THE
ECONOMIC
JOURNAL

The Economic Journal, 1–46 https://doi.org/10.1093/ej/uead120
Advance Access Publication Date: 5 January 2024

SCHOOL CHOICE WITH CONSENT: AN EXPERIMENT*

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Public school choice often yields student assignments that are neither fair nor efficient. The efficiency-adjusted deferred acceptance mechanism allows students to consent to waive priorities that have no effect on their assignments. A burgeoning recent literature places the efficiency-adjusted deferred acceptance mechanism at the centre 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 the efficiency-adjusted deferred acceptance mechanism against the celebrated deferred acceptance mechanism. We find that both efficiency and truth-telling rates are higher under the efficiency-adjusted deferred acceptance mechanism than under the deferred acceptance mechanism, even though the efficiency-adjusted deferred acceptance mechanism is not strategy proof. When the priority waiver is enforced, efficiency further increases, while truth-telling rates decrease relative to variants of the efficiency-adjusted deferred acceptance mechanism 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.

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 the DA algorithm. Several school districts in the United States and other countries have adopted some version of the DA algorithm, not least for its fairness virtues (Abdulkadiroğlu *et al.*, 2005a,b; Pathak and Sönmez, 2013).

On the one hand, the DA algorithm produces stable outcomes, which means that the DA algorithm 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, the DA

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This paper was received on 23 June 2022 and accepted on 29 December 2023. The Editor was Steffen Huck.

The data and codes for this paper are available on the Journal repository. They were checked for their ability to reproduce the results presented in the paper. The replication package for this paper is available at the following address: https://doi.org/10.5281/zenodo.10438859.

We would like to thank Estelle Cantillon, Yan Chen, Christoph Engel, Aytek Erdil, Pablo Guillen, Guillaume Haeringer, Rustamdjan Hakimov, Thilo Klein, Andrew Kloosterman, Dorothea Kübler, Pascal Langenbach, Antonio Miralles, Thayer Morrill, Josué Ortega, Juan Sebastián Pereyra, Alex Rees-Jones, Ran Shorrer, Peter Troyan, Bertan Turhan, Yuqi Wang, Thomas Wouters, reviewers of the ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization (EAAMO '21), participants at the 2022 Easter Workshop on School Choice at Queen's University Belfast, the 2022 World Economic Science Association Conference at the MIT Sloan School of Management in Cambridge, MA (2022 World ESA), the Workshop & Lecture Series in Law & Economics at ETH Zurich, the University of St. Gallen and the University of Zurich, and the 2023 Workshop on Advances in Behavioural and Experimental Economics at King's College London for helpful discussions and comments. This study was conducted in compliance with the laboratory rules of the Max Planck Institute for Research on Collective Goods. We would like to thank the entire lab team at the Max Planck Institute, especially Ali Seyhun Saral and Michael Seebauer, for their unwavering support and valuable comments.

This study was funded by the Max Planck Institute for Research on Collective Goods.

[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.

algorithm 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). The DA algorithm 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).

The DA algorithm, 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 *et al.* (2009) showed for the New York City High School match in 2006–7 that approximately 4,300 eight graders could have been assigned to more preferred options without hurting other students.

Kesten (2010) traced the source of the welfare loss under the DA mechanism 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 the DA mechanism to recover the welfare losses. More specifically, the DA mechanism is based on iterated applications of students in the order of their preferences. As further explained below, EADAM systematically 'revises' the applications under the DA mechanism whenever they give rise to a *rejection cycle* (see Section 1.2). 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]

EADAM, not only became a serious contender to the DA mechanism, as evidenced by a growing literature that puts it at the centre of the stability and efficiency trade-off (see Section 1.1), 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 favourably 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.*

[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 characterised 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 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 May 17, 2019 (2019041360) amending the primary education decree of February 25, 1997, the Codex Secondary Education of December 17, 2010 and the codification of certain provisions for education of October 28, 2016 regarding the right of enrolment.

This provision was conjointly adopted with other rules mandating the protection of underrepresented 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 the DA mechanism. We investigate the performance of EADAM relative to the DA mechanism 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 behavioural 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 legitimise 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.

Our results are intended to contribute to the research areas of market design and behavioural 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 the DA mechanism. 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 behavioural response of students to EADAM.

Second, we observe a relatively high prevalence of preference misrepresentation under the DA mechanism, 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 the DA mechanism. 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 *et al.* (2019), Bó and Hakimov (2020) and Hakimov and Raghavan (2020) compared the DA mechanism to a dynamic version of the DA mechanism where students apply for one school at a time. They found that, even though the dynamic DA mechanism is not strategy proof, it yields higher truth-telling rates than the DA mechanism. Afacan *et al.* (2022) compared the DA mechanism to the

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

iterative deferred acceptance (IDA) mechanism with two iterations, which is not strategy proof. They found that, under the IDA mechanism, strategic students who play undominated strategies cannot gain at the expense of truthful students.[7] Cho *et al.* (2022) compared the DA mechanism to the stable improvement cycle (SIC) and the choice-augmented deferred acceptance (CADA) mechanism and found no difference in truth-telling rates and higher efficiency of SIC over the DA mechanism.

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 strategise or strategise 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 manipulations, our experiment contributes a novel perspective on the potential drivers of this finding. While non-strategy-proof mechanisms such as the dynamic DA and IDA mechanisms 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 behavioural 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 *et al.*, 2012; Ferguson *et al.*, 2019; Fan *et al.*, 2020; Engel and Van Lange, 2021), that is, individual behaviour 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 centrepiece in behavioural 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 admission procedure. More generally, our results provide important evidence for policy makers and school authorities keen on implementing a school admission procedure that mitigates the stability and efficiency trade-off with little disruption to the compelling stability and incentive properties of the DA mechanism.

[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 *et al.*, 2018).

[8] Budish and Cantillon (2012) raised a similar point in the context of course allocation. They used theory and field data to study the draft mechanism for allocating courses at Harvard Business School. They found 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.

[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.

An alternative way of addressing the inefficiency arising from the DA mechanism is to allow students to trade the seats they have been assigned under the DA mechanism 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 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 the DA mechanism with multiple tiebreaking used until 2016 (de Haan, 2017; de Haan *et al.*, 2023):[12]

> *If swapping were allowed, (...) a student with an unfavourable lottery number [lower priority] could bypass a student with a more favourable 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 the DA mechanism. 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 admission system in 2005 (Abdulkadiroğlu *et al.*, 2005b) 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 eliminates

[10] Alternatively, an efficient procedure such as the the top trading cycle (TTC) mechanism (Abdulkadiroğlu and Sönmez, 2003) can be adopted at the expense of stability. However, such procedures have not been viewed as favourable as the DA mechanism by practitioners. For example, a memo from the superintendent of Boston school district articulated how the DA mechanism was chosen over TTC due to concerns over the way priorities are treated (Abdulkadiroğlu *et al.*, 2005b). Similarly, New Orleans abandoned TTC in favour of the DA mechanism 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 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, paragraphs 4.8 and 4.9.

