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A Comment on "Preference Discovery in University Admissions: The Case for Dynamic Multioffer Mechanisms"

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Paul Rosmer

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I4R DP No. 166

A Comment on “Preference Discovery in University Admissions: The Case for Dynamic Multioffer Mechanisms”

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A comment on “Preference discovery in university admissions: The case for dynamic multioffer mechanisms”^{*}

Paul Rosmer

September 19, 2024

Abstract

[Grenet et al. \(2022\)](#) examine the effect of quasi-random early offers on the probability of accepting an offer in the Germany’s university admission process. The authors demonstrate that the early offers lead to a statistically significant increase in the likelihood of accepting an offer. Their preferred explanation for this early-offer effect is that students gradually discover their preferences over time, a hypothesis also supported by survey data. First, we successfully computationally reproduce the main claims of the paper in STATA. Second, we reproduce the results in R, including producing the analysis data from scratch. Third, we test the robustness of the results by checking the identification assumption with new data, applying different standard errors for the main estimation, and using an alternative empirical model specification.

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1 Introduction

[Grenet et al. \(2022\)](#), henceforth GHK, examine the impact of early offers on students' acceptance decisions within the context of the multi-phase university admissions process in Germany. The authors aim to identify the effect of these early offers by utilizing a quasi-experimental design, which relies on the identifying assumption that the timing of offer arrivals is exogenous. GHK state this exogeneity is due to the quasi-random administrative process of sending out offers and not due to the quality of the programs or other factors. The conditional logit analysis reveals that students are significantly more likely to accept early offers, although early offers do not expire and often waiting would yield a preferred program according to their initial rank-order list (ROL). Specifically, the authors find a significant (1 % level) first early-offer effect with a coefficient of 0.424 (0.108), and that the first early offer has the strongest effect on acceptance probability with a significant (1 % level) coefficient of 0.147 (0.023) based on estimates in column 5.

GHK suggest that the early-offer effect is best explained by costly preference discovery of students. Students do not possess full information about their own preferences at the start of the admissions process. If students possessed complete knowledge of their preferences, the observed early-offer effect would likely be nonexistent, as they cannot do worse than their best early offer in subsequent phases of the admission process. To confirm this hypothesis, GHK (1) control for various factors to ensure identification, (2) rule out other possible channels that could explain the early-offer effect, (3) conduct a survey among students, and (4) develop a theoretical model with an endogenous learning decision. The survey data indicates that many students initially lack clear preferences and subsequently invest time in learning about the programs that extend early offers.

The present report, prepared for the Institute for Replication, will contribute to the upcoming second meta paper and follows a similar approach taken in [Brodeur et al. \(2024\)](#), the first meta paper. In particular, we investigate whether the main claims, as stated in their abstract, are computationally reproducible and further test the replicability and robustness of the results. We are grateful to the original authors for providing the raw data, which was not included in the replication package and is subject to a confidential agreement.

In terms of reproducibility in Section 2, we successfully reproduce all tables and figures from the empirical part, including the Appendix, using the authors' codes. In Section 3, we successfully reproduce GHK's main table (Table 3) and figures (Figures 3 and 4) using our developed R code.

Lastly, in the replication detailed in Section 4, we assess the robustness of the identifying assumption regarding quasi-random offers by evaluating program quality through publicly available university rankings. We find no evidence of violation. Next, we alter the method used to compute the standard errors of the weighted mean for calculating the confidence intervals and find that the results remain robust. We also test the sensitivity of the results to changing the robust standard errors to clustered standard errors. As anticipated, clustering at the program level has minimal impact on the standard errors due to the inclusion of program fixed effects. All estimates remain at the same significance level. Additionally, we also employ a conditional probit model instead of conditional logit model and find no qualitatively different results.

In summary, our analysis confirms the qualitative findings reported by [Grenet et al. \(2022\)](#).

