1.3) and consent rates between EADAM Consent and EADAM Object (Section 4.1.4). Finally, we turn to the analysis of our manipulable markets (Section 4.2), where we focus on the effect of EADAM Consent on truth-telling and efficiency relative to DA.[24]

4.1 Non-Manipulable Market

4.1.1 Efficiency

We first compare the effect of DA and EADAM on efficiency using non-parametric tests, where matching groups are treated as our unit of observation. To obtain a coarse efficiency measure, we compute a binary variable based on the payoffs obtained under the Pareto-efficient matching according to the theoretical predictions for our matching market (see Appendix B.1). This efficiency measure is coded as a binary variable ω that takes value 1 if assignments are Pareto-efficient, and 0 otherwise. Using this measure, we observe high efficiency levels under EADAM Enforced (80.42%), EADAM Object (54.79%), and EADAM Consent (43.93%) but a very low proportion of efficient assignments under DA (6.04%, Figure 1). When pooling observations of all EADAM variants, we find that the fraction of efficient assignments is significantly higher under all variants of EADAM (58.88%) than under DA (6.04%, chi-square, $p < 0.001$).

23. We ran our sessions for the manipulable markets with 610 participants. 14 participants timed out of these sessions for technical or personal reasons and were replaced with a robot participant to enable the remaining 9 students in each matching group to finish the experiment. As this may have affected participant behavior, we decided to adopt a conservative approach and avoid an artificial inflation of our sample. We therefore decided to exclude each matching group in which a timeout occurred (140 participants), thus using a sample of 470 participants for our main analysis.

24. For all the analysis in this section we use all periods, as we did not observe significant variation over time and our results do not change when we use a subset of periods.

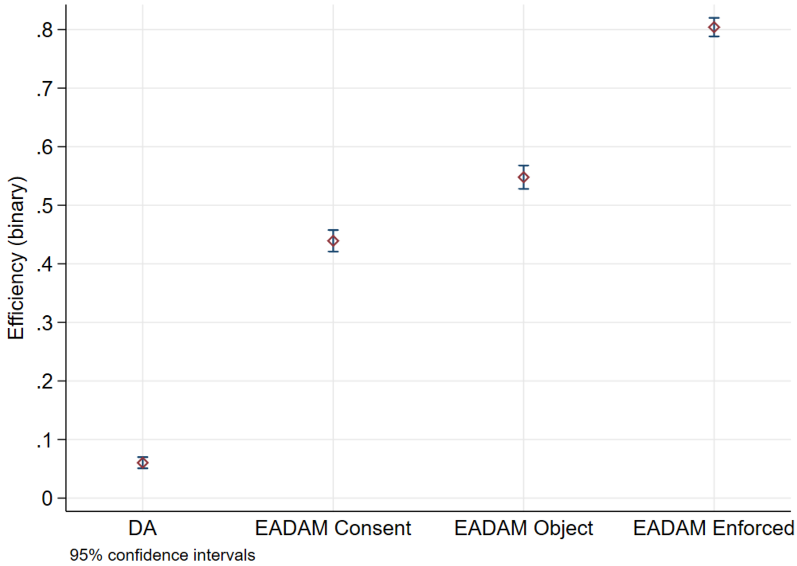

Figure 1: Treatment effects on efficiency (ω)

In addition to non-parametric tests, we estimate multilevel logistic regression models and multilevel linear regression models. In the former, we use ω as our dependent variable. In the latter, the dependent variable π is continuous and given by the number of points earned by students. Our parameter estimates are based on the following basic specification of a three-level model:

$$Y_{igt} = \beta_0 + \beta_1 EADAM_{Consent} + \beta_2 EADAM_{Object} + \beta_3 EADAM_{Enforced} + v_i + u_{g(it)} + \epsilon_{igt} \tag{1}$$

where β_0 denotes the constant, and *EADAM Consent*, *EADAM Object* and *EADAM Enforced* are treatment dummies taking value 1 if i participated in the treatment, and 0 otherwise. The indicator i denotes the second level of clustering that accounts for 20 observations of each participant i over time, with v_i denoting the participant-specific random effect. The indicator g denotes the third and highest level of clustering that accounts for each participant nested in a matching group, with $u_{g(it)}$ capturing the group-specific random effect. ϵ_{igt} is the error term. To test the robustness of treatment effects, we include a categorical variable for student type (*Type*), a continuous variable for period (*Period*), and a dummy variable for truth-telling (*Truth-telling*) as controls in our additional specifications. Moreover, we use Wald tests to assess differences across treatments and expect to reject the null when comparing the coefficients of our treatment dummies.

Estimating a three-level mixed-effects logistic regression model for our binary efficiency measure, we observe that all variants of EADAM yield a significant increase in the rate of efficient assignments relative to DA (Table 1). The marginal efficiency increase is approximately twice as high under EADAM Enforced than under EADAM Consent. Overall, the effect of

EADAM is robust to the inclusion of type, period and truth-telling as controls. These results lend clear support to Hypothesis 1.

Table 1: Impact of EADAM on efficiency compared to DA (ω)

DV: Efficiency Baseline: DA	(1)	(2)	(3)	(4)
EADAM Consent	0.374***	0.374***	0.374***	0.366***
	(0.044)	(0.044)	(0.044)	(0.044)
EADAM Object	0.487***	0.487***	0.487***	0.481***
	(0.048)	(0.048)	(0.048)	(0.048)
EADAM Enforced	0.739***	0.739***	0.739***	0.737***
	(0.034)	(0.034)	(0.034)	(0.034)
Type		Yes	Yes	Yes
Period			Yes	Yes
Truth				0.041***
				(0.010)
Wald test	41.86***	41.86***	41.88***	43.58***
N_I	10.000	10.000	10.000	10.000
N_G	50	50	50	50

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. All coefficients are reported as average marginal effects. *Efficiency* is a dummy variable that takes value 1 if assignments are Pareto-efficient, and 0 otherwise. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

To obtain a more granular resolution of the effects on efficiency, we next estimate the effect of EADAM relative to DA for our continuous efficiency measure. These results corroborate the results obtained for our binary efficiency measure and show that all variants of EADAM yield significantly higher efficiency levels than DA (Table 9).

Result 1: Assignments are more efficient under all variants of EADAM than under DA.

Turning to a comparison of efficiency levels between all variants of EADAM, we observe that both EADAM Enforced and EADAM Object yield higher efficiency than EADAM Consent (chi-square, $p = 0.003$). These results are in line with the results obtained from a three-level mixed-effects logistic regression model (Table 2) when estimating the effect of EADAM Object relative to EADAM Consent (Column 1) and of EADAM Enforced relative to EADAM Object (Column 2) using our binary efficiency measure. On the one hand, we observe that shifting the default from opt-in under EADAM Consent to opt-out under EADAM Object yields a marginally significant efficiency increase. On the other hand, we find that enforcing priority waivers leads to significantly higher efficiency levels than nudging students with an opt-out default. These results support Hypothesis 2.

Table 2: Efficiency comparison between EADAM variants (ω)

DV: Efficiency Baseline:	Object vs. Consent EADAM Consent (1)			Enforced vs. Object EADAM Object (2)			Consent vs. Enforced EADAM Enforced (3)		
EADAM Object	0.113* (0.063)	0.113* (0.063)	0.113* (0.063)						
EADAM Enforced				0.259*** (0.041)	0.259*** (0.041)	0.259*** (0.041)			
EADAM Consent							-0.363*** (0.056)	-0.363*** (0.056)	-0.363*** (0.056)
Type		Yes	Yes		Yes	Yes		Yes	Yes
Period			Yes			Yes			Yes
N_I	5.200	5.200	5.200	4.800	4.800	4.800	5.200	5.200	5.200
N_G	26	26	26	24	24	24	26	26	26

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. *Efficiency* is a dummy variable that takes value 1 if assignments are Pareto-efficient, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups. Column 1: All coefficients are reported as average marginal effects at DA and EADAM Enforced = 0. Column 2: All coefficients are reported as average marginal effects at DA and EADAM Consent = 0. Column 3: All coefficients are reported as average marginal effects at DA and EADAM Object = 0.

To obtain a more granular estimate of efficiency, we again use our continuous efficiency measure to compare the effect of EADAM Object relative to EADAM Consent (Table 10, Column 1, Appendix A) and of EADAM Enforced relative to EADAM Object (Table 10, Column 2, Appendix A). Overall, the results we obtain from the continuous measure are in line with the results for our binary efficiency measure although the difference between EADAM Consent and EADAM Object now turns out insignificant. In sum, we find a robust efficiency-enhancing effect of EADAM Enforced compared to the other variants of EADAM.

Result 2: Assignments are more efficient under EADAM Enforced than under EADAM Consent and EADAM Object.

These results beg the question what exactly causes the efficiency of EADAM relative to DA and the efficiency gains produced by EADAM Enforced relative to the other variants of EADAM. While these efficiency gains may be driven by the elimination of interrupters under EADAM, part of these differences may well be caused by higher degrees of truthfulness under EADAM. To disentangle the effect of eliminated interrupters and truthfulness, we conduct an analysis of interaction effects and test whether our treatment effects on efficiency depend on the level of truth-telling observed in each treatment.

Figure 2 plots the average marginal effect of treatments and truth-telling on efficiency. Using our continuous efficiency measure, we observe a relatively modest slope under DA, with intermediate slopes under EADAM Consent and EADAM object (lines are parallel) and the steepest slope under EADAM Enforced.

This difference in slopes indicates an interaction between treatment and truth-telling. While

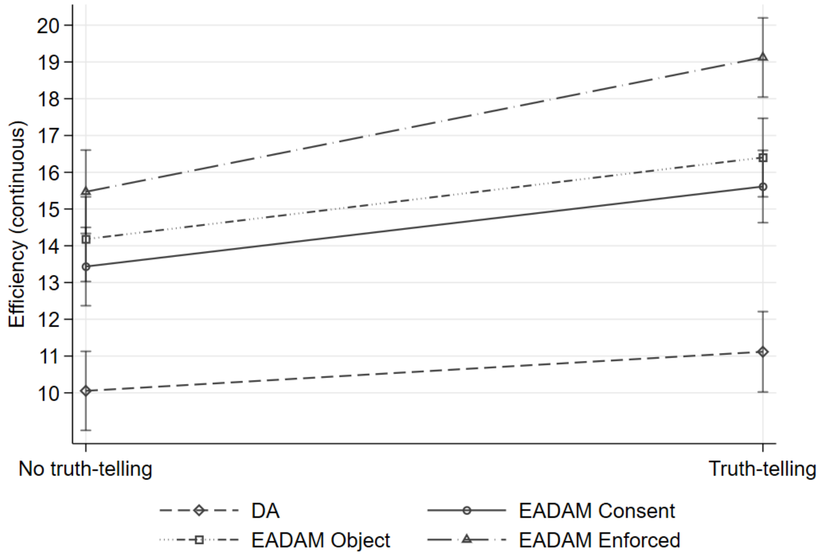

Figure 2: Interaction between treatment and truth-telling

truth-telling yields only minor efficiency gains under DA, it entails stronger efficiency increases under all variants of EADAM, especially under EADAM Enforced. Estimating a three-level mixed-effects linear regression model, we find that these interaction effects are highly significant (Table 11, Appendix A).[25] This suggests that the differences in efficiency do not mechanically result from the higher number of interrupters eliminated under EADAM. Rather, the efficiency increases observed under EADAM are in part due to the higher fraction of students reporting their preferences truthfully. Overall, we can conclude that truth-telling is more beneficial under EADAM than under DA and that preference manipulations entail comparatively small efficiency losses under DA.

These results show that truth-telling pays off under EADAM. The efficiency gains from truth-telling are particularly high when priority waivers are enforced. Market designers striving to maximize efficiency gains under EADAM may achieve that goal by offering a clear recommendation that truth-telling is very likely to be best for students.