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

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 1 discusses the theoretical properties of EADAM and illustrates how it operates through an example. Section 2 presents the experimental design and the hypotheses. Section 3 presents the results of the experiment. Section 4 concludes.

1. EADAM

1.1. *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 *et al.*, 2020), *weak stability* (Tang and Zhang, 2021),[14] α*-equity* (Alcalde and Romero-Medina, 2017), *sticky stability* (Afacan *et al.*, 2017) and *priority neutrality* (Reny, 2022). Tang and Yu (2014) proposed an efficient and simpler version of EADAM.[15] EADAM is the unique minimally stable mechanism 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 the DA mechanism 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 Featherstone *et al.*, 2021; Hakimov and Kübler, 2021). Even under mechanisms based on the DA mechanism, 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 *et al.*, 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

[14] Tang and Zhang (2021) also showed 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) introduced a fast algorithm and showed that EADAM can be run with similar time complexity as Gale and Shapley's deferred acceptance algorithm.

[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, 2023) 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).

vein, Reny (2022) showed 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 *et al.*, 2019). EADAM is also *regret-free truth telling* (Chen and Möller, 2023), a weaker incentive property than strategy proofness introduced by Fernandez (2020). Finally, Shirakawa (2023) characterised 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.

1.2. *A Simple Example*

Let $I \equiv \{i_1, \dots, i_n\}$ denote a finite set of students and $S \equiv \{s_1, \dots, s_m\}$ 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 *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

[17] Appendices B.1 and B.2 present and explain the markets we investigate in the experiment.

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 the DA algorithm 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 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 the DA algorithm 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 the DA algorithm 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 the DA algorithm. 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	$\boxed{i_1}$	$\boxed{i_3}$	$\boxed{i_2}$

2. 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 the DA mechanism. Both the DA mechanism and EADAM are implemented in a non-manipulable market (Section 2.1) and in two manipulable markets (Section 2.2). The non-manipulable market has a key advantage: it enables us to compare the DA mechanism 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 behaviour 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 analyse 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.

2.1. *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 the DA mechanism 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

	$\succ_{s_1}$	$\succ_{s_2}$	$\succ_{s_3}$	$\succ_{s_4}$	$\succ_{s_5}$
First	i_2	i_4	i_3	i_4	i_1
Second	i_4	i_1	i_2	i_5	i_3
Third	i_1	i_2	i_4	i_3	i_2
Fourth	i_5	i_3	i_5	i_2	i_5
Fifth	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 behaviour, 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 ten participants before the first period. At the beginning of each period, each participant is randomly assigned to a different group of five 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. Students can neither 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 the DA treatment (see Calsamiglia *et al.*, 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 the DA mechanism. 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 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 the DA mechanism 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

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

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 the DA mechanism.

Given that there is no way of telling who is an interrupter and who is not prior to the admission 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 the DA mechanism, 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 (Guillen and Hing, 2014; Hermstrüwer, 2019).

Third, while comprehensive advice is offered under some assignment procedures such as the National Resident Matching Program (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 Online 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]

2.1.1. *Hypotheses*

As discussed in the introduction and Section 1, 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. Because of status quo bias, we expect consent rates to be higher under EADAM Object

[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.

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 the DA mechanism (Hypothesis 3). Finally, given that the market is non-manipulable, truth telling is not expected to differ between EADAM and the DA mechanism (Hypothesis 5).

HYPOTHESIS 1 (EFFICIENCY DA-EADAM). Assignments are more efficient under EADAM than under the DA mechanism.

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 the DA mechanism.[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 the DA mechanism.

2.2. *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 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

	$\succ_{s_1}$	$\succ_{s_2}$	$\succ_{s_3}$	$\succ_{s_4}$	$\succ_{s_5}$
First	i_5	i_4	i_4	i_2	i_1
Second	i_3	i_1	i_5	i_4	i_4
Third	i_4	i_2	i_1	i_5	i_5
Fourth	i_1	i_3	i_2	i_3	i_2
Fifth	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

	$\succ_{s_1}$	$\succ_{s_2}$	$\succ_{s_3}$	$\succ_{s_4}$	$\succ_{s_5}$
First	i_5	i_5	i_2	i_4	i_1
Second	i_4	i_2	i_3	i_1	i_3
Third	i_1	i_3	i_4	i_3	i_2
Fourth	i_2	i_4	i_5	i_5	i_5
Fifth	i_3	i_1	i_1	i_2	i_4

[20] As further explained in Section 3.1.2, our definition of stability under EADAM is subject to students waiving their priorities.

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

2.2.1. *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 a 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' that 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.

Formally, let P be the true preference profile. Then

(i) a profile report Q is a *truthful equilibrium* if 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 strategising, 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 actually be played. Nevertheless, we find that students never play these equilibria under EADAM, as discussed in Section 3.2.1. This suggests that other non-truthful Nash equilibria are even more unlikely to be played.

2.2.2. *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 the DA mechanism 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).

[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 characterisation of the full set of Nash equilibria under EADAM. Even under the DA mechanism, while a dominant strategy equilibrium always exists, we are not aware of a paper that calculates the full set of equilibria.

HYPOTHESIS 6 (TRUTH TELLING). Students are more likely to report their preferences truthfully under the DA mechanism than under EADAM.

HYPOTHESIS 7 (EFFICIENCY). In markets without interrupters (market 1), the EADAM Consent and DA treatments yield the same efficiency levels. In markets with interrupters (market 2), assignments are more efficient under EADAM Consent than under the DA treatment.

2.3. *Procedure*

The experiment was programmed using the experimental software *o-Tree* (Chen *et al.*, 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 *hroot* (Bock *et al.*, 2014) from the common participant pool of the University of Bonn and the Max Planck Institute for Research on Collective Goods. We ran nine independent sessions for the non-manipulable market (500 participants) and 14 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.

3. Results

In this section, we present the results of the experiment. We begin with the analysis of the non-manipulable market (Section 3.1). Within this market, we first examine the effect of EADAM on efficiency relative to the DA mechanism and how efficiency varies across the three variants of EADAM (Section 3.1.1). We then present results on stability (Section 3.1.2), truth telling (Section 3.1.3) and consent rates between EADAM Consent and EADAM Object (Section 3.1.4). Finally, we turn to the analysis of our manipulable markets (Section 3.2), where we focus on the effect of EADAM Consent on truth telling and efficiency relative to the DA treatment.[24]

3.1. *Non-Manipulable Market*

3.1.1. *Efficiency*

We first compare the effect of the DA mechanism and EADAM on efficiency using non-parametric tests, where matching groups are treated as our unit of observation. To obtain a coarse efficiency

[23] We ran our sessions for the manipulable markets with 610 participants. Fourteen participants timed out of these sessions for technical or personal reasons and were replaced with a robot participant to enable the remaining nine students in each matching group to finish the experiment. As this may have affected participant behaviour, 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] The data analysis in Section 3.1 uses the dataset `allsessions_clean.dta`. The data analysis in Section 3.2 uses the datasets `allsessions2_clean.dta` and `allsessions2_clean_python.dta` (Cerrone *et al.*, 2024). 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.