2 Computational Reproducibility

The publicly available part of the replication package can be found under Supplemental Material [here](#). It includes only the analysis code and does not include any data or cleaning code. The final dataset analyzed in the paper is derived from several data files provided by the Stiftung für Hochschulzulassung (SfH), the German university admissions clearinghouse. These files include confidential details on students who applied to German universities for the winter term 2015/16. The authors have a formal agreement with SfH that restricts them from sharing the data with third parties. Fortunately, it was possible to make an exception for the author of this paper. See Table 1 for details.

2.1 Raw Data

GHK provide the full SAS code that is used to clean, modify, and merge the raw data. The extent of data cleaning and wrangling required is substantial, owing to the raw data being distributed across ten different files containing varying student information with instances of missing or duplicated entries. To optimize the use of the data, GHK must undertake several operations, such as grade imputation, manually exclude numerous programs and students, and address complex ranking rules, among other challenges. Given our limited expertise in SAS and the seemingly arbitrary coding decisions, we deem it instructive to recode the entire analysis data in R (see Section 3).

2.2 Analysis Data

The empirical analysis is coded in STATA, whereas the simulation results of the theoretical model is coded in Matlab. We will focus only on the empirical analysis. The code executes without issues. We successfully ran all files provided in the replication package and compared all generated figures and tables (including those corresponding to the empirical analysis in the appendix) against the figures reported in the original paper. We find no mismatches. Overall, we want to acknowledge the high quality of the authors' replication package.

3 Recreate Reproducibility

3.1 Raw Data

As mentioned in Section 2.1, due to the nature of the data, the cleaning and wrangling of the data turns out to be extremely time consuming. We reproduce the main dataset almost entirely from the raw data in R. In particular, due to privacy concerns of the clearinghouse we cannot produce the distance measure from scratch but rely on the existing distance measure in the analysis dataset. However, we reproduce the most important variables such as `feasible`, `stu_abitur_pctile`, `accepted_pgm` and `ratio_cutoff` (see ReadMe of the publicly available replication package for definitions). Overall, this process is surprisingly complex and we deem

it as almost impossible to reproduce the exact main dataset without access to the cleaning codes.

3.2 Analysis Data

We recode the main tables and figures of the original study in R. In particular, we show that Figure 1, which separates the reason for exiting DoSV procedure, can be exactly reproduced in R. Moreover, Figures 2 and 3, which are important evidence for the identification assumption, match the reported figures in the original paper.¹ We also reproduce the main estimation in Table 2. We find no mismatches.

4 Robustness Replication

We now focus on the replication process. First, we test the robustness of our results through a direct replication by collecting new university ranking data. Next, we perform a robustness replication by replacing bootstrapping standard errors with reliability standard errors and by replacing robust standard errors with clustered standard errors at the program level of Table 3 in GHK. Finally, we specify a conditional probit model in place of the conditional logit model.²

4.1 Ranking data

GHK use Figures 2 and 3 as evidence that their identification assumption of exogenous offer arrival is satisfied. Naturally, the measures of program selectivity and desirability are imperfect. To test the robustness to other measures, we collect data on how the universities offering these programs were ranked. We use the CWTS Leiden ranking 2015, which was available at the time of the application to the DoSV procedure, to proxy (perceived) program selectivity and desirability.³ We also find

¹We also identify that the critical value from the t-distribution used to calculate the confidence intervals in Figure 4 of GHK did not account for degrees of freedom (i.e., t_n was used instead of t_{n-1}). However, since the paper presents the confidence intervals solely in a visual format and adjusting for degrees of freedom does not produce a discernible difference in the figure, this error is negligible. The corrected figures generated in R are shown in Figure 2 and Figure 3.

²The decision to conduct these robustness checks was taken after reading the paper and after observing the codes/programs.

³We used this ranking data as it is easily accessible and it consists of one of the highest amount of German universities (we still had to drop a considerable amount of observations that were not ranked).

no systematic variation over time in Figure 4, which confirms the findings of GHK.