4.1.2 Stability

EADAM is designed to increase efficiency while maintaining the stability properties of the DA matching. To compare the effects on stability, we again use the theoretical predictions for our matching market as a benchmark (see Appendix B.1) and code a stability variable that takes value 1 if the DA stable assignment or one of the two efficiency-adjusted stable assignments is achieved, and 0 otherwise. Note that our definition of stability under EADAM is based on Kesten (2010) and is an "adjustment" of DA stability, as it is subject to students waiving their

25. The interaction effects of treatment and truth-telling slightly vary depending on whether a binary or a continuous efficiency measure is used. Using our binary efficiency measure, the interaction effect remains highly significant under EADAM Enforced (Table 11, Appendix A).

priorities. Theoretically, there should be no difference in the proportion of stable assignments between DA and all variants of EADAM. As illustrated by Figure 3, stability rates are highest under EADAM Object (81.46%) and lowest under EADAM Enforced (67.92%). Intermediate stability rates can be observed under EADAM Consent (77.14%) and DA (73.54%).[26]

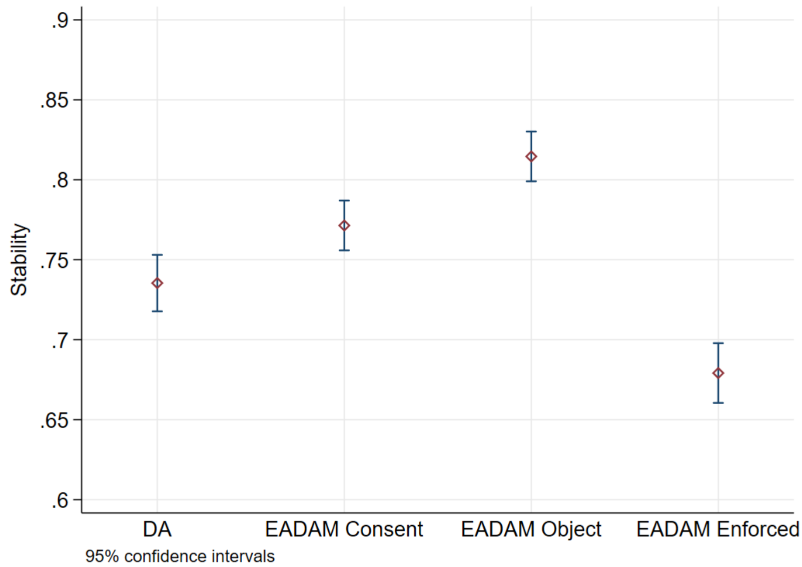

Figure 3: Treatment effects on stability

The results of a three-level mixed-effects logistic regression model show that this difference is mainly driven by EADAM Object (Table 3). EADAM Object produces a marginally significant increase of stable assignments compared to DA. However, this difference is no longer significant when including truth-telling as a control variable. We conclude that, in line with Hypothesis 3, stability rates are not significantly different under EADAM and DA.

Result 3: The proportions of stable assignments under DA and under EADAM are not significantly different.

When analyzing the difference between all variants of EADAM, we find that EADAM Enforced yields a significantly lower proportion of stable assignments than EADAM Object (Table 4, Column 2). Although close to marginally significant, we observe no difference between EADAM Enforced and EADAM Consent (Table 4, Column 3).

Result 4: Assignments are less stable under EADAM Enforced than under EADAM Consent and EADAM Object.

This result suggests that EADAM Enforced reintroduces the very stability and efficiency trade-off it is designed to mitigate in the first place. This can be explained as the result of

26. In Appendix A.1, we show that the DA stable assignment is achieved significantly more frequently under DA than under each of the EADAM variants (Figure 12).

Table 3: Impact of EADAM on stability compared to DA

DV: Stability Baseline: DA	(1)	(2)	(3)	(4)
EADAM Consent	0.045	0.045	0.044	0.013
	(0.044)	(0.044)	(0.044)	(0.042)
EADAM Object	0.076*	0.076*	0.076*	0.049
	(0.044)	(0.044)	(0.044)	(0.042)
EADAM Enforced	-0.045	-0.045	-0.045	-0.067
	(0.050)	(0.050)	(0.050)	(0.048)
Type		Yes	Yes	Yes
Period			Yes	Yes
Truth				0.114***
				(0.011)
Wald test	7.38**	7.38**	7.39**	6.91**
N_I	10.000	10.000	10.000	10.000
N_G	50	50	50	50

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. All coefficients are reported as average marginal effects. *Stability* is a dummy variable that takes value 1 if assignments are stable, and 0 otherwise. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

Table 4: Stability comparison between EADAM variants

DV: Stability	Object vs. Consent				Enforced vs. Object				Consent vs. Enforced			
Baseline:	EADAM Consent (1)				EADAM Object (2)				EADAM Enforced (3)			
EADAM Object	0.032	0.032	0.032	0.035								
	(0.039)	(0.039)	(0.039)	(0.037)								
EADAM Enforced					-0.122***	-0.122***	-0.122***	-0.115**				
					(0.045)	(0.045)	(0.045)	(0.044)				
EADAM Consent									0.088	0.088	0.088	0.077
									(0.056)	(0.056)	(0.056)	(0.054)
Type		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Period			Yes	Yes			Yes	Yes			Yes	Yes
Truth				0.123***				0.121***				0.128***
				(0.016)				(0.017)				(0.017)
N_I	5.200	5.200	5.200	5.200	4.800	4.800	4.800	4.800	5.200	5.200	5.200	5.200
N_G	26	26	26	26	24	24	24	24	26	26	26	26

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. *Stability* is a dummy variable that takes value 1 if assignments are stable, and 0 otherwise. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups. Column 1: All coefficients are reported as average marginal effects at DA and EADAM Enforced = 0. Column 2: All coefficients are reported as average marginal effects at DA and EADAM Consent = 0. Column 3: All coefficients are reported as average marginal effects at DA and EADAM Object = 0.

a behavioral backfiring effect: EADAM Enforced curtails students' right to choose and may thus induce them to manipulate their preferences more often than under the other variants of EADAM, as further discussed in the next subsection.

4.1.3 Truth-Telling

We begin with a comparison of truth-telling rates under DA and EADAM and consider the proportion of participants submitting truthful rank-order preference lists. A participant is considered to be truth-telling if she submits a truthful rank-order preference list of all five schools.[27]

We observe significantly higher truth-telling rates under all variants of EADAM (67.03%) than under DA (43.88%, chi-square, $p < 0.001$). These results are in line with the results of a multilevel mixed-effects logistic regression models estimating the effect of EADAM on truth-telling relative to DA (Table 5).

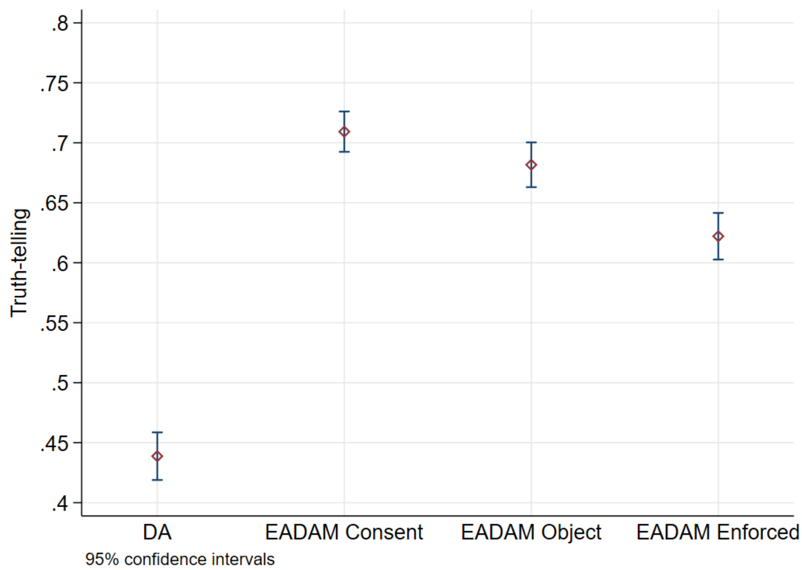

Figure 4: Treatment effects on truth-telling

Result 5: Truth-telling rates are higher under all variants of EADAM than under DA.

This is a remarkable result – at odds with our theoretical predictions (Hypothesis 5). Although not strategy-proof, EADAM generates higher truth-telling rates than DA, a mechanism often hailed for its strategy-proofness virtues.[28] As previously mentioned, however, the

27. We decided to use a truth-telling variable based on the full preference vector because, while there is a minimum guaranteed assignment for students i_2 and i_4 (assignment to their third choice is guaranteed), this does not hold for the other students. For robustness, we also replicated the analysis using a truth-telling variable based on a truncated preference vector (removing the last two choices of students i_2 and i_4). Our results remain unchanged.

28. Previous evidence shows that truth-telling rates strongly vary across strategy-proof mechanisms such as DA and TTC (Hakimov and Kübler 2021).

Table 5: Impact of EADAM on truth-telling compared to DA

DV: Truth Baseline: DA	(1)	(2)	(3)
EADAM Consent	0.253***	0.246***	0.246***
	(0.039)	(0.033)	(0.033)
EADAM Object	0.246***	0.235***	0.235***
	(0.040)	(0.034)	(0.034)
EADAM Enforced	0.183***	0.177***	0.177***
	(0.041)	(0.035)	(0.035)
Type		Yes	Yes
Period			Yes
Wald test	5.19*	5.45*	5.46*
N_I	10.000	10.000	10.000
N_G	50	50	50

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Three-level mixed-effects logit regression. Standard errors in parentheses. All coefficients are reported as average marginal effects. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

non-manipulability of the market poses a conundrum: Could the higher truth-telling rates observed under EADAM be driven by the lack of manipulation incentives in the specific market? To address this question, in Section 4.2, we analyze the impact of EADAM on truth-telling in two manipulable markets. As further discussed below, truth-telling rates are significantly higher under EADAM than under DA even when the markets can be manipulated.

Truth-telling over time It is worth noting, that we observe a relatively steep drop in truth-telling rates in the first few periods (Figure 5). While truth-telling rates start high in all treatments (although slightly lower under EADAM Enforced), they decrease across periods. Under DA, truth-telling rates drop more after the first few periods but increase again in the last few periods.[29] One potential explanation is that it may feel natural for participants to start off by ranking schools truthfully, truth-telling being a "behavioral default" of sorts. After a few periods, however, they may want to see what happens if they try something else. These results are in line with previous studies showing a slow decline in truth-telling rates over time under DA in a 6-school environment, but a more stable pattern in a 4-school environment (Chen and Kesten 2019). More generally, our results are consistent with evidence portending relatively low truth-telling rates (between 40 and 50%) under DA with more than four schools (see Hakimov and Kübler 2021).

29. This sharp drop does not entail a significant difference in truth-telling between the first half and the second half of the game, and does not justify dropping the first observations from our analysis.

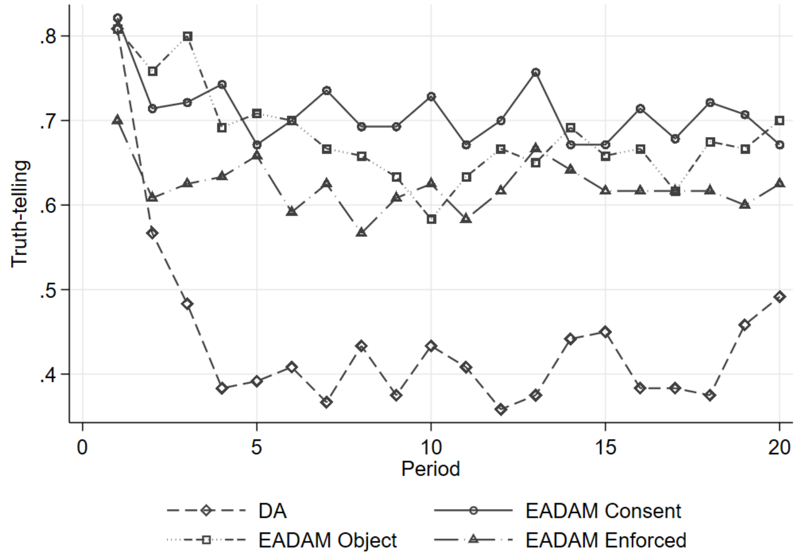

Figure 5: Treatment effects on truth-telling by period

Drivers of truth-telling While our design does not enable us to identify the specific behavioral force underlying the effect of EADAM on truth-telling, it is likely that welfare concerns may have partly motivated truth-telling behavior. Students may have sensed that misrepresenting their preferences under a mechanism that is designed to increase their welfare may actually hamper their chances of being admitted at their preferred school. Being aware of the benefits generated by the efficiency-adjustment under EADAM, they may have trusted the algorithm to produce the best outcomes when refraining from preference manipulation. Given that not all students can equally benefit from EADAM, we expect these effects to differ across student types.