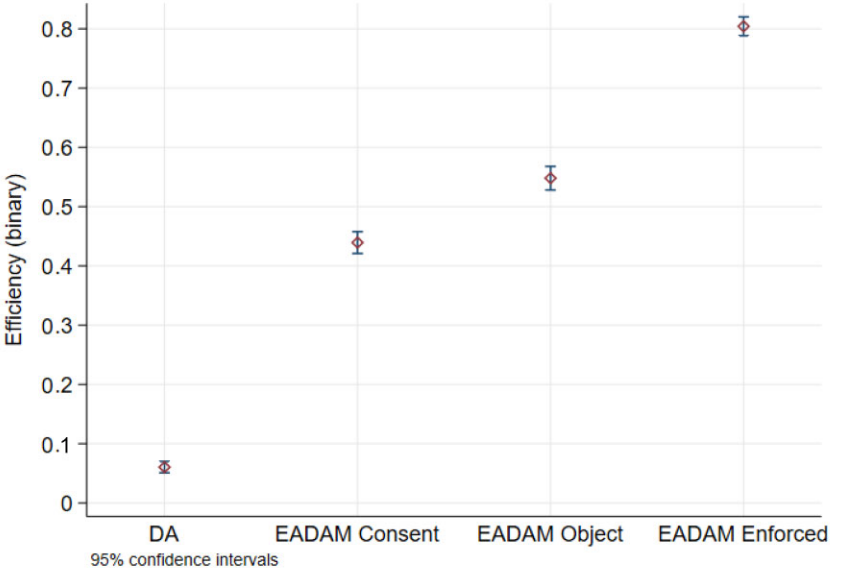

Fig. 1. *Treatment Effects on Efficiency (ω).*

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 the DA treatment (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 the DA treatment (6.04%, χ^2 test, $p < 0.001$).

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:

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

Here 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. We denote by ϵ_{igt} the error term. To test the robustness of treatment effects, we include a categorical variable for student type (*Type*), a

Table 1. *Impact of EADAM on Efficiency Compared to the DA Mechanism (ω).*

Dep. var.: *Efficiency* Baseline: DA treatment	(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***	41.85***	41.88***	43.58***
N_I	10.000	10.000	10.000	10.000
N_G	50	50	50	50

Notes: *** $p < 0.01$. Three-level mixed-effect logit regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

continuous variable for period (*Period*) and a dummy variable for truth telling (*Truth*) 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-effect 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 the DA treatment (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.

To obtain a more granular resolution of the effects on efficiency, we next estimate the effect of EADAM relative to the DA mechanism 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 the DA treatment (Table A1).

RESULT 1. Assignments are more efficient under all variants of EADAM than under the DA treatment.

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 (χ^2 test, $p = 0.003$). These results are in line with the results obtained from a three-level mixed-effect 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

Table 2. *Efficiency Comparison between EADAM Variants (ω).*

Dep. var.: *Efficiency*	Object versus Consent			Enforced versus Object			Consent versus Enforced		
Baseline:	EADAM Consent			EADAM Object			EADAM Enforced		
	(1)			(2)			(3)		
EADAM Object	0.113*	0.113*	0.113*						
	(0.063)	(0.063)	(0.063)						
EADAM Enforced				0.252***	0.252***	0.252***			
				(0.056)	(0.056)	(0.056)			
EADAM Consent							−0.365***	−0.365***	−0.365***
							(0.053)	(0.053)	(0.053)
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

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

significantly higher efficiency levels than nudging students with an opt-out default. These results support Hypothesis 2.

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 A2, column (1), Appendix A) and of EADAM Enforced relative to EADAM Object (Table A2, 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 of what exactly causes the efficiency of EADAM relative to the DA mechanism 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 the DA treatment, with intermediate slopes under EADAM Consent and EADAM Object (lines are parallel) and the steepest slope under EADAM Enforced.

This difference in the slopes indicates an interaction between treatment and truth telling. While truth telling yields only minor efficiency gains under the DA treatment, it entails stronger efficiency increases under all variants of EADAM, especially under EADAM Enforced. Estimating a three-level mixed-effect linear regression model, we find that these interaction

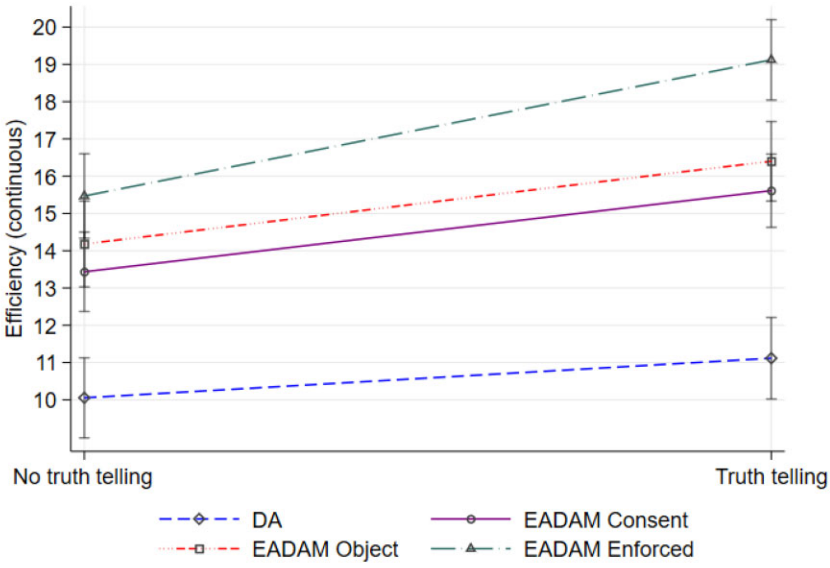

Fig. 2. *Interaction between Treatment and Truth Telling.*

effects are highly significant (Table A3, Appendix A.1).[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 the DA treatment and that preference manipulations entail comparatively small efficiency losses under the DA treatment.

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 maximise efficiency gains under EADAM may achieve that goal by offering a clear recommendation that truth telling is very likely to be best for students.

3.1.2. *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 priorities. Theoretically, there should be no difference in the proportion of stable assignments between the DA treatment and all variants of EADAM. As illustrated by Figure 3, stability rates are highest under EADAM

[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 A3, Appendix A.1).