4.2 Weighted Standard Errors

Further testing the robustness of Figures 2 and 3, we change the way standard errors are computed. GHK use a bootstrapping formula from Gatz and Smith (1995) to estimate the standard errors of the weighted mean. Instead, we use reliability weights for the weighted variance that correct for possible non-randomness of the weights. Figure 5 and Figure 6 show the reliability standard errors. Generally, the confidence intervals become slightly larger.

4.3 Clustered Standard Errors

Kwak et al. (2023) show that a conditional logit estimation can be severely biased if there is serial dependence between the error terms. In Grenet et al. (2022), unobserved factors (e.g. quality of the program) might influence the timing of early offers and the probability of accepting an early offer. GHK use program fixed effects to account for observed and unobserved program-specific characteristics and therefore use robust standard errors throughout their analysis, assuming there is conditional serial independence within programs. However, Cameron and Miller (2015) state that including cluster-specific fixed effects may not account for all correlation within clusters. Hence, we run the regressions of Table 2 (Table 3 in GHK) with clustered standard errors at the program level. Table 4 shows that the standard errors change slightly and do not change any significance level. This finding supports the assumption that program fixed effects effectively absorb intra-cluster correlation, thereby enabling an unbiased estimation.

4.4 Probit model

GHK use a conditional logit model in their main estimation, which assumes that the unobserved factors are uncorrelated over alternatives (IIA). To assess the sensitivity of the results to the empirical model specification, we employ a conditional probit model, which accommodates correlation in the error terms. As expected, we find lower probit coefficients in Table 3 and the significance levels mostly remain the same. In particular, only the coefficients on the program's ranking of students

become insignificant (from 10% significance). Applying the rule of thumb from [Wooldridge \(2010\)](#) - multiply the probit coefficients by 1.6 to approximately compare them to the logit coefficients - we find quantitatively very similar results.

5 Conclusion

This analysis successfully reproduces the main findings of [Grenet et al. \(2022\)](#), confirming that early offers significantly influence students' decision-making in university admissions. The results reinforce the hypothesis that students undergo a costly preference discovery process, leading them to accept early offers.

Additionally, the robustness checks conducted, including the use of a different quality measure for programs, different standard errors, and a conditional probit model, support the reliability of the original results.

Future research could extend this work by exploring the impact of early offers in different admission processes or by investigating a completely different context to further explore the dynamics of preference formation.

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6 Figures

Figure 1: Reasons for exiting the DoSV procedure. Replication of Figure 3 in GHK.