To explore this conjecture and facilitate the visual comparison of truth-telling and efficiency, we compute an individual welfare measure π_N by calculating the z-score of our continuous efficiency variable π. Following the standard procedure for the normalization of variables, we rescale our continuous efficiency variable to have a mean of 0 and a standard deviation of 1, using the following formula: $\pi_N = \pi - m(\pi)/sd(\pi)$. Figure 6 plots the average level of truth-telling and individual welfare for each student type in each treatment, and reveals an interesting pattern.

While EADAM imposes welfare losses on student $i1$ and entails modest welfare gains for student $i5$, it yields consistent and partly strong welfare improvements for the other students. Conversely, both students $i1$ and $i5$ are much less likely to rank schools truthfully than the other students. This indicates a positive effect of individual welfare gains on truthfulness: the more a student benefits from EADAM in terms of individual welfare, the more inclined she will be to report her preferences truthfully. The positive effect of EADAM on truthfulness therefore seems to be at least partly caused by the welfare improvements it generates. Students who are assigned to one of their top choices seem to realize that there is little to gain from gaming the

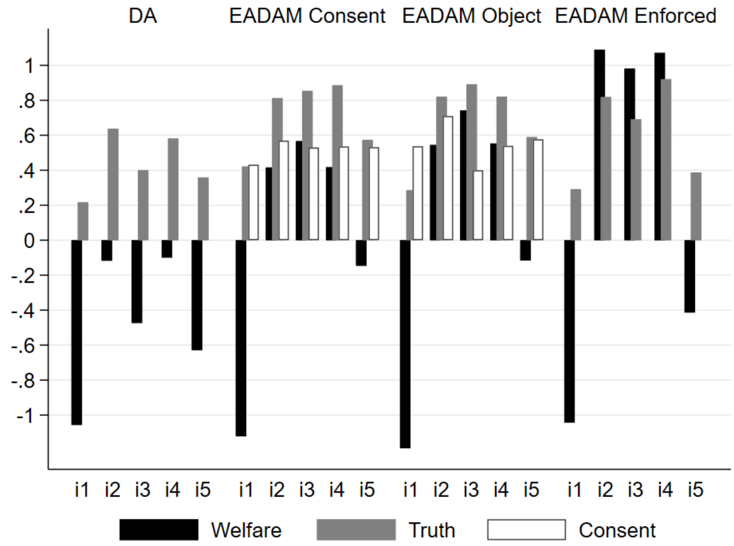

Figure 6: Truth-telling and welfare by student type and treatment

system. Overall, we can conclude that the individual welfare gains produced under EADAM mitigate students' propensity to misrepresent their preferences.

Comparison between EADAM variants When comparing all variants of EADAM, it can be noticed that individual welfare gains can only partly account for the positive effect of EADAM on truthfulness. As illustrated in Figure 6, as we move from EADAM Consent to EADAM Enforced, welfare increases, while truth-telling decreases. While in theory truth-telling rates should not differ between the variants of EADAM, we observe the highest truth-telling rates under EADAM Consent (70.93%), slightly lower truth-telling rates under EADAM Object (68.17%), and the lowest truth-telling rates under EADAM Enforced (62.20%, chi-square, $p = 0.004$).

A closer comparison of EADAM Object relative to EADAM Consent (Table 6, Column 1) and of EADAM Enforced relative to EADAM Object (Table 6, Column 2) confirms that EADAM Enforced has a negative impact on truth-telling. While we do not find a significant difference in truth-telling rates when comparing EADAM Object and EADAM Consent, we observe a marginally significant reduction in truth-telling rates under EADAM Enforced compared to EADAM Consent and EADAM Object.

Result 6: Truth-telling rates are lower under EADAM Enforced than under EADAM Consent and EADAM Object.

This behavioral pattern indicates that the positive effect of EADAM on truthfulness is partly driven by behavioral motives that are unrelated to individual welfare improvements. While our experiment is not designed to disentangle these behavioral effects, they may have

Table 6: Truth-telling comparison between EADAM variants

DV: Truth Baseline:	Object vs. Consent EADAM Consent (1)			Enforced vs. Object EADAM Object (2)			Consent vs. Enforced EADAM Enforced (3)		
EADAM Object	-0.006 (0.030)	-0.006 (0.031)	-0.006 (0.031)						
EADAM Enforced				-0.057* (0.031)	-0.060* (0.033)	-0.060* (0.033)			
EADAM Consent							0.064** (0.032)	0.066** (0.032)	0.066** (0.032)
Type		Yes	Yes		Yes	Yes		Yes	Yes
Period			Yes			Yes			Yes
N_I	5.200	5.200	5.200	4.800	4.800	4.800	5.200	5.200	5.200
N_G	26	26	26	24	24	24	26	26	26

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups. Column 1: All coefficients are reported as average marginal effects at DA and EADAM Enforced = 0. Column 2: All coefficients are reported as average marginal effects at DA and EADAM Consent = 0. Column 3: All coefficients are reported as average marginal effects at DA and EADAM Object = 0.

been the result of choice constraints. On the one hand, by eliminating the option to consent or object to the priority waiver, EADAM Enforced reduces the degrees of freedom that students have when applying to schools. Constraining students' choice set may have triggered the perception that the only way of influencing the outcome is through the rank-order preference list. On the other hand, students' ranking behavior may have been driven by reactance, a state of motivational arousal emerging when people experience a threat to their behavioral freedoms or a limitation to the set of choice options from which they can pick (Brehm 1966). In sum, these results suggest that less obtrusive matching mechanisms may produce higher truth-telling rates without necessarily having to rely on strategy-proofness.

4.1.4 Consent

EADAM Object is designed as a behavioral intervention – a nudge – to increase consent rates. Corroborating our behavioral predictions (Hypothesis 4), a non-parametric test reveals that consent rates are significantly higher under EADAM Object (55.29%) than under EADAM Consent (52.00%, chi-square, $p = 0.018$). However, this difference is relatively small (Figure 10, Appendix A). In line with this observation, the estimates of a multilevel mixed-effects logistic regression model show that the difference in consent rates is not robust (Table 12, Appendix A).

Result 7: Consent rates under EADAM Consent and under EADAM Object are not significantly different.

On closer inspection, we observe that consent rates slightly vary by student type, though none of these differences follows a systematic pattern (Figure 6). However, we observe that under EADAM Consent consent rates start very high and experience a steep drop in the first nine periods (Figure 11, Appendix A). The average difference in consent rates between EADAM Object (53.58%) and EADAM Consent (51.80%) is small. In the last ten periods, consent rates follow a more stable pattern. Despite some variation across periods, consent rates remain consistently higher under EADAM Object (57.00%) than under EADAM Consent (52.21%). This suggests that the effect of the default rule might increase over time.

This tendency may be the result of two different behavioral channels. On the one hand, status quo bias may become stronger over time, as students become weary of ranking the same schools over and over again. On the other hand, this pattern may be driven by a learning effect and a concern for efficiency, as students may understand the positive impact of consent on aggregate welfare over time. Despite this tendency, we do not find robust evidence of a default effect on consent rates.

4.2 Manipulable Markets

Our results in the non-manipulable market raise two interesting questions. First, is the observed increase in truth-telling rates under EADAM relative to DA driven by the lack of manipulation incentives in the specific market? More generally, how does the manipulability of a market affect truth-telling under EADAM and DA? Second, how does the number of interrupters affect truth-telling and the efficiency of assignments?

To address these questions, we ran additional sessions using two manipulable markets. The first manipulable market (Market 1) has no interrupters, while the second manipulable market (Market 2) has three interrupters like our non-manipulable market. This allows us to compare (i) two markets with the same number of interrupters but different manipulation incentives, and (ii) two manipulable markets with different numbers of interrupters. While the first comparison allows us to isolate the impact of manipulation incentives, the second comparison enables us to identify the impact of the number of interrupters. Given our questions, the following analysis will focus on truth-telling and efficiency. We relegate the analysis of stability and consent rates in the manipulable markets to the Appendix (see Appendix A.2).

4.2.1 Truth-telling

The theoretical prediction for our manipulable markets is straightforward: we should observe significantly higher truth-telling rates under DA than under EADAM Consent (Hypothesis 6). Yet, as in our non-manipulable market, we observe the opposite effect (see Figure 13 in Appendix A.2). EADAM Consent significantly increases truth-telling rates relative to DA in both Market 1 (EADAM Consent: 70.29%, DA: 54.65%, chi-square, $p < 0.001$) and Market 2 (EADAM Consent: 64.36%, DA: 55.04%, chi-square, $p < 0.001$). These results are in line with the results of a multilevel mixed-effects logistic regression estimating the effect of EADAM

Consent on truth-telling relative to DA (Table 7).[30]

Our results are noteworthy for various reasons. First, they corroborate our findings in the non-manipulable market. The positive effect of EADAM on truth-telling is not driven by the lack of manipulation incentives in the specific market. Rather, we find strong evidence that EADAM is less vulnerable to manipulations than DA regardless of whether truth-telling is an equilibrium in the specific market or not. Second, the marginal effects of EADAM Consent on truth-telling are very similar in all our model specifications across both manipulable markets (see Table 7), thereby confirming the robustness of our findings. Third, as can be reasonably expected, the positive effect of EADAM Consent on truth-telling is smaller in the manipulable markets than in the non-manipulable market. Yet, it remains highly significant in both manipulable markets.

Table 7: Impact of EADAM on truth-telling compared to DA

DV: Truth Baseline: DA	**Manipulable Market 1**			**Manipulable Market 2**		
	(1)	(2)	(3)	(1)	(2)	(3)
EADAM Consent	0.155***	0.156***	0.156***	0.120***	0.124***	0.124***
	(0.040)	(0.040)	(0.040)	(0.039)	(0.038)	(0.038)
Type		Yes	Yes		Yes	Yes
Period			Yes			Yes
N_I	4,800	4,800	4,800	4,600	4,600	4,600
N_G	24	24	24	23	23	23

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. All coefficients are reported as average marginal effects. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

Result 8: Truth-telling rates are higher under EADAM Consent than under DA, irrespective of whether the specific market is manipulable or not.

We now turn to analyze whether the student types who have an incentive to manipulate do indeed attempt manipulations. According to our theoretical predictions, i_2 has an incentive to manipulate their preferences in Market 1; and if i_2 manipulates, i_1 has an incentive to counter-manipulate. As illustrated by Figure 14 in Appendix A.2, our results show that, under both DA and EADAM Consent, i_2 is indeed the student type who manipulates the most, and i_1 manipulates substantially as well. While EADAM Consent reduces manipulation rates for any type, the reduction is not significant for i_2.

In Market 2, theory predicts that i_1 and i_5 have an incentive to manipulate. As illustrated by

30. As for the non-manipulable market, we replicate our analysis for the manipulable markets using a truth-telling variable based on a truncated preference vector. Our results remain unchanged.

Figure 15 in Appendix A.2, under both DA and EADAM Consent, i_1 is indeed the student type who manipulates the most, whereas i_5 does not manipulate much. Again, EADAM Consent reduces manipulation rates for any type, although this reduction is not significant for i_1. This indicates that even students who have manipulation incentives are not more likely to misreport their preferences under EADAM Consent than under DA.

Finally, we check how often the students play the truthful equilibria.[31] We find that in both markets students never play these equilibria under EADAM. This suggests that other (non-truthful) Nash equilibria are even less likely to be played.

Our findings are in line with recent experimental evidence about other non-strategy-proof mechanisms. Klijn, Pais, and Vorsatz (2019), Bó and Hakimov (2020) and Hakimov and Raghavan (2020) find that a dynamic version of DA where students apply for one school at a time generates higher truth-telling rates than DA. Afacan et al. (2022) find that under iterative DA strategic reporting can only lead to higher efficiency for all participants. Cho, Hafalir, and Lim (2022) find that under the stable improvement cycle (SIC) and the choice-augmented deferred acceptance mechanism (CADA) truth-telling rates are not lower than under DA but efficiency is higher under SIC. This indicates that non-strategy-proof mechanisms may have desirable properties without necessarily increasing participants' attempts to game the system.

While our results confirm this emerging and important finding in the recent experimental literature, it also contributes a novel perspective on it. Non-strategy-proof mechanisms such as dynamic DA and iterative DA may lead to higher truth-telling because of their simplicity. In contrast, EADAM may generate higher truth-telling because of its complexity. When facing a mechanism that is hard to game, students may just default to truthful reporting (see Troyan and Morrill 2020).