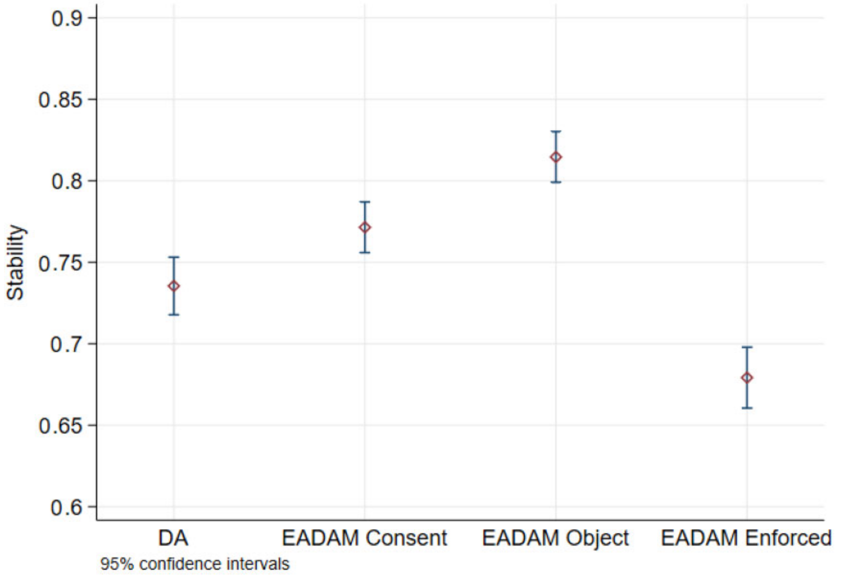

Fig. 3. *Treatment Effects on Stability.*

Object (81.46%) and lowest under EADAM Enforced (67.92%). Intermediate stability rates can be observed under EADAM Consent (77.14%) and the DA treatment (73.54%).[26]

The results of a three-level mixed-effect 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 the DA treatment. 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 the DA mechanism.

RESULT 3. The proportions of stable assignments under the DA mechanism and under EADAM are not significantly different.

When analysing 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 a behavioural 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.

[26] In Appendix A.1, we show that the DA stable assignment is achieved significantly more frequently under the DA treatment than under each of the EADAM variants (Figure A6).

Table 3. *Impact of EADAM on Stability Compared to the DA Mechanism.*

Dep. var.: *Stability* Baseline: DA treatment	(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

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Three-level mixed-effect logit regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

3.1.3. *Truth telling*

We begin with a comparison of truth-telling rates under the DA mechanism 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]

As illustrated by Figure 4, we observe significantly higher truth-telling rates under all variants of EADAM (67.03%) than under the DA mechanism (43.88%, χ^2 test, $p < 0.001$). These results are in line with the results of a multilevel mixed-effect logistic regression models estimating the effect of EADAM on truth telling relative to the DA mechanism (Table 5).

RESULT 5. Truth-telling rates are higher under all variants of EADAM than under the DA treatment.

This is a remarkable result—at odds with our theoretical predictions (Hypothesis 5). Although not strategy proof, EADAM generates higher truth-telling rates than the DA mechanism, a mechanism often hailed for its strategy-proofness virtues.[28] As previously mentioned, however, the 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 3.2, we analyse 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 the DA mechanism even when the markets can be manipulated.

[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 the DA and TTC mechanisms (Hakimov and Kübler, 2021).

Table 4. *Stability Comparison between EADAM Variants.*

Dep. var.: *Stability*	Object versus Consent				Enforced versus Object				Consent versus Enforced			
	EADAM Consent				EADAM Object				EADAM Enforced			
Baseline:	(1)				(2)				(3)			
EADAM Object	0.032	0.032	0.032	0.035								
	(0.040)	(0.040)	(0.040)	(0.039)								
EADAM Enforced					−0.121***	−0.121***	−0.121***	−0.116**				
					(0.046)	(0.046)	(0.046)	(0.045)				
EADAM Consent									0.090*	0.090*	0.089*	0.080*
									(0.047)	(0.047)	(0.047)	(0.046)
Type		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Period			Yes	Yes			Yes	Yes			Yes	Yes
Truth				0.108***				0.107***				0.125***
				(0.012)				(0.012)				(0.012)
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

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Three-level mixed-effect logit regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups. Column (1): all coefficients are reported as average marginal effects at DA mechanism = 0 and EADAM Enforced = 0. Column (2): all coefficients are reported as average marginal effects at DA mechanism = 0 and EADAM Consent = 0. Column (3): all coefficients are reported as average marginal effects at DA mechanism = 0 and EADAM Object = 0.

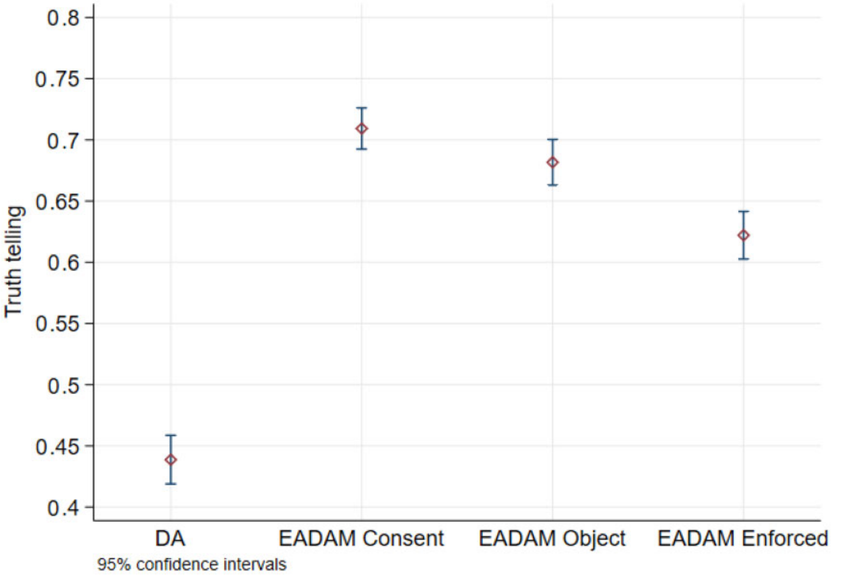

Fig. 4. *Treatment Effects on Truth Telling.*

Table 5. *Impact of EADAM on Truth Telling Compared to the DA Mechanism.*

Dep. var.: *Truth* Baseline: DA treatment	(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

Notes: *** $p < 0.01$; * $p < 0.1$. Three-level mixed-effect logit regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

***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 the DA treatment, 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

[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.

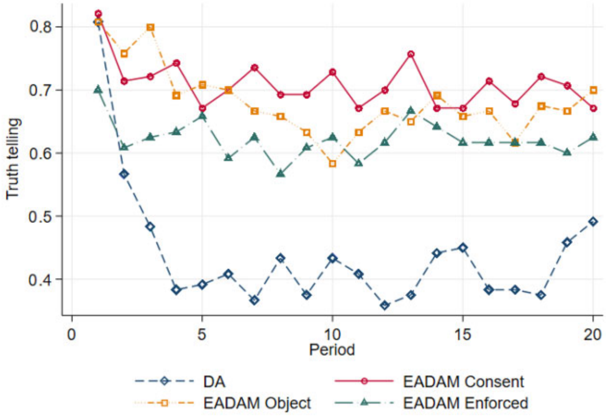

Fig. 5. *Treatment Effects on Truth Telling by Period.*

ranking schools truthfully, truth telling being a 'behavioural 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 the DA treatment in a six-school environment, but a more stable pattern in a four-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 the DA treatment with more than four schools (see Hakimov and Kübler, 2021).