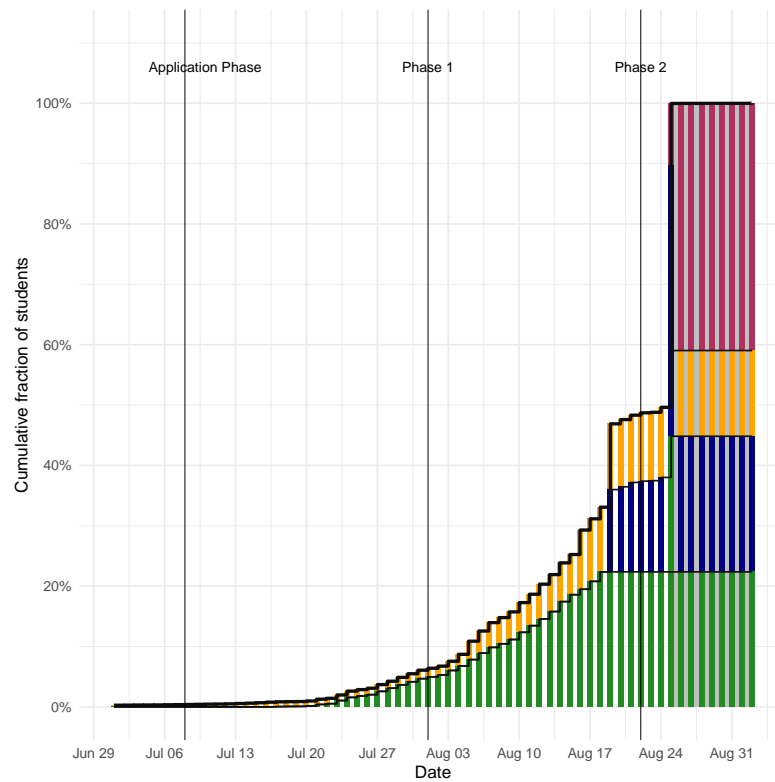


Figure 2: Program selectivity. Replication of Figure 4a in GHK.

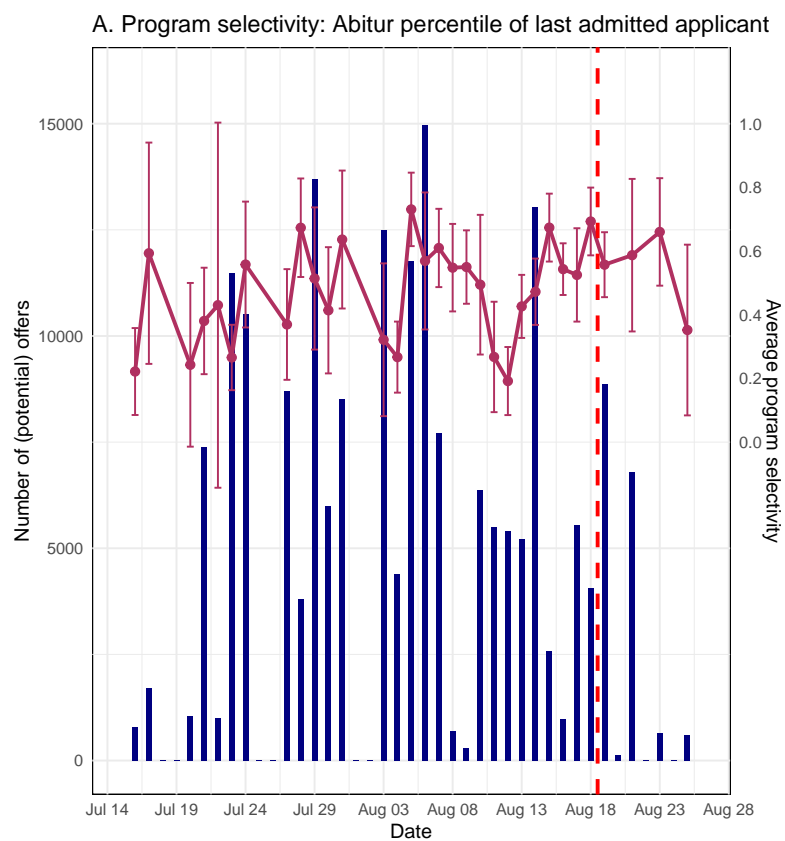


Figure 3: Program desirability. Replication of Figure 4b in GHK.