Our results have important implications for the protection of vulnerable families and students that are most likely to be harmed when failing to successfully strategize under manipulable mechanisms. While the literature has offered formal support for strategy-proofness as a condition to level the playing field (Pathak and Sönmez 2008), our findings suggest that strategy-proofness can be relaxed at no expense to unsophisticated families. An efficiency-enhancing mechanism that is not obviously manipulable – in the sense proposed by Troyan and Morrill (2020) – may even decrease attempts to game the system.

4.2.2 Efficiency

The theoretical predictions for efficiency differ between the two manipulable markets. While efficiency levels should be equivalent across both mechanisms in Market 1 (there are no interrupters), EADAM Consent should entail an efficiency increase in Market 2 (there are three interrupters). We begin the analysis using our binary efficiency variable ω that takes value 1 if assignments are Pareto-efficient, and 0 otherwise. Using this measure, we observe that

31. In Market 1, in the truthful equilibrium i_1 and i_2 manipulate and the other students tell the truth. In Market 2, we look at two truthful equilibria: in one, only i_1 manipulates, and in the other, only i_5 manipulates.

EADAM Consent (60.80%) yields a significantly higher proportion of efficient assignments than DA (37.05%, chi-square, $p < 0.001$). As hypothesized, we observe that the efficiency adjustments obtained under EADAM Consent significantly vary across markets. While EADAM Consent significantly increases the proportion of efficient assignments relative to DA under both Market 1 (EADAM: 83.21%, DA: 73.25%, chi-square, $p < 0.001$) and Market 2 (EADAM: 32.27%, DA: 6.88%, chi-square, $p < 0.001$), the order of magnitude of this increase is considerably larger in Market 2 (see Figure 16 in Appendix A.2).

We obtain similar results for our continuous efficiency variable π given by the number of points earned by students (see Figure 17 in Appendix A.2). EADAM Consent significantly increases the efficiency of assignments in both markets, but the increase is larger in Market 2 (Market 1: EADAM Consent: $m = 18.00$, DA: $m = 17.04$, chi-square, $p < 0.001$; Market 2: EADAM Consent: $m = 15.34$, DA: $m = 14.02$, chi-square, $p < 0.001$).

Table 8: Impact of EADAM on efficiency compared to DA (ω)

DV: Efficiency (ω) Baseline: DA	**Manipulable Market 1**				**Manipulable Market 2**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
EADAM Consent	0.053	0.053	0.053	0.042	0.269***	0.269***	0.269***	0.268***
	(0.089)	(0.089)	(0.089)	(0.088)	(0.055)	(0.055)	(0.055)	(0.055)
Type		Yes	Yes	Yes		Yes	Yes	Yes
Period			Yes	Yes			Yes	Yes
Truth				0.068***				0.009
				(0.013)				(0.010)
N_I	4,800	4,800	4,800	4,800	4,600	4,600	4,600	4,600
N_G	24	24	24	24	23	23	23	23

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. All coefficients are reported as average marginal effects. *Efficiency* is a dummy variable that takes value 1 if assignments are Pareto-efficient, and 0 otherwise. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

Finally, we estimate the effect of EADAM Consent relative to DA on our binary and continuous efficiency variables using a multilevel logistic regression model (Table 8) and a multilevel linear regression model (Table 13 in Appendix A.2), respectively. When using our binary efficiency variable, we observe a positive effect of EADAM Consent on the fraction of Pareto-efficient assignments in Market 2. These results lend clear support to Hypothesis 7. However, we also observe that EADAM Consent entails a significant increase in efficiency in both Market 1 and 2 when using our continuous efficiency variable. These results indicate that assignments under EADAM Consent are Pareto-superior to the DA matching irrespective of the number of interrupters.

Result 9: In the market without interrupters, assignments are Pareto-superior under EADAM Consent but not generally more efficient than under DA. In the market with interrupters, assignments are more efficient under EADAM Consent than under DA.

5 Conclusion

One of the core challenges in the study and implementation of matching mechanisms is to accommodate the stability and efficiency trade-off. In this article, we offer first experimental evidence of the performance of EADAM, the efficiency-adjusted deferred acceptance mechanism introduced by Kesten (2010). The magnitude of the efficiency increases that EADAM generates crucially depends on whether priorities that only entail a tentative admission but do not have an impact on the final placement under DA can be removed from the students' rank-order preference lists. We study three variants of EADAM to achieve such a removal: in the first, corresponding to the original version of EADAM, students can consent to a priority waiver (opt-in default rule); in the second, students can object to a priority waiver (opt-out default rule); in the third, the removal of schools from students' rank-order preference lists is enforced (enforced priority waivers). We explore these variants in a market in which no student can benefit from preference misrepresentations. In addition, we investigate the original version of EADAM in two markets in which some students have an incentive to submit manipulated rank-order preference lists.

Maximizing placements at preferred schools and abiding by the admissions criteria at the same time is challenging, but our results highlight that it can be done in practice, not just in theory. We find that efficiency levels are substantially higher under EADAM than under DA. This result holds irrespective of whether some students can improve their assignment by submitting manipulated rank-order preference lists in the specific market or not. The efficiency gains generated by EADAM are caused not only by the reduction of rejection cycles but also by students who report their preferences truthfully. Moreover, truth-telling rates are much higher under EADAM than under DA, even though EADAM is not strategy-proof. Students whose welfare is improved by the reduction of rejection cycles seem to understand that there is little to gain from submitting manipulated rank-order preference lists. Depending on political or legal objectives, a mechanism that is not obviously manipulable may therefore be preferable over a strategy-proof mechanism.

When we compare different variants of EADAM, we find that the marginal efficiency increase is approximately twice as high when priority waivers are enforced than when students are offered an opt-in default rule. Thus, EADAM with enforced priority waivers may be an attractive option, whenever alternative mechanisms such as TTC are not an option for public policy reasons (see Abdulkadiroğlu et al. 2020). However, it should be noted that while enforcement increases efficiency, it also comes at a cost: when students cannot dodge the waiver, the likelihood of preference manipulations is significantly higher than under the variants of EADAM where the removal is optional. This points to a hitherto rarely considered trade-off between efficiency and vulnerability to preference manipulation. Guaranteeing sufficient degrees of freedom may come at a small cost for efficiency but may well serve students' autonomy and help level the playing field.

As EADAM has been sparking the interest of policy makers and school authorities, our findings are relevant and timely. They indicate that transitioning from DA to EADAM can improve efficiency without sacrificing truthfulness. This insight is of particular importance to vulnerable populations, because it suggests that theoretical opportunities to game the system need not always penalize socially disenfranchised families who are unsophisticated about the procedure or have limited access to strategic advice.

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Appendix

A Additional Results

A.1 Non-manipulable market

In this subsection, we present an overview of additional results for the non-manipulable market.

Efficiency: Continuous Measure Figure 7 shows our treatment effects on efficiency using our continuous efficiency measure π, given by per capita payoffs (points earned). Table 9 reports the results of a three-level mixed-effects linear regression model for the comparison between DA and EADAM. Table 10 reports the results of a three-level mixed-effects linear regression model for the comparison between all variants of EADAM.

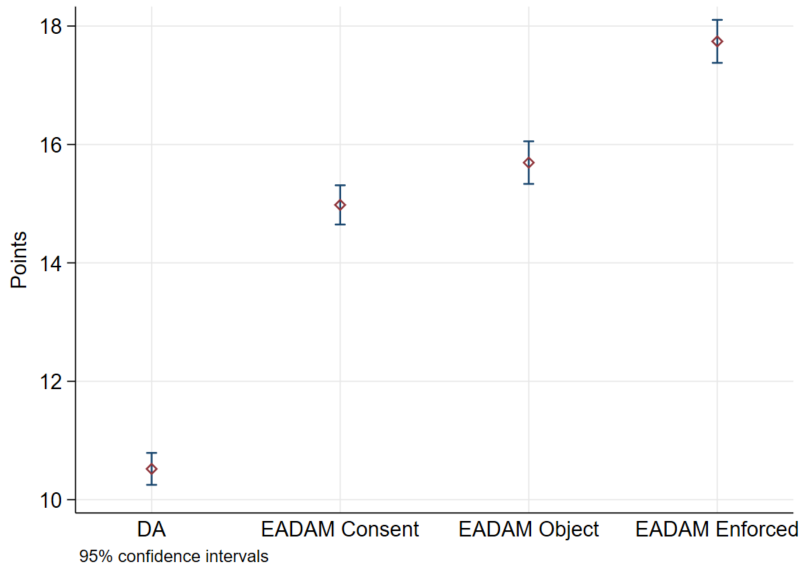

Figure 7: Treatment effects on efficiency (π)

A further analysis of efficiency corroborates the main results we report in the main text. The proportion of students being assigned to their first choice school is higher under EADAM Consent and EADAM Object relative to DA, and highest under EADAM Enforced (Figure 8). This coincides with a shift in the welfare distribution. While efficiency is rather normally distributed under DA (σ^2 = 45.38), it takes a slightly bimodal shape with a much higher variance under EADAM Enforced (σ^2= 82.44).[32] This shift in the distribution notwithstanding, EADAM reduces welfare inequality as measured by the Gini coefficient.[33] We find that the Gini coefficient is highest under DA (0.33) and lowest under EADAM Enforced (0.26).[34] Overall, this suggests that, EADAM not only increases efficiency but also reduces welfare inequality.

Causes of Efficiency-Adjustments: Truth-Telling or Elimination of Interrupters Figure 9 shows the interaction effect of treatment and truth-telling on efficiency, using our binary efficiency measure ω. The slopes indicate that the main effect of truth-telling on efficiency is very small under DA, EADAM Consent

32. Variance is sightly lower under EADAM Object (σ^2= 80.81) and EADAM Consent (σ^2= 79.85).
33. A Gini coefficient of 0 denotes that everyone receives the same income (perfect equality), whereas a coefficient of 1 expresses that a single individual receives all the income (perfect inequality).
34. The Gini coefficient under EADAM Consent (0.33) is the same as under DA, and only slightly lower under EADAM Object (0.31)

Table 9: Impact of EADAM on efficiency compared to DA (π)

DV: Efficiency (π) Baseline: DA	(1)	(2)	(3)	(4)
EADAM Consent	4.459***	4.459***	4.459***	3.929***
	(0.791)	(0.449)	(0.449)	(0.439)
EADAM Object	5.174***	5.174***	5.174***	4.697***
	(0.821)	(0.465)	(0.465)	(0.455)
EADAM Enforced	7.222***	7.222***	7.222***	6.863***
	(0.821)	(0.465)	(0.465)	(0.454)
Type		Yes	Yes	Yes
Period			Yes	Yes
Truth				1.961***
				(0.161)
Wald test	12.84***	39.92***	39.92***	47.41***
N_I	10.000	10.000	10.000	10.000
N_G	50	50	50	50

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects linear regression. Standard errors in parentheses. *Efficiency* is a continuous variable that captures the number of points earned by students. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

Table 10: Efficiency comparison between EADAM variants (π)

DV: Efficiency (π) Baseline:	Object vs. Consent EADAM Consent (1)			Enforced vs. Object EADAM Object (2)			Consent vs. Enforced EADAM Enforced (3)		
EADAM Object	0.714	0.714	0.714						
	(0.796)	(0.729)	(0.729)						
EADAM Enforced				2.048**	2.048**	2.048**			
				(0.958)	(0.917)	(0.917)			
EADAM Consent							-2.763***	-2.763***	-2.763***
							(0.892)	(0.855)	(0.855)
Type		Yes	Yes		Yes	Yes		Yes	Yes
Period			Yes			Yes			Yes
N_I	5.200	5.200	5.200	4.800	4.800	4.800	5.200	5.200	5.200
N_G	26	26	26	24	24	24	26	26	26

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects linear regression. Standard errors in parentheses. *Efficiency* is a continuous variable that captures the number of points earned by students. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

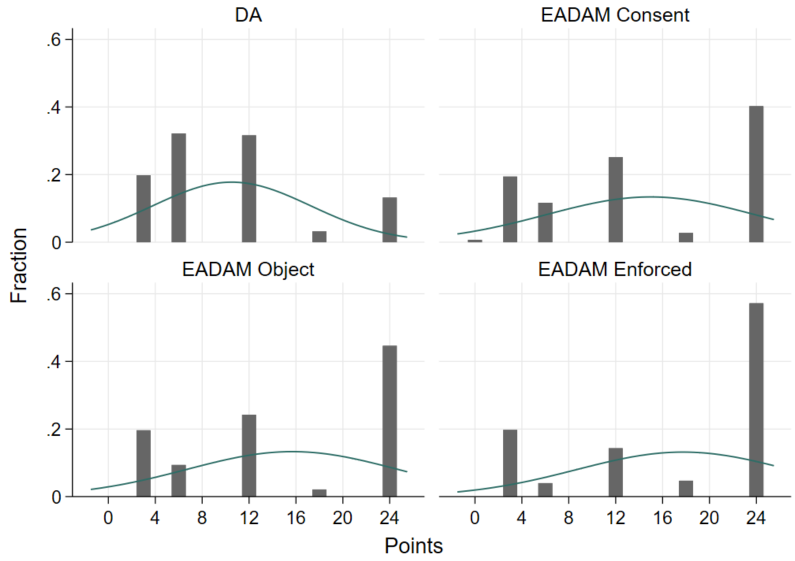

Figure 8: Treatment effects on the distribution of points (π)

and EADAM Object (lines are parallel), but slightly higher under EADAM Enforced. Table 11 reports the results of a three-level mixed-effects linear regression model for the comparison between DA and EADAM with interaction terms for treatment and truth-telling.