***Drivers of truth telling*:** While our design does not enable us to identify the specific behavioural force underlying the effect of EADAM on truth telling, it is likely that welfare concerns may have partly motivated truth-telling behaviour. 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 normalisation of variables, we rescale our continuous efficiency variable to have a mean of 0 and an SD of 1, using the 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 i_1 and entails modest welfare gains for student i_5, it yields consistent and partly strong welfare improvements for the other students. Conversely, both students i_1 and i_5 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

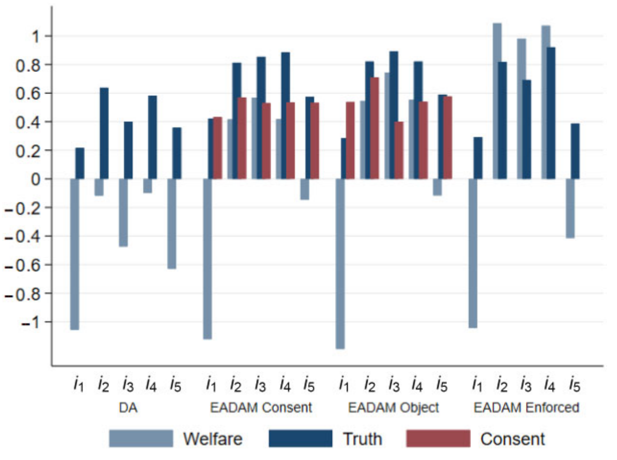

Fig. 6. *Truth Telling and Welfare by Student Type and Treatment.*

to one of their top choices seem to realise that there is little to gain from gaming the 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%, χ^2 test, $p = 0.004$).

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 behavioural pattern indicates that the positive effect of EADAM on truthfulness is partly driven by behavioural motives that are unrelated to individual welfare improvements. While our experiment is not designed to disentangle these behavioural effects, they may have 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 behaviour may have been driven by reactance, a state of motivational arousal

Table 6. *Truth-Telling Comparison between EADAM Variants.*

Dep. var.: *Truth*	Object versus Consent			Enforced versus Object			Consent versus Enforced		
Baseline:	EADAM Consent			EADAM Object			EADAM Enforced		
	(1)			(2)			(3)		
EADAM Object	−0.007	−0.011	−0.011						
	(0.031)	(0.030)	(0.030)						
EADAM Enforced				−0.063*	−0.058*	−0.058*			
				(0.035)	(0.033)	(0.033)			
EADAM Consent							0.070**	0.069**	0.069**
							(0.034)	(0.031)	(0.031)
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

Notes: ** $p < 0.05$; * $p < 0.1$. Three-level mixed-effect logit regression. SEs are reported in parentheses. *Truth* is a dummy variable that takes value 1 if students report their preferences truthfully, and 0 otherwise. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups. Column (1): all coefficients are reported as average marginal effects at DA mechanism = 0 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 mechanism = 0 and EADAM Object = 0.

emerging when people experience a threat to their behavioural 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.

3.1.4. *Consent*

EADAM Object is designed as a behavioural intervention—a nudge—to increase consent rates. Corroborating our behavioural 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%, χ^2 test, $p = 0.018$). However, this difference is relatively small (Figure A4, Appendix A). In line with this observation, the estimates of a multi-level mixed-effect logistic regression model show that the difference in consent rates is not robust (Table A4, 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 A5, 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 behavioural 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

Table 7. *Impact of EADAM on Truth Telling Compared to the DA Mechanism.*

Dep.var.: *Truth* Baseline: DA treatment	Manipulable market 1 (1)	(2)	(3)	Manipulable market 2 (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

Notes: *** $p < 0.01$. Three-level mixed-effect logit regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

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.

3.2. *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 the DA mechanism 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 the DA mechanism? 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 Appendix A.2.

3.2.1. *Truth telling*

The theoretical prediction for our manipulable markets is straightforward: we should observe significantly higher truth-telling rates under the DA treatment than under EADAM Consent (Hypothesis 6). Yet, as in our non-manipulable market, we observe the opposite effect (see Figure A7 in Appendix A.2). EADAM Consent significantly increases truth-telling rates relative to the DA treatment in both market 1 (EADAM Consent, 70.29%; DA, 54.65%; χ^2 test, $p < 0.001$) and market 2 (EADAM Consent, 64.36%; DA, 55.04%; χ^2 test, $p < 0.001$). These results are in line with the results of a multi-level mixed-effect logistic regression estimating the effect of EADAM Consent on truth telling relative to the DA treatment (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

[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.

of manipulation incentives in the specific market. Rather, we find strong evidence that EADAM is less vulnerable to manipulations than the DA mechanism 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.

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

We now turn to analyse 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 A8 in Appendix A.2, our results show that, under both the DA treatment 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 Figure A9 in Appendix A.2, under both the DA treatment 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 the DA treatment.

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 *et al.* (2019), Bó and Hakimov (2020) and Hakimov and Raghavan (2020) found that a dynamic version of the DA mechanism where students apply for one school at a time generates higher truth-telling rates than the DA mechanism. Afacan *et al.* (2022) found that, under an iterative DA mechanism, strategic reporting can only lead to higher efficiency for all participants. Cho *et al.* (2022) found that, under the SIC and the CADA mechanism, truth-telling rates are not lower than under the DA mechanism, 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 the dynamic DA and iterative DA mechanisms 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).

[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.

Table 8. *Impact of EADAM on Efficiency Compared to the DA Mechanism (ω).*

Dep. var.: *Efficiency*	Manipulable market 1				Manipulable market 2			
Baseline: DA treatment	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
EADAM Consent	0.160***	0.160***	0.160***	0.144***	0.269***	0.269***	0.269***	0.268***
	(0.044)	(0.044)	(0.043)	(0.041)	(0.055)	(0.055)	(0.055)	(0.055)
Type		Yes	Yes	Yes		Yes	Yes	Yes
Period			Yes	Yes			Yes	Yes
Truth				0.097***				0.009
				(0.014)				(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

Notes: *** $p < 0.01$. Three-level mixed-effect logit regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

Our results have important implications for the protection of vulnerable families and students that are most likely to be harmed when failing to successfully strategise 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.