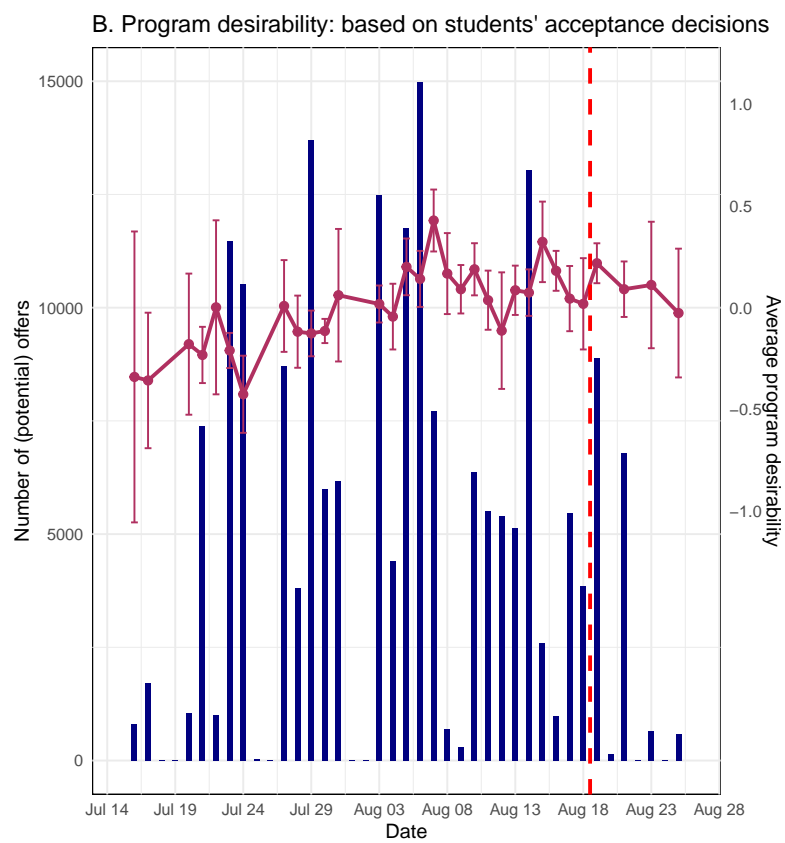


Figure 4: Replication of Figure 4 in GHK with new (ranking) data.