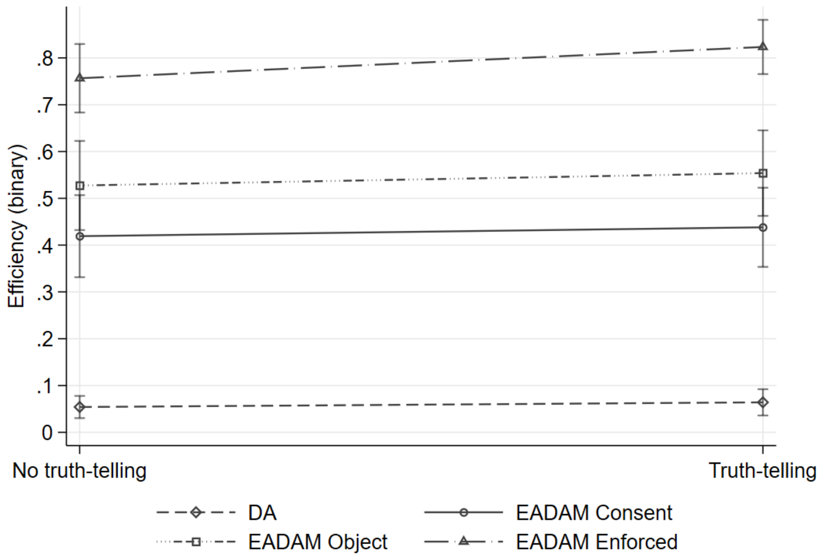

Figure 9: Average marginal effect of interaction between truth-telling and treatment

Consent Figure 10 shows our treatment effects on the probability of consent. Figure 11 shows how the probability of consent varies across periods. Table 12 reports the results of a three-level mixed-effects linear regression model for the comparison between DA and EADAM.

Stability In Figure 12, we show the fraction of DA stable assignments across treatments. We code a stability value that takes value 1 if the DA stable assignment is achieved, and 0 otherwise. We find that the proportion of DA stable assignment is significantly higher under DA than under each variant of EADAM, as it is reasonable

Table 11: Impact of EADAM on efficiency compared to DA with interaction

DV: Efficiency Baseline: DA	(1)	(2)
EADAM Consent	0.365***	3.382***
	(0.046)	(0.772)
EADAM Object	0.473***	4.126***
	(0.050)	(0.803)
EADAM Enforced	0.702***	5.415***
	(0.039)	(0.797)
Truth	0.1853	1.063***
	(0.1751)	(0.300)
EADAM Consent*Truth	0.019	1.114**
	(0.020)	(0.441)
EADAM Object*Truth	0.027	1.158**
	(0.020)	(0.473)
EADAM Enforced*Truth	0.067***	2.591***
	(0.018)	(0.473)
Constant	-3.076	10.054***
	(0.244)	(0.548)
N_I	10.000	10.000
N_G	50	50

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Column 1: Three-level mixed-effects logit regression. Standard errors in parentheses. Treatment coefficients are reported as average marginal treatment effects under no truth-telling. Interaction coefficients are reported as average marginal effects of truth-telling relative to no truth-telling. *Efficiency* is a dummy variable that takes value 1 if assignments are Pareto-efficient, and 0 otherwise. Column 2: Three-level mixed-effects linear regression. Standard errors in parentheses. Treatment coefficients are reported as average marginal treatment effects under no truth-telling. Interaction coefficients are reported as average marginal effects of truth-telling relative to no truth-telling. *Efficiency* is a continuous variable that captures the number of points earned by students. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

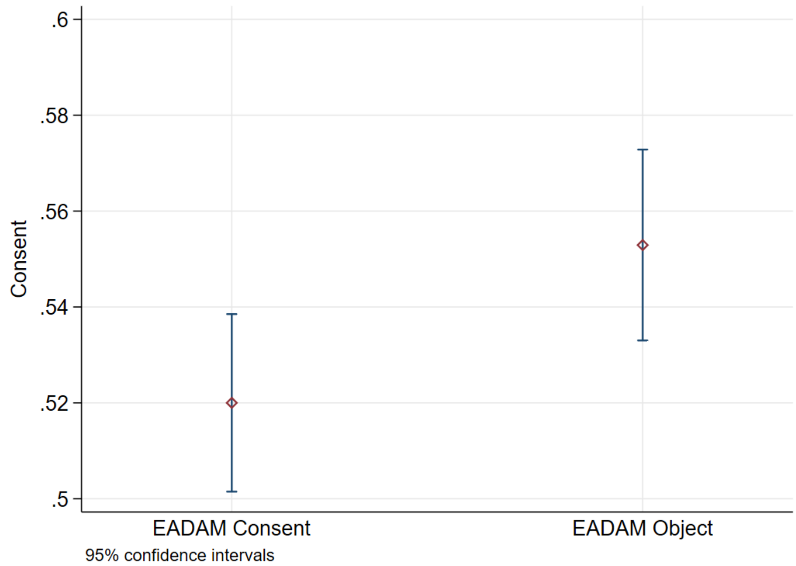

Figure 10: Treatment effects on consent

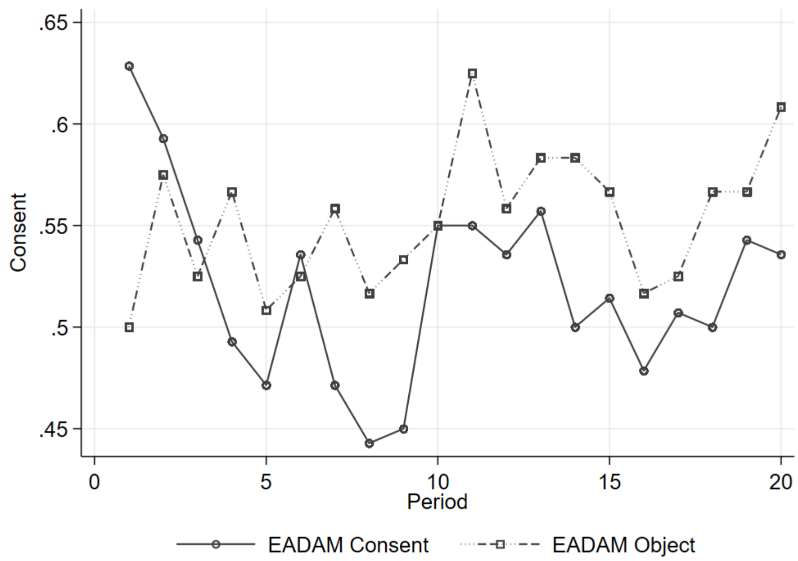

Figure 11: Treatment effects on consent by period

Table 12: Comparison of consent rates between EADAM Consent and EADAM Object

DV: Consent Baseline: EADAM Consent	(1)	(2)	(3)
EADAM Object	0.036 (10.928)	0.035 (0.041)	0.035 (0.041)
Type		Yes	Yes
Period			Yes
N_I	5.200	5.200	5.200
N_G	26	26	26

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects logit regression. Standard errors in parentheses. All coefficients are reported as average marginal effects. *Consent* is a dummy variable that takes value 1 if students consented or did not object, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

to expect. In particular, DA stable assignments are 64% under DA, 19% under EADAM Consent and 15% under EADAM Object. No DA stable assignments are achieved under EADAM Enforced.

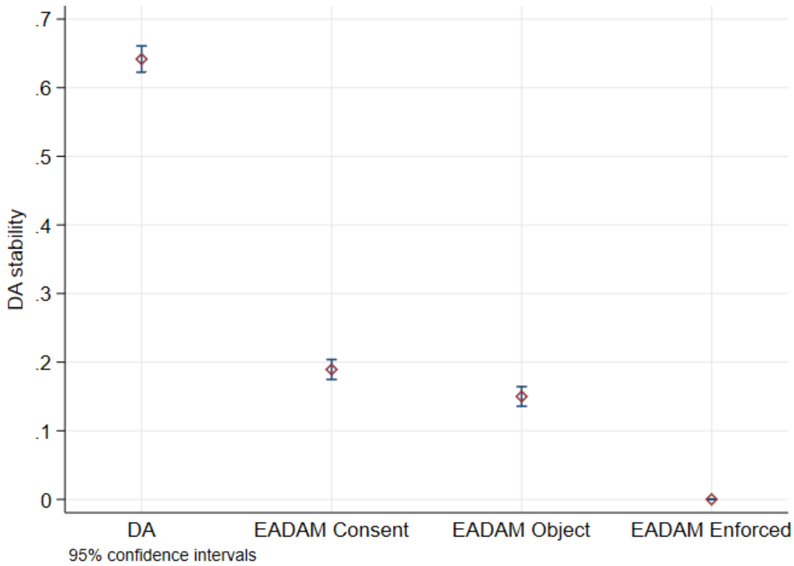

Figure 12: Treatment effects on DA stability

A.2 Manipulable Markets

In this subsection, we present an overview of additional results for both manipulable markets.

Truth-telling Figure 13 shows the treatment effects on truth-telling for the two manipulable markets. Figure 14 shows the treatment effects on truth-telling by student type in Market 1, and Figure 15 shows the treatment effects on truth-telling by student type in Market 2.

Efficiency Table 13 reports the results of a three-level mixed-effects linear regression model for the comparison between DA and EADAM Consent. Figure 16 shows our treatment effects on efficiency using our binary