3.2.2. *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 EADAM Consent (59.60%) yields a significantly higher proportion of efficient assignments than the DA treatment (33.41%, χ^2 test, $p < 0.001$). As hypothesised, we observe that the efficiency adjustments obtained under EADAM Consent vary across markets. While EADAM Consent significantly increases the proportion of efficient assignments relative to the DA treatment under both market 1 (EADAM, 81.07%; DA, 65.25%; χ^2, $p < 0.001$) and market 2 (EADAM, 32.27%; DA, 6.88%; χ^2, $p < 0.001$), the order of magnitude of this increase is considerably larger in market 2 (see Figure A10 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 A11 in Appendix A.2). EADAM Consent significantly increases the efficiency of assignments in both markets, but the increase is larger in market 2. For market 1, under EADAM Consent $m = 18.00$, while under the DA treatment $m = 17.04$ and the χ^2 test gives $p < 0.001$. For market 2, under EADAM Consent $m = 15.34$, while under the DA treatment $m = 14.02$ and the χ^2 test gives $p < 0.001$.

Finally, we estimate the effect of EADAM Consent relative to the DA treatment on our binary and continuous efficiency variables using a multi-level logistic regression model (Table 8) and a multi-level linear regression model (Table A5 in Appendix A.2), respectively. We observe a positive effect of EADAM Consent on the fraction of Pareto-efficient assignments and on our continuous efficiency measure in both market 1 and market 2. EADAM Consent thus yields more efficient assignments relative to the DA treatment irrespective of the number of interrupters. These results indicate that the efficiency increases obtained under EADAM Consent are even stronger than those predicted in Hypothesis 7.

RESULT 9. Assignments are more efficient under EADAM Consent than under the DA treatment irrespective of the number of interrupters.

4. 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 the DA mechanism 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.

Maximising placements at preferred schools and abiding by the admission 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 the DA mechanism. 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 the DA mechanism, 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 the DA mechanism 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 penalise socially disenfranchised families who are unsophisticated about the procedure or have limited access to strategic advice.

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 A1 shows our treatment effects on efficiency using our continuous efficiency measure π, given by per capita payoffs (points earned). Table A1 reports the results of a three-level mixed-effect linear regression model for the comparison between the DA mechanism and EADAM. Table A2 reports the results of a three-level mixed-effect linear regression model for the comparison between all variants of EADAM.

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 the DA treatment, and highest under EADAM Enforced (Figure A2). This coincides with a shift in the welfare distribution. While efficiency is rather normally distributed under the DA treatment ($\sigma^2 = 45.38$), it takes a slightly bimodal shape with a much higher variance under EADAM Enforced ($\sigma^2 = 82.44$).[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 the DA treatment (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 A3 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 the DA treatment, EADAM Consent and EADAM Object (lines are parallel), but slightly higher under EADAM Enforced. Table A3 reports the results of a three-level mixed-effect linear regression model for the comparison between the DA mechanism and EADAM with interaction terms for treatment and truth telling.

***Consent*:** Figure A4 shows our treatment effects on the probability of consent. Figure A5 shows how the probability of consent varies across periods. Table A4 reports the results of a

[32] Variance is sightly lower under EADAM Object ($\sigma^2 = 80.81$) and EADAM Consent ($\sigma^2 = 79.85$).

[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 the DA treatment, and only slightly lower under EADAM Object (0.31).

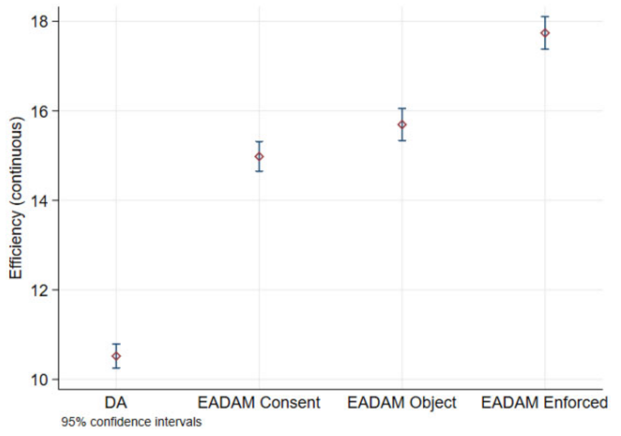

Fig. A1. *Treatment Effects on Efficiency (π).*

Table A1. *Impact of EADAM on Efficiency Compared to the DA Mechanism (π).*

Dep. var.: *Efficiency* Baseline: DA treatment	(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

Notes: *** $p < 0.01$; ** $p < 0.05$. Three-level mixed-effect linear regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

three-level mixed-effect linear regression model for the comparison between the DA mechanism and EADAM.

***Stability*:** In Figure A6, 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 assignments is significantly higher under the DA treatment than under each variant of EADAM, as it is reasonable to expect. In particular, DA stable assignments are 64% under the DA treatment, 19% under EADAM Consent and 15% under EADAM Object. No DA stable assignments are achieved under EADAM Enforced.

Table A2. *Efficiency Comparison between EADAM Variants (π).*

	Object versus Consent			Enforced versus Object			Consent versus Enforced		
Dep. var.: *Efficiency*	EADAM Consent			EADAM Object			EADAM Enforced		
Baseline:	(1)			(2)			(3)		
EADAM Objectr	0.714	0.714	0.714						
	(0.791)	(0.449)	(0.449)						
EADAM Enforced				2.048**	2.048**	2.048**			
				(0.821)	(0.465)	(0.465)			
EADAM Consent							−2.763***	−2.763***	−2.763***
							(0.791)	(0.449)	(0.449)
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

Notes: *** $p < 0.01$; ** $p < 0.05$. Three-level mixed-effect linear regression. SEs are reported in parentheses. *Efficiency* is a continuous variable that captures the number of points earned by students. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

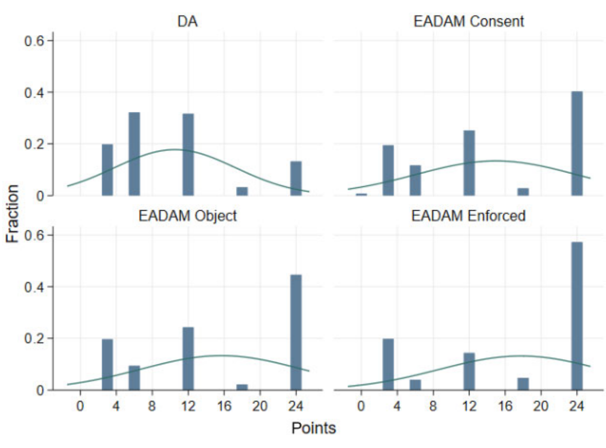

Fig. A2. *Treatment Effects on the Distribution of Points (π).*

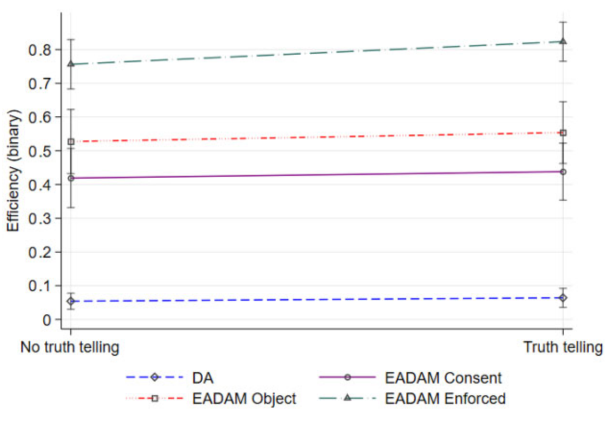

Fig. A3. *Average Marginal Effect of Interaction between Truth Telling and Treatment.*