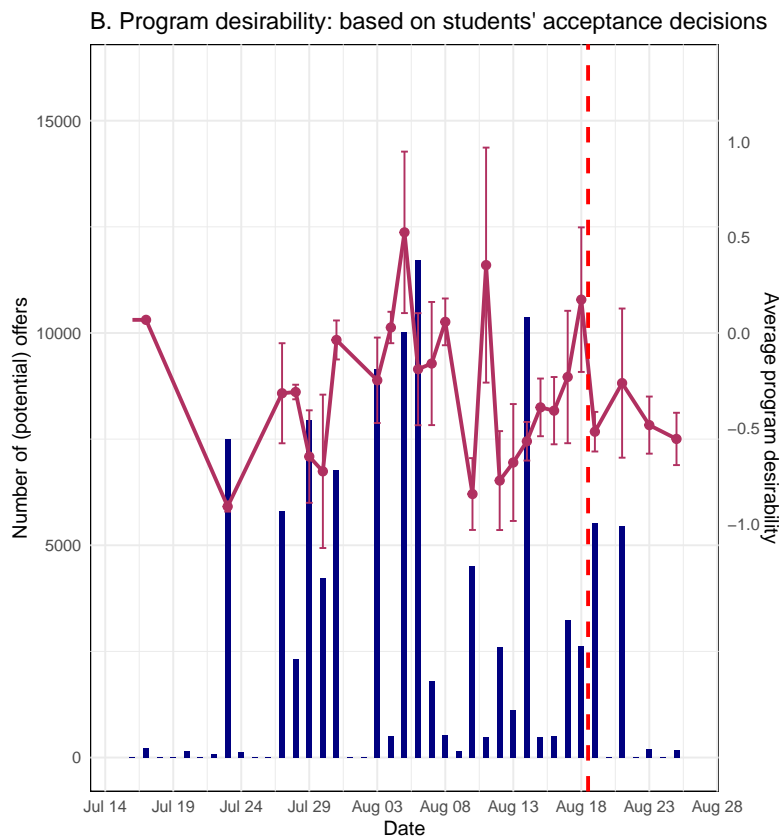


Figure 5: Replication of Figure 4a in GHK with Reliability Weights

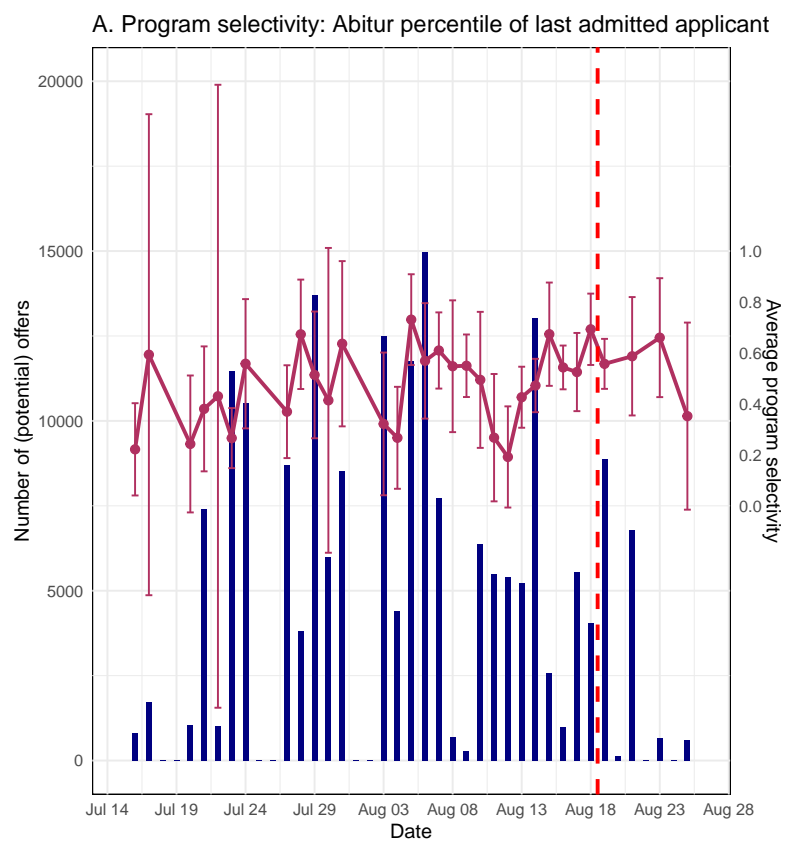
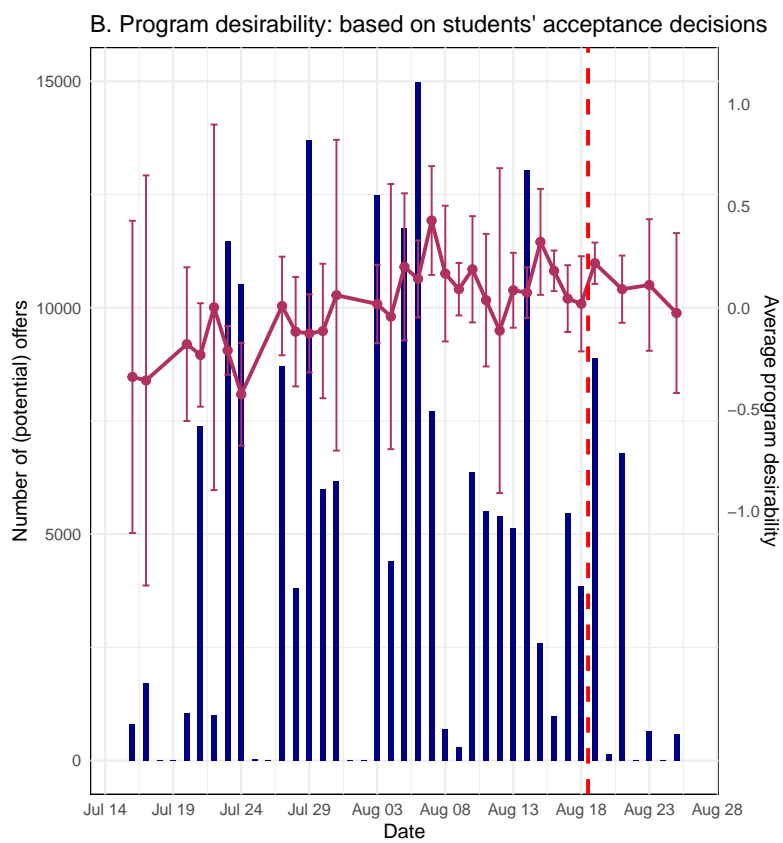