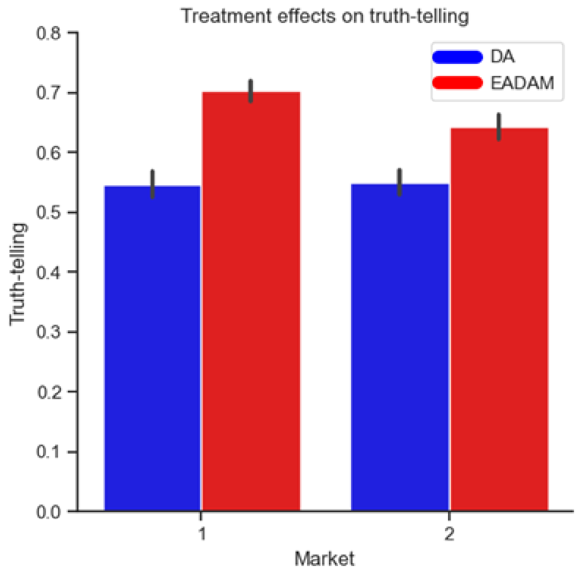

Figure 13: Treatment effects on truth-telling

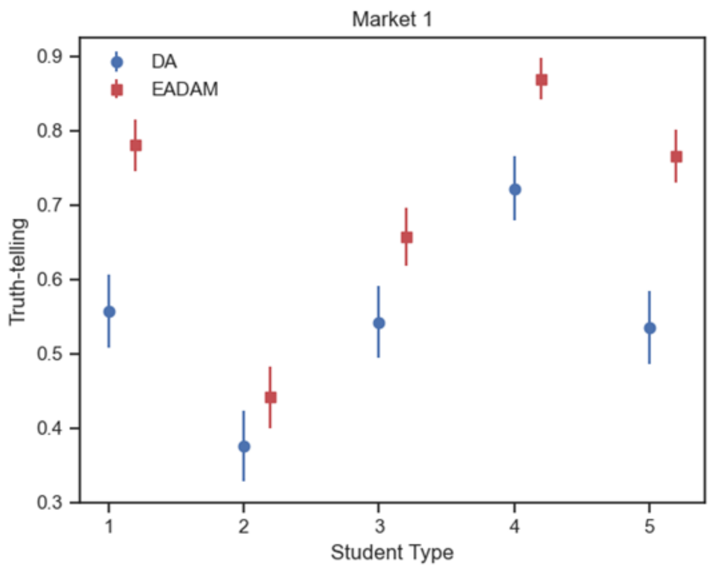

Figure 14: Truth-telling by student type

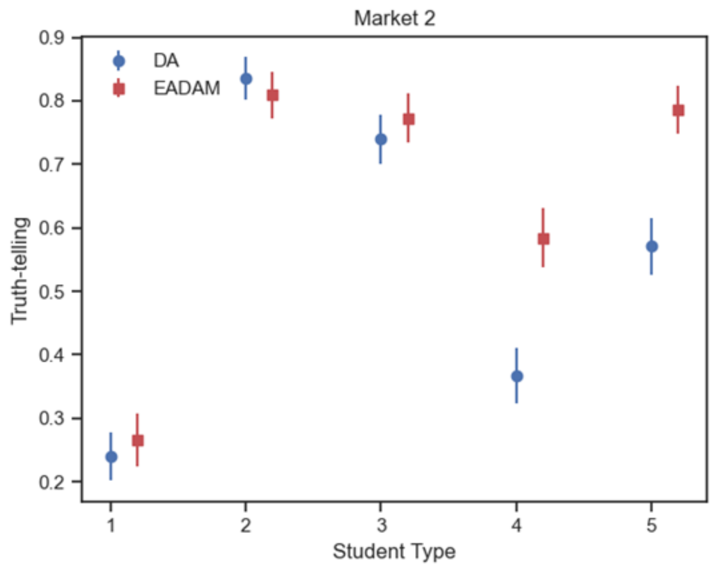

Figure 15: Truth-telling by student type

efficiency measure ω that takes value 1 if assignments are Pareto-efficient, and 0 otherwise. Figure 17 shows our treatment effects on efficiency using our continuous efficiency measure π, given by per capita payoffs (points earned).

Table 13: Impact of EADAM on efficiency compared to DA (π)

DV: Efficiency (π) Baseline: DA	**Manipulable Market 1**				**Manipulable Market 2**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
EADAM Consent	0.962**	0.962**	0.962**	0.624*	1.316**	1.316**	1.316**	1.173**
	(0.464)	(0.401)	(0.401)	(0.370)	(0.629)	(0.593)	(0.593)	(0.551)
Type		Yes	Yes	Yes		Yes	Yes	Yes
Period			Yes	Yes			Yes	Yes
Truth				2.160***				1.533***
				(0.145)				(0.160)
N_I	4,800	4,800	4,800	4,800	4,600	4,600	4,600	4,600
N_G	24	24	24	24	23	23	23	23

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
Three-level mixed-effects linear regression. Standard errors in parentheses. *Efficiency* is a continuous variable that captures the number of points earned by students. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. N_I denotes the number of individual observations. N_G denotes the number of experimental matching groups.

Consent Consent rates in the manipulable markets are very similar to consent rates in the non manipulable market (Market 1: 48.11%, Market 2: 54.41%). As in the non manipulable market, consent rates slightly vary by student type, but none of these differences follow a systematic pattern.

Stability In both the manipulable markets, the proportions or stable assignments under DA and under EADAM are not significantly different. This is in line with our theoretical predictions. In particular, in Market 1 the pro-

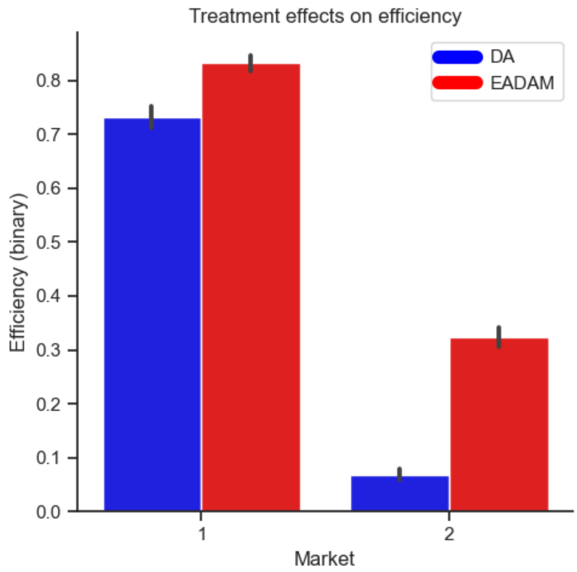

Figure 16: Treatment effects on efficiency (ω)

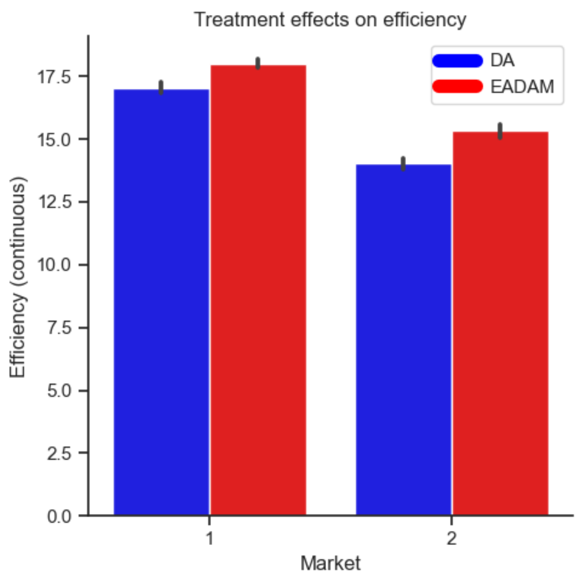

Figure 17: Treatment effects on efficiency (π)

portion of stable assignments is 48.50% under DA and 56.61% under EADAM. In Market 2, the proportion of stable assignments is 58.96% under DA and 54.32% under EADAM.

B Markets

B.1 Experiment 1: Non-manipulable Market

Consider a set of five students $I \equiv \{i_1, i_2, i_3, i_4, i_5\}$ and a set of five schools $S \equiv \{s_1, s_2, s_3, s_4, s_5\}$, where each school has a capacity of only one seat. Each student has strict preferences over schools, denoted by P_i, and each school has strict priorities over students, denoted by $\succ_s$. Preferences and priorities are as stated in subsection 3.1.

As described in Section 2.2, Round 0 of the EADAM algorithm involves running the DA algorithm. R is the rank distribution matrix for assignments in each iteration of the algorithm where rows represent students in ascending order (row 1: i_1, row 2: i_2, etc.) and columns represent the position of schools in each student's rank-order preference list (column 1: top choice, column 2: second choice, etc.) If each student reveals her preferences truthfully, EADAM proceeds as follows. Run DA.

Step	s_1	s_2	s_3	s_4	s_5
1	i_1	i_2	$\boxed{i_4}, i_5$	i_3	
2	i_1	$\boxed{i_2}, i_5$	i_4	i_3	
3	$\boxed{i_1}, i_5$	i_2	i_4	i_3	
4	i_1	i_2	i_4	$\boxed{i_5}, i_3$	
5	$\boxed{i_1}, i_3$	i_2	i_4	i_5	
6	i_1	$\boxed{i_2}, i_3$	i_4	i_5	
7	i_1	i_2	$\boxed{i_3}, i_4$	i_5	
8	$\boxed{i_4}, i_1$	i_2	i_3	i_5	
9	i_4	i_2	$\boxed{i_3}, i_1$	i_5	
10	i_4	i_2	i_3	$\boxed{i_5}, i_1$	
11	i_4	$\boxed{i_1}, i_2$	i_3	i_5	
12	i_4	i_1	i_3	$\boxed{i_5}, i_2$	
13	$\boxed{i_2}, i_4$	i_1	i_3	i_5	
14	i_2	$\boxed{i_4}, i_1$	i_3	i_5	
15	i_2	i_4	i_3	i_5	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

The matching produced by DA in Step 15 is stable but Pareto-inefficient. No student is assigned to her top or second choice. Two students (i_2, i_4) are assigned to their third choice, two students (i_3, i_5) are assigned to their fourth choice, and one student (i_1) is assigned to her last choice.

These efficiency losses are caused by students whom we refer to as *interrupters*. For the sake of clarity, interrupters are highlighted in blue. In this school choice problem, DA generates five interruptions: (i_4, s_3), (i_2, s_2), (i_1, s_1), (i_4, s_1), (i_1, s_2). The efficiency losses caused by these interruptions can be recovered by applying EADAM.

In Round 1 of the EADAM algorithm, we first identify the last interruption: (i_1, s_2). Suppose i_1 consents. Schools s_1 and s_2 are removed from her rank-order preference list. Re-running DA with updated rank-order preference list $P_{i_1} = s_3, s_4, s_5$ produces a Pareto-efficient matching. Three students (i_2, i_3, i_4) are assigned to their top choice, one student (i_5) is assigned to her third choice, and one student (i_1) is assigned to her last choice.

Step	s_1	s_2	s_3	s_4	s_5
1		i_2	$\boxed{i_4}, i_1, i_5$	i_3	
2		$\boxed{i_2}, i_5$	i_4	$\boxed{i_3}, i_1$	
3	i_5	i_2	i_4	i_3	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

If i_1 does not consent, we identify the next interruption: (i_4, s_1). Suppose i_4 consents. Schools s_1 and s_3 are removed from her rank-order preference list. Re-running DA with updated rank-order preference list $P_{i_4} = s_2, s_5, s_4$ produces a Pareto-superior matching. Two students (i_3, i_5) are assigned to their top choice, two students (i_2, i_4) are assigned to their third choice, and one student (i_1) is assigned to her last choice.

Step	s_1	s_2	s_3	s_4	s_5
1	i_1	$\boxed{i_4}, i_2$	i_5	i_3	
2	i_1	i_4	i_5	$\boxed{i_3}, i_2$	
3	$\boxed{i_2}, i_1$	i_4	i_5	i_3	
4	i_2	i_4	$\boxed{i_5}, i_1$	i_3	
5	i_2	i_4	i_5	$\boxed{i_3}, i_1$	
6	i_2	$\boxed{i_4}, i_1$	i_5	i_3	
7	i_2	i_4	i_5	i_3	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

If neither i_1 nor i_4 consents, we identify the next interruption: (i_2, s_2). Suppose i_2 consents. School s_2 is removed from her rank-order preference list. Re-running DA with updated rank-order preference list $P_{i_2} = s_4, s_1, s_5, s_3$ produces a Pareto-inefficient matching that is equivalent to the DA matching. No student is assigned to her top or second choice. Two students (i_2, i_4) are assigned to their third choice, two students (i_3, i_5) are assigned to their fourth choice, and one student (i_1) is assigned to her last choice.

Step	s_1	s_2	s_3	s_4	s_5
1	i_1		$\boxed{i_4}, i_5$	$\boxed{i_3}, i_2$	
2	$\boxed{i_2}, i_1$	i_5	i_4	i_3	
3	i_2	i_5	$\boxed{i_4}, i_1$	i_3	
4	i_2	i_5	i_4	$\boxed{i_3}, i_1$	
5	i_2	$\boxed{i_1}, i_5$	i_4	i_3	
6	$\boxed{i_2}, i_5$	i_1	i_4	i_3	
7	i_2	i_1	i_4	$\boxed{i_5}, i_3$	
8	$\boxed{i_2}, i_3$	i_1	i_4	i_5	
9	i_2	$\boxed{i_1}, i_3$	i_4	i_5	
10	i_2	i_1	$\boxed{i_3}, i_4$	i_5	
11	$\boxed{i_2}, i_4$	i_1	i_3	i_5	
12	i_2	$\boxed{i_4}, i_1$	i_3	i_5	
13	i_2	i_4	i_3	i_5	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

B.2 Experiment 2: Manipulable Markets

Consider a set of five students $I \equiv \{i_1, i_2, i_3, i_4, i_5\}$ and a set of five schools $S \equiv \{s_1, s_2, s_3, s_4, s_5\}$, where each school has a capacity of only one seat. Each student has strict preferences over schools, denoted by P_i, and each school has strict priorities over students, denoted by $\succ_s$.