Table A3. *Impact of EADAM on Efficiency Compared to the DA Mechanism with Interaction.*

Dep. var.: *Efficiency* Baseline: DA treatment	(1)	(2)
EADAM Consent	2.713***	3.382***
	(0.318)	(0.772)
EADAM Object	3.198***	4.126***
	(0.327)	(0.803)
EADAM Enforced	4.327***	5.415***
	(0.329)	(0.797)
Truth	0.185	1.063***
	(0.175)	(0.300)
EADAM Consent × Truth	−0.100	1.114**
	(0.198)	(0.441)
EADAM Object × Truth	−0.066	1.158**
	(0.198)	(0.473)
EADAM Enforced × Truth	0.253	2.591***
	(0.206)	(0.473)
Constant	−3.076***	10.054***
	(0.244)	(0.548)
N_I	10.000	10.000
N_G	50	50

Notes: *** $p < 0.01$; ** $p < 0.05$. Column (1): three-level mixed-effect logit regression. SEs are reported 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-effect linear regression. SEs are reported 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. Here N_I denotes the number of individual observations, N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

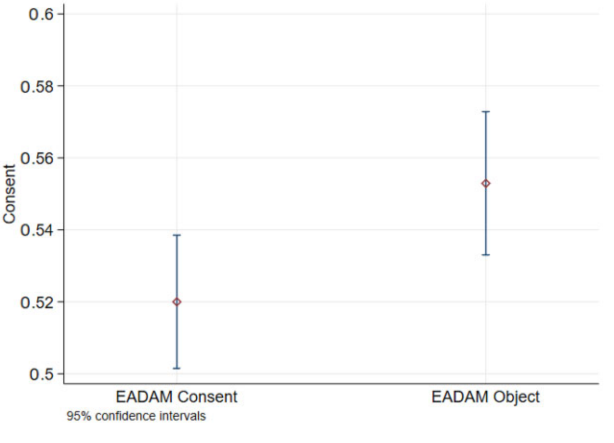

Fig. A4. *Treatment Effects on Consent.*

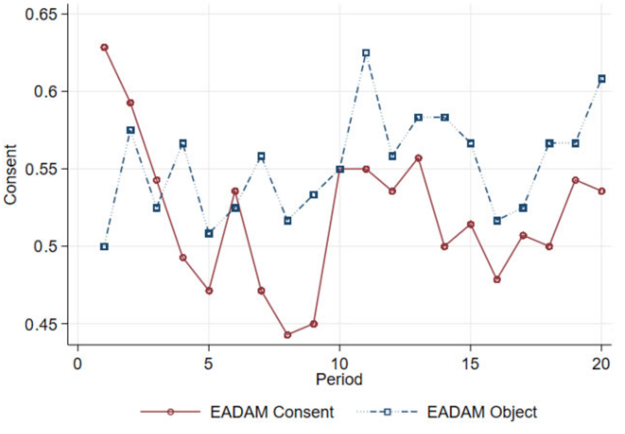

Fig. A5. *Treatment Effects on Consent by Period.*

Table A4. *Comparison of Consent Rates between EADAM Consent and EADAM Object.*

Dep. var.: *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

Notes: Three-level mixed-effect logit regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

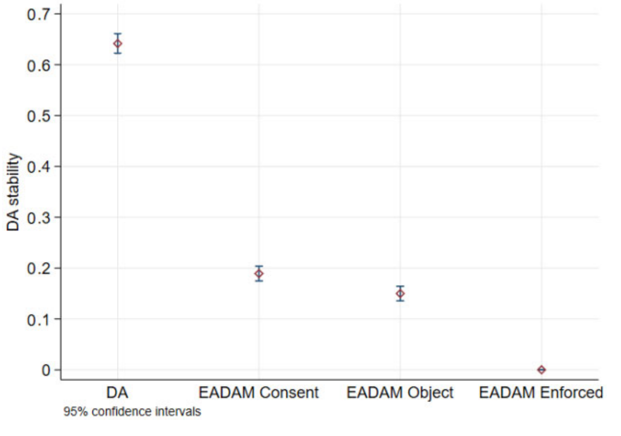

Fig. A6. *Treatment Effects on DA Stability.*

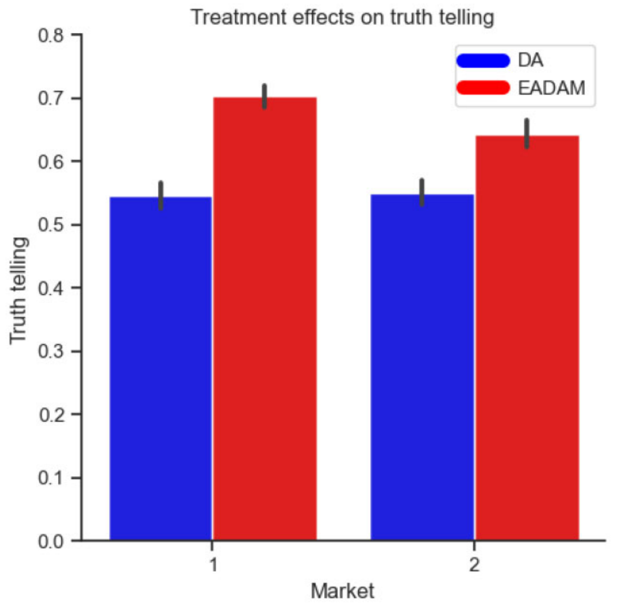

Fig. A7. *Treatment Effects on Truth Telling.*

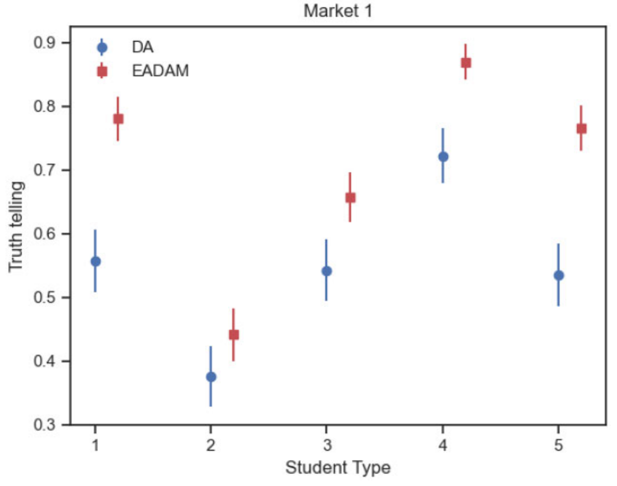

Fig. A8. *Truth Telling by Student Type.*

A.2. *Manipulable Markets*

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

***Truth telling*:** Figure A7 shows the treatment effects on truth telling for the two manipulable markets. Figure A8 shows the treatment effects on truth telling by student type in market 1, and Figure A9 shows the treatment effects on truth telling by student type in market 2.