Figure 6: Replication of Figure 4b in GHK with Reliability Weights



7 Tables

Table 1: Replication Package Contents and Reproducibility

Replication Package Item	Fully	Partial	No
Raw data provided	✓		
Analysis data provided	✓		
Cleaning code provided	✓		
Analysis code provided	✓		
Reproducible from raw data	✓		
Reproducible from analysis data	✓		

Notes: This table summarizes the replication package contents contained in [Grenet et al. \(2022\)](#) and includes the full data and code that we received after contacting the authors.

Table 2: Early Offer and Acceptance among Feasible Programs: Conditional Logit
(Table 3 of GHK)

	<i>Dependent variable:</i>				
	Accepted program by the student (binary)				
	(1)	(2)	(3)	(4)	(5)
(Potential) Early Offer	0.484*** (0.041)	0.410*** (0.043)	0.411*** (0.044)	0.404*** (0.044)	0.424*** (0.108)
(Potential) First Early Offer		0.133*** (0.022)	0.147*** (0.023)	0.147*** (0.023)	0.147*** (0.023)
Distance			-9.36*** (0.33)	-9.37*** (0.33)	-9.37*** (0.33)
Distance squared			12.52*** (0.55)	12.54*** (0.55)	12.54*** (0.55)
Program in student's region			-0.005 (0.039)	-0.006 (0.039)	-0.006 (0.039)
Program's ranking of student				0.439* (0.227)	0.442* (0.227)
Chances to not receive an offer					0.016 (0.076)
Program fixed effects (376 programs)	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Early Offer and Acceptance among Feasible Programs: Conditional Probit
(instead of Logit as in Table 3 of GHK)

	<i>Dependent variable:</i>				
	Accepted program by the student (binary)				
	(1)	(2)	(3)	(4)	(5)
(Potential) Early Offer	0.313*** (0.030)	0.266*** (0.031)	0.257*** (0.031)	0.253*** (0.031)	0.253*** (0.081)
(Potential) First Early Offer		0.089*** (0.017)	0.094*** (0.017)	0.094*** (0.017)	0.094*** (0.017)
Distance			-5.72*** (0.23)	-5.72*** (0.23)	-5.72*** (0.23)
Distance squared			7.65*** (0.39)	7.69*** (0.39)	7.69*** (0.39)
Program in student's region			-0.007 (0.028)	-0.007 (0.028)	-0.007 (0.028)
Program's ranking of student				0.220 (0.164)	0.219 (0.164)
Chances to not receive an offer					0.0002 (0.057)
Program fixed effects (376 programs)	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Early Offer and Acceptance among Feasible Programs: Conditional Logit
(Table 3 of GHK with cluster SE)

	<i>Dependent variable:</i>				
	Accepted program by the student (binary)				
	(1)	(2)	(3)	(4)	(5)
(Potential) Early Offer	0.484*** (0.039)	0.410*** (0.038)	0.411*** (0.038)	0.404*** (0.039)	0.424*** (0.090)
(Potential) First Early Offer		0.133*** (0.025)	0.147*** (0.025)	0.147*** (0.025)	0.147*** (0.025)
Distance			-9.36*** (0.57)	-9.37*** (0.56)	-9.37*** (0.56)
Distance squared			12.52*** (0.91)	12.54*** (0.91)	12.54*** (0.91)
Program in student's region			-0.005 (0.050)	-0.006 (0.050)	-0.006 (0.050)
Program's ranking of student				0.439* (0.222)	0.442* (0.220)
Chances to not receive an offer					0.016 (0.057)
Program fixed effects (376 programs)	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263

Note: *p<0.1; **p<0.05; ***p<0.01