Market 1: Market Without Interrupters In Market 1, preferences and priorities are as stated in subsection 3.2. As described in Section 2.2, Round 0 of the EADAM algorithm involves running the DA algorithm. R is the rank distribution matrix for assignments in each iteration of the algorithm where rows represent students in ascending order (row 1: i_1, row 2: i_2, etc.) and columns represent the position of schools in each student's rank-order preference list (column 1: top choice, column 2: second choice, etc.). If each student reveals her preferences truthfully, EADAM proceeds as follows. Run DA.

Step	s_1	s_2	s_3	s_4	s_5
1				$i_1, i_3, \boxed{i_4}, i_5$	i_2
2	i_1		i_3	i_4	$i_2, \boxed{i_5}$
3	$\boxed{i_1}, i_2$		i_3	i_4	i_5
4	i_1	i_2	i_3	i_4	i_5

$$R = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

There are no interrupters. Therefore DA is equivalent to EADAM. The matching produced by DA in Step 4 is stable but Pareto-inefficient. One student (i_4) is assigned to her top choice, three students (i_1, i_3, i_5) are assigned to their second choice, and one student (i_2) is assigned to her third choice.

Manipulation by i_2

Truth-telling is not an equilibrium. i_2 has an incentive to manipulate her rank-order preference list by changing the order of s_2 and s_3: $P\prime_{i_2} = s_5, s_1, s_3, s_4, s_2$. Now, in Step 4 i_2 applies to s_3 rather than to s_2. Run DA.

Step	s_1	s_2	s_3	s_4	s_5
1				$i_1, i_3, \boxed{i_4}, i_5$	i_2
2	i_1		i_3	i_4	$i_2, \boxed{i_5}$
3	$\boxed{i_1}, i_2$		i_3	i_4	i_5
4	i_1		$\boxed{i_2}, i_3$	i_4	i_5
5	i_1		i_2	i_4	$i_3, \boxed{i_5}$
6	$i_1, \boxed{i_3}$	i_1	i_2	i_4	i_5
7	i_3	i_1	i_2	i_4	i_5

$$R = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

There is one interrupter: i_1 causes a rejection chain to the detriment of i_2 at s_1 (Step 3). The matching produced by DA in Step 7 is Pareto-inefficient. One student (i_4) is assigned to her top choice, one student (i_5) is assigned to her second choice, one student (i_1) is assigned to her third choice, one student (i_3) is assigned to her fourth choice, and one student (i_2) is assigned to her last choice.

Suppose i_1 consents. Rerun DA with updated rank-order preference list $P_{i_1} = s_4, s_2, s_5, s_3$.

Step	s_1	s_2	s_3	s_4	s_5
1				$i_1, i_3, \boxed{i_4}, i_5$	i_2
2		i_1	i_3	i_4	$i_2, \boxed{i_5}$
3	i_2	i_1	i_3	i_4	i_5

$$R = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

This manipulation is profitable for i_2 (if i_1 consents), as she is assigned to her second choice rather than to her third choice. One student (i_4) is assigned to her top choice, three students (i_2, i_3, i_5) are assigned to their second choice, and one student (i_1) is assigned to her third choice.

(Counter-)Manipulation by i_1

i_1 can (best-)respond by changing the order of s_2 and s_3: $P\prime_{i_1} = s_4, s_1, s_3, s_5, s_2$. Now, in Step 7 i_1 applies to s_3 rather than to s_2. Run DA.

Step	s_1	s_2	s_3	s_4	s_5
1				$i_1, i_3, \boxed{i_4}, i_5$	i_2
2	i_1		i_3	i_4	$i_2, \boxed{i_5}$
3	$\boxed{i_1}, i_2$		i_3	i_4	i_5
4	i_1		$\boxed{i_2}, i_3$	i_4	i_5
5	i_1		i_2	i_4	$i_3, \boxed{i_5}$
6	$i_1, \boxed{i_3}$		i_2	i_4	i_5
7	i_3		$\boxed{i_1}, i_2$	i_4	i_5
8	i_3		i_1	$\boxed{i_2}, i_4$	i_5
9	i_3	i_4	i_1	i_2	i_5

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

There is one interrupter: i_2 causes a rejection chain to the detriment of i_3 at s_3 (Step 4). The matching produced by DA in Step 9 is Pareto-inefficient. No student is assigned to her top choice. Two students (i_4, i_5) are assigned to their second choice, two students (i_2, i_3) are assigned to their fourth choice, and one student (i_1) is assigned to her last choice.

Suppose i_2 consents. Rerun DA with updated manipulated rank-order preference list $P\prime_{i_2} = s_5, s_1, s_4, s_2$.

Step	s_1	s_2	s_3	s_4	s_5
1				$i_1, i_3, \boxed{i_4}, i_5$	i_2
2	i_1		i_3	i_4	$i_2, \boxed{i_5}$
3	$\boxed{i_1}, i_2$		i_3	i_4	i_5
4	i_1		i_3	$\boxed{i_2}, i_4$	i_5
5	i_1	i_4	i_3	i_2	i_5

$$R = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

This manipulation is profitable for i_1, as she is assigned to her second choice rather than to her third choice. No student is assigned to her top choice. Four students (i_1, i_3, i_4, i_5) are assigned to their second choice and one student (i_2) is assigned to her fourth choice.

Market 2: Market With Three Interrupters In Market 2, preferences and priorities are as stated in subsection 3.2. As described in Section 2.2, Round 0 of the EADAM algorithm involves running the DA algorithm. R is the rank distribution matrix for assignments in each iteration of the algorithm where rows represent students in ascending order (row 1: i_1, row 2: i_2, etc.) and columns represent the position of schools in each student's rank-order preference list (column 1: top choice, column 2: second choice, etc.). If each student reveals her preferences truthfully, EADAM proceeds as follows. Run DA.

Step	s_1	s_2	s_3	s_4	s_5
1	i_2	$i_1, \boxed{i_3}, i_4$	i_5		
2	i_2	i_3	$i_1, \boxed{i_4}, i_5$		
3	$\boxed{i_1}, i_2$	i_3	i_4	i_5	
4	i_1	$\boxed{i_2}, i_3$	i_4	i_5	
5	i_1	i_2	$\boxed{i_3}, i_4$	i_5	
6	$i_1, \boxed{i_4}$	i_2	i_3	i_5	
7	i_4	i_2	i_3	i_5	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

There are three interrupters: i_1, i_3, and i_4. i_1 causes a rejection chain to the detriment of i_2 at s_1 (Step 3), i_3 causes a rejection chain to the detriment of i_1 and i_4 at s_2 (Step 1), and i_4 causes a rejection chain to the detriment of i_1 and i_5 at s_3 (Step 2). i_1 is the last interrupter (at s_1 in Step 3). The matching produced by DA in Step 7 is stable but Pareto-inefficient. No student is assigned to her top choice. Three students (i_2, i_3, i_5) are assigned to their second choice, one student (i_3) is assigned to her third choice, and one student (i_1) is assigned to her fourth choice.

Suppose i_1 consents. Rerun DA with updated rank-order preference list $P_{i_1} = s_2, s_3, s_5, s_4$.

Step	s_1	s_2	s_3	s_4	s_5
1	i_2	$i_1, \boxed{i_3}, i_4$	i_5		
2	i_2	i_3	$i_1, \boxed{i_4}, i_5$		
3	i_2	i_3	i_4	i_5	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

There are no more interrupters. The efficiency-adjusted stable matching is achieved. Two students (i_2, i_3) are assigned to their top choice, two students (i_4, i_5) are assigned to their third choice, and one student (i_1) is assigned to her fourth choice.

Manipulation by i_1

Truth-telling is not an equilibrium. i_1 has an incentive to manipulate her rank-order preference list by changing the order of s_4 and s_5: $P\prime_{i_1} = s_2, s_3, s_1, s_4, s_5$. Run DA.

Step	s_1	s_2	s_3	s_4	s_5
1	i_2	$i_1, \boxed{i_3}, i_4$	i_5		
2	i_2	i_3	$i_1, \boxed{i_4}, i_5$		
3	$\boxed{i_1}, i_2$	i_3	i_4	i_5	
4	i_1	$\boxed{i_2}, i_3$	i_4	i_5	
5	i_1	i_2	$\boxed{i_3}, i_4$	i_5	
6	$i_1, \boxed{i_4}$	i_2	i_3	i_5	
7	i_4	i_2	i_3	$\boxed{i_1}, i_5$	
8	$i_4, \boxed{i_5}$	i_2	i_3	i_1	
9	i_5	i_2	i_3	i_1	i_4

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

There are three interrupters: i_1, i_3, and i_4. i_1 causes a rejection chain to the detriment of i_2 at s_1 (Step 3), i_3 causes a rejection chain to the detriment of i_1 and i_4 at s_2 (Step 1), and i_4 causes a rejection chain to the detriment of i_1 and i_5 at s_3 (Step 2) and to the detriment of i_1 at s_1 (Step 6). i_4 is the last interrupter (at s_1 in Step 6). The matching produced by DA in Step 9 is Pareto-inefficient. No student is assigned to her top choice. Two students (i_2, i_3) are assigned to their second choice, one student (i_5) is assigned to her third choice, one student (i_4) is assigned to her fourth choice, and one student (i_1) is assigned to her last choice.

Suppose i_4 consents. Rerun DA with updated rank-order preference list $P_{i_4} = s_2, s_3, s_5, s_4$.

Step	s_1	s_2	s_3	s_4	s_5
1	i_2	$i_1, \boxed{i_3}, i_4$	i_5		
2	i_2	i_3	$i_1, \boxed{i_4}, i_5$		
3	$\boxed{i_1}, i_2$	i_3	i_4	i_5	
4	i_1	$\boxed{i_2}, i_3$	i_4	i_5	
5	i_1	i_2	$\boxed{i_3}, i_4$	i_5	
6	i_1	i_2	i_3	i_5	i_4

$$R = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

This manipulation is profitable for i_1, as she is assigned to her third choice rather than to her fourth choice. No student is assigned to her top choice. Three students (i_2, i_3, i_5) are assigned to their second choice, one student (i_1) is assigned to her third choice, and one student (i_4) is assigned to her fourth choice.

Manipulation by i_5

Truth-telling is not an equilibrium. i_5 has an incentive to manipulate her rank-order preference list by ranking s_2 as second choice rather than as fifth choice: $P\prime_{i_5} = s_3, s_2, s_4, s_1, s_5$. Run DA.

Step	s_1	s_2	s_3	s_4	s_5
1	i_2	$i_1, \boxed{i_3}, i_4$	i_5		
2	i_2	i_3	$i_1, \boxed{i_4}, i_5$		
3	$\boxed{i_1}, i_2$	$i_3, \boxed{i_5}$	i_4		
4	i_1	$i_2, \boxed{i_5}$	$\boxed{i_3}, i_4$		
5	$i_1, \boxed{i_4}$	i_5	$\boxed{i_2}, i_3$		
6	i_4	i_5	i_2	i_3	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

There are three interrupters: i_1, i_3, and i_4. i_1 causes a rejection chain to the detriment of i_2 at s_1 (Step 3), i_3 causes a rejection chain to the detriment of i_1 and i_4 at s_2 (Step 1) and to the detriment of i_4 at s_3 (Step 4), and i_4 causes a rejection chain to the detriment of i_1 and i_5 at s_3 (Step 2). i_3 is the last interrupter (at s_3 in Step 4). i_1 is the penultimate interrupter (at s_1 in Step 3). The matching produced by DA in Step 6 is Pareto-inefficient. No student is assigned to her top or second choice. Three students (i_2, i_3, i_4) are assigned to their third choice, one student (i_1) is assigned to her fourth choice, and one student (i_5) is assigned to her last choice.

Suppose i_1 and i_3 consent. Rerun DA with updated rank-order preference lists $P_{i_1} = s_2, s_3, s_5, s_4$ and $P_{i_3} = s_4, s_5, s_1$.

Step	s_1	s_2	s_3	s_4	s_5
1	i_2	$i_1, \boxed{i_4}$	i_5	i_3	
2	i_2	i_4	$i_1, \boxed{i_5}$	i_3	
3	i_2	i_4	i_5	i_3	i_1

$$R = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

This manipulation is profitable for i_5, as she is assigned to her first choice rather than to her second choice. Three students (i_2, i_4, i_5) are assigned to their top choice, one student (i_3) is assigned to her third choice, and one student (i_1) is assigned to her fourth choice.

C Instructions

C.1 EADAM Consent

INTRODUCTION

In this study, we simulate a procedure to assign students to schools.