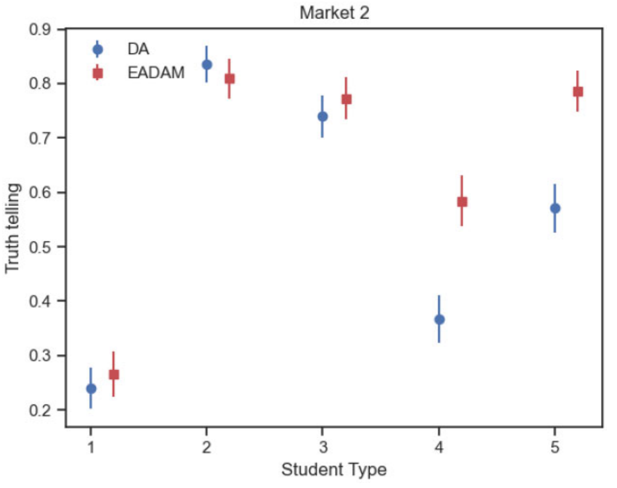

Fig. A9. *Truth Telling by Student Type.*

Table A5. *Impact of EADAM on Efficiency Compared to the DA Mechanism (π).*

Dep. var.: *Efficiency*	Manipulable market 1				Manipulable market 2			
Baseline: DA treatment	(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

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Three-level mixed-effect linear regression. SEs are reported 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. Here N_I denotes the number of individual observations and N_G denotes the number of experimental matching groups.

***Efficiency*:** Table A5 reports the results of a three-level mixed-effect linear regression model for the comparison between the DA treatment and EADAM Consent. Figure A10 shows our treatment effects on efficiency using our binary efficiency measure ω that takes value 1 if assignments are Pareto efficient, and 0 otherwise. Figure A11 shows our treatment effects on efficiency using our continuous efficiency measure π, given by per capita payoffs (points earned).

***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 follows a systematic pattern.

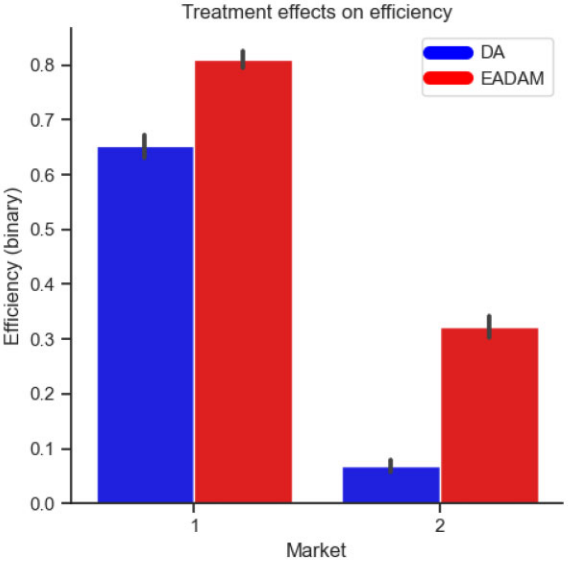

Fig. A10. *Treatment Effects on Efficiency (ω).*

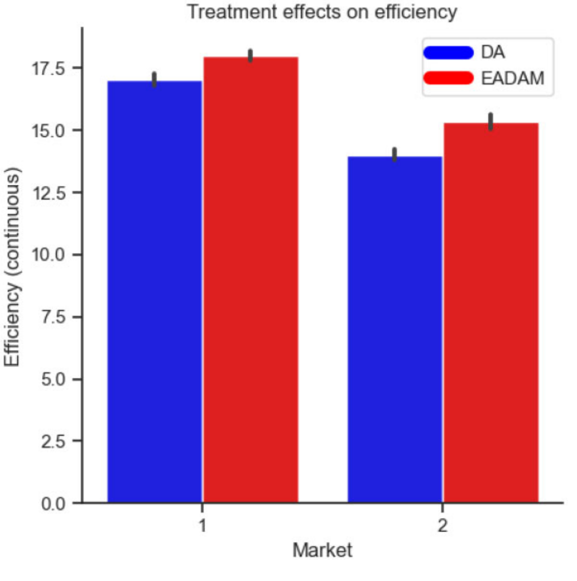

Fig. A11. *Treatment Effects on Efficiency (π).*

***Stability*:** In market 1, the proportion of stable assignments is higher under EADAM (63.57%) than under the DA mechanism (56.75%, $p < 0.001$). In market 2, the proportion of stable assignments is slightly lower under EADAM (54.32%) than under the DA mechanism (58.96%, $p < 0.01$).

Appendix 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 2.1.

As described in Section 1.2, round 0 of the EADAM algorithm involves running the DA algorithm. Here 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 the DA algorithm.

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 the DA algorithm 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*. In this school choice problem, the DA algorithm 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 that i_1 consents. Schools s_1 and s_2 are removed from her rank-order preference list. Re-running the DA algorithm 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 that i_4 consents. Schools s_1 and s_3 are removed from her rank-order preference list. Re-running the DA algorithm 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 that i_2 consents. School s_2 is removed from her rank-order preference list. Re-running the DA algorithm 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 2.2. As described in Section 1.2, round 0 of the EADAM algorithm involves running the DA algorithm. Here 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 the DA algorithm.

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, the DA mechanism is equivalent to EADAM. The matching produced by the DA algorithm 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. Student 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 the DA algorithm.

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 the DA algorithm 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 that i_1 consents. Rerun the DA algorithm 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. Student 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 the DA algorithm.

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 the DA algorithm 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 that i_2 consents. Rerun the DA algorithm 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 2.2. As described in Section 1.2, round 0 of the EADAM algorithm involves running the DA algorithm. Here 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 the DA algorithm.

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). Student i_1 is the last interrupter (at s_1 in step 3). The matching produced by the DA algorithm 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 that i_1 consents. Rerun the DA algorithm 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. Student 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 the DA algorithm.

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). Student i_4 is the last interrupter (at s_1 in step 6). The matching produced by the DA algorithm 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 that i_4 consents. Rerun the DA algorithm 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. Student i_5 has an incentive to manipulate her rank-order preference list by ranking s_2 as second choice rather than as fifth choice:

$P'_{i_5} = s_3, s_2, s_4, s_1, s_5$. Run the DA algorithm.

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). Student i_3 is the last interrupter (at s_3 in step 4). Student i_1 is the penultimate interrupter (at s_1 in step 3). The matching produced by the DA algorithm 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 that i_1 and i_3 consent. Rerun the DA algorithm 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.

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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The Economic Journal, 1–46 https://doi.org/10.1093/ej/uead120
Advance Access Publication Date: 5 January 2024