Please give this study your full attention. You will have a limited amount of time to complete the study. If you are inactive for long and time runs out, you will be unable to continue the study and will only be paid **€4.00** for your participation.

Your earnings are given in points. At the end of the study, you will be paid based on the following exchange rate:

1 point = €0.25.

Your earnings depend on your decisions and those made by other participants. In addition, you will be paid **€4.00** for your participation. No other participant will be informed about your payment.

Note: As you can see on top of this screen, these instructions are organized in different tabs (Introduction, Procedure, Example, Practice Questions). You can switch back and forth between these tabs. All tabs (except the tab with the Practice Questions) will be accessible any time during the entire experiment.

PROCEDURE

Periods and groups. The experiment consists of 20 periods. At the beginning of each period, you will be randomly matched with four other people in this session to form a group of five. All members of your group will assume the role of students applying for a school.

Types. Each group contains one of each of the five different student types: Student 1, Student 2, Student 3, Student 4 and Student 5. Student types are randomly assigned at the beginning of the experiment and remain the same throughout the experiment.

Schools and seats. For each group of participants, five schools are available: A, B, C, D, and E. Each school has one seat. Each seat is assigned to one student.

Ranking decision. In each period, you will be asked to rank the schools to indicate your preferences on a list (preference list). Note that you need to rank all five schools in order to indicate your preferences.

Earnings. Your earnings in each period depend on the school you are assigned to at the end of each period. Your assignment to a school depends on your type, your choices, and the choices made by the other four students in your group.

There will be 20 periods. At the end, two of these periods will be chosen randomly (with all periods being equally likely to be chosen). Your total earnings will equal the sum of your earnings in these two randomly chosen periods, plus €4.00 for your participation in the experiment. At the end of the experiment, you will be informed about the periods chosen, your earnings in those periods, and the total earnings.

For each student, each school is associated with a different number of points. You can think of this number of points as reflecting how desirable a school is to a student in terms of location and quality of education. The earnings for each of the five student types are outlined in the following table.

	Student 1	**Student 2**	**Student 3**	**Student 4**	**Student 5**
25 points	A	B	D	C	C
18 points	C	D	A	A	B
12 points	D	A	B	B	A
7 points	B	E	C	E	D
3 points	E	C	E	D	E

Note: You do not have to memorize this table. We will show you this table again in each period before you make your decision.

School priorities. Each school ranks each of the five student types in a different way. You can think of each school's ranking (priority list) as being based on how far each of the students live from the school. The priority lists for each of the five schools are outlined in the following table.

	School A	**School B**	**School C**	**School D**	**School E**
First priority	Student 2	Student 4	Student 3	Student 4	Student 1
Second priority	Student 4	Student 1	Student 2	Student 5	Student 3
Third priority	Student 1	Student 2	Student 4	Student 3	Student 2
Fourth priority	Student 5	Student 3	Student 5	Student 2	Student 5
Fifth priority	Student 3	Student 5	Student 1	Student 1	Student 4

Temporary and final admissions. In this procedure, we distinguish between temporary and final admissions. As illustrated below and in the example (**see next tab**), in some parts of the procedure the admission of a student is temporary.

In case of a **temporary** admission, the following three cases can occur:

1) The temporary admission of a student at a school becomes final at the end of the procedure.

2) The temporary admission of a student at a school differs from her final admission and **does not prevent** any other student from being admitted there.

3) The temporary admission of a student at a school differs from her final admission and **prevents** other students from being admitted there.

We refer to the student in case 3) as a **blocking student**.

Depending on the preference list you and others submit, you might turn out to be a blocking student at one or more schools.

Consent. In each period, we will ask you to decide whether you consent to waive your priority at a school in the event that you are identified as a blocking student there.

If you consent, the respective school(s) will be removed from your preference list without changing the relative ranking of the remaining schools on the list.

Note: Consenting to waive your priorities will never change your final admission but may improve other students' final admissions. We illustrate that in the example (see next tab).

Admissions procedure. After all participants have submitted their preference lists, the computer will assign each student in each group to a school. At the end of each period, each student will be informed about everybody's assignment. Note that your assignment in each period is not affected by your assignments in the previous periods.

The assignment is generated according to the following procedure:

Part 1

Step 1

- For each student, an application is sent to the school that she ranked first on her preference list (see paragraph on ranking decision).
- If a school receives only one application, the student is temporarily admitted. If a school receives more than one application, the student with the highest priority is temporarily admitted and the remaining students are rejected.

Step 2

- For each student who was rejected in the previous step, an application is sent to the school that she ranked second on her preference list.
- Each school that receives new applications considers the student it admitted in the previous step together with the new applicants. Among these, the student with the highest priority is temporarily admitted and the remaining students are rejected.

Following steps

- The procedure continues according to the same rules.

End of Part 1

- The procedure in Part 1 ends when no student is rejected, that is, each student is assigned a seat at a school.

Part 2

Step 1

- The computer looks for the last step of the procedure in Part 1 in which a student has become a blocking student.
- If a student is a blocking student at a school and has consented to waive her priorities, the computer will remove the respective school(s) from the student's preference list and rerun the procedure described in Part 1.
- If no student is a blocking student, the procedure ends and the final admission is the same as in the last step of Part 1.

Step 2

- If the procedure has not ended, the procedure described in the previous step is repeated.

Final Step

- The procedure ends when there is no step in which a student becomes a blocking student.

Note: Until the final step, admissions are **temporary**: a student admitted at one step may be rejected in a later step.

EXAMPLE

We will go through a simple example to illustrate how the allocation procedure works. In this example, there are four students (1, 2, 3 and 4) and four schools (A, B, C and D). Each school has one seat. Students submit the following preference lists:

	Student 1	**Student 2**	**Student 3**	**Student 4**
10 points	A	A	A	C
6 points	D	B	B	A
3 points	B	C	C	B
1 point	C	D	D	D

The priority list of each of the four schools is the following:

	School A	**School B**	**School C**	**School D**
First priority	Student 4	Student 2	Student 3	Student 1
Second priority	Student 1	Student 3	Student 4	Student 4
Third priority	Student 2	Student 1	Student 2	Student 3
Fourth priority	Student 3	Student 4	Student 1	Student 2

Note: At any step, any student temporarily admitted at a school is shown in a box.

Part 1

Step 1 For each student, an application is sent to the school that she ranked first. That is, students 1, 2 and 3 apply to school A, and student 4 applies to school C. Thus, school A receives three applications. It temporarily admits the applicant with the highest priority (student 1) and rejects students 2 and 3. School C temporarily admits student 4.

	School A	**School B**	**School C**	**School D**
Step 1	$\boxed{1}$, 2, 3		$\boxed{4}$	

Step 2 Both student 2 and student 3 have been rejected by school A in Step 1 and thus apply to the school that they ranked second (school B). School B receives two applications. It temporarily admits student 2 and rejects student 3, as student 2 has a higher priority at school B than student 3. (For student 1 and student 4, there is no change at this step.)

	School A	**School B**	**School C**	**School D**
Step 2	$\boxed{1}$	$\boxed{2}$, 3	$\boxed{4}$	

Step 3 Student 3 has been rejected by school B in Step 2 and thus applies to the school that she ranked third (school C). Now school C receives two applications. It temporarily admits student 3 and rejects student 4, as student 3 has a higher priority at school C than student 4. (For student 1 and student 2, there is no change at this step.)

	School A	**School B**	**School C**	**School D**
Step 3	$\boxed{1}$	$\boxed{2}$	4, $\boxed{3}$	

Step 4 Student 4 has been rejected by school C in Step 3 and thus applies to the school that she ranked second (school A). Now school A receives two applications. It temporarily admits student 4 and rejects student 1, as student 4 has a higher priority at school A than student 1. (For student 2 and student 3, there is no change at this step.)

	School A	**School B**	**School C**	**School D**
Step 4	1, $\boxed{4}$	$\boxed{2}$	$\boxed{3}$	

Step 5 Student 1 has been rejected by school A in Step 4 and thus applies to the school that she ranked second (school D). Now no student is rejected. The procedure in Part 1 ends.

	School A	**School B**	**School C**	**School D**
Step 5	$\boxed{4}$	$\boxed{2}$	$\boxed{3}$	$\boxed{1}$

Part 2

We now look for blocking students in Part 1. In the example presented above, student 1 is a blocking student. In Step 1, her application has prevented students 2 and 3 from being admitted at school A. However, being temporarily admitted at school A does not benefit student 1, as she is assigned to school D in the last step (Step 5).

If student 1 **does not consent** to waive her priority, the admissions in the last step of Part 1 (Step 5) become final and Part 2 ends with no change.

If student 1 **consents** to waive her priority, school A is removed from her preference list. Her preference list is adjusted as follows:

	Student 1	**Student 2**	**Student 3**	**Student 4**
10 points		A	A	C
6 points	D	B	B	A
3 points	B	C	C	B
1 point	C	D	D	D

Now we repeat the admissions procedure described in Part 1.

Step 1 Each student applies to the school that she ranked first on her (adjusted) preference list. That is, student 1 applies to school D, students 2 and 3 apply to school A, and student 4 applies to school C. School A receives two applications. It temporarily admits student 2 and rejects student 3, as student 2 has a higher priority than student 3 at school A.

	School A	**School B**	**School C**	**School D**
Step 1	$\boxed{2}$, 3		$\boxed{4}$	$\boxed{1}$

Step 2 Student 3 has been rejected by school A in Step 1 and thus applies to the school that she ranked second (school B). No student is rejected. The admission is final. There is no step in which a student becomes a blocking student.

	School A	**School B**	**School C**	**School D**
Step 2	$\boxed{2}$	$\boxed{3}$	$\boxed{4}$	$\boxed{1}$

Note: The final admission of student 1 has not changed (she is still admitted at school D), but the admissions of the other three students have improved.

PRACTICE QUESTIONS

1. How many participants are there in your group in each period?

2. Do participants in your group remain the same in each period?

3. If you are admitted at School A, how many points do you earn?

4. Do you keep your student type in each period?

5. Does each school have the same priorities over students?

6. If you are admitted at a school, can another student be simultaneously be admitted at the same school?

7. Is the admission final at the end of each step?

8. If a school does not reject you at any of the steps, does this mean that you are finally admitted at that school?

9. Is your final admission affected by whether you consent to waive your priorities?

C.2 EADAM Object

PROCEDURE

⋮

Objection.

In each round, we will ask you to decide whether you object to waive your priority at a school in the event that you are identified as a blocking student there.

If you do not object, the respective school(s) will be automatically removed from your preference list without changing the relative ranking of the remaining schools on the list.

Note: Not objecting to waiving your priorities will never change your final admission but may improve other students' final admissions. We illustrate that in the example (see next tab).

⋮

Part 2

Step 1

- The computer looks for the last step of the procedure in Part 1 in which a student has become a blocking student.
- If a student is a blocking student at a school and has not objected to waiving her priorities, the computer will remove the respective school(s) from the student's preference list and rerun the procedure described in Part 1.
- If no student is a blocking student, the procedure ends and the final admission is the same as in the last step of Part 1.

⋮

EXAMPLE

⋮

Part 2

⋮

If student 1 **objects** to waive her priority, the admissions in the last step of Part 1 (Step 5) become final and Part 2 ends with no change.

If student 1 **does not object** to a waiver, school A is removed from her preference list. Her preference list is adjusted as follows:

C.3 EADAM Enforced

PROCEDURE

⋮

Automatic waiver.

The computer will automatically waive your priority at a school in the event that you are identified as a blocking student there.

Through the automatic waiver, the respective school(s) will be removed from your preference list without changing the relative ranking of the remaining schools on the list.

Note: The automatic waiver of your priorities will never change your final admission but may improve other students' final admissions. We illustrate that in the example (see next tab).

⋮

Part 2

Step 1

- The computer looks for the last step of the procedure in Part 1 in which a student has become a blocking student.
- If a student is a blocking student at a school, the computer will remove the respective school(s) from the student's preference list and rerun the procedure described in Part 1.
- If no student is a blocking student, the procedure ends and the final admission is the same as in the last step of Part 1.

⋮

EXAMPLE

⋮

Part 2

⋮

Through the automatic waiver, school A is removed from the preference list of student 1. Her preference list is adjusted as follows:

C.4 DA

These instructions are the same as the instructions for EADAM, with two key differences. First, the three paragraphs about the consent decision are missing in the instructions for DA. Second, we omit Part 2 of the example in the instructions for DA.