Academic career effects of participating in the Erasmus programme: Evidence from administrative data on students' applications

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Abstract

The Erasmus programme is one of the most popular programmes financed by the EU. In this paper we provide novel evidence on the causal effect of studying abroad with an Erasmus scholarship on students' academic outcomes. It is the first study to use rich administrative data on all Erasmus applications from students enrolled at the University of Bologna, the oldest university in Europe and one of the biggest public universities in Italy. To solve the endogeneity problem of studying abroad, we use a Regression Discontinuity Design (RDD) exploiting the scholarships allocation mechanism, where the winner of the last scholarship determines the cut-off score. Our first results show that studying abroad through an Erasmus scholarship does not lead to significant effects in terms of graduating on time, but has a positive effect on the final graduation grade, especially for undergraduate students, with the effect being heterogeneous across both students' and exchange study programme's characteristics.

Keywords: Erasmus, student mobility, university, administrative data, Regression Discontinuity Design

1 Introduction

The Erasmus programme is one of the oldest programmes financed by the European Union and among the most popular ones. It was established in 1987 with the aim of increasing the number of students spending a period of study in a Member State, but over time it has widened its scope, with the current Erasmus+ programme (2014-2020) covering further aspects in higher education including training or sports. As of 2019, thirty-two years after its creation, the programme has promoted the mobility of more than 5 million students in more than 30 countries.

A considerable part of the literature has examined the association between studying abroad and outcomes later on, especially labour market careers, probability to live or work abroad, etc. However, the number of studies establishing a causal link is limited, because we cannot simply compare students who choose to study abroad with those who decide to remain at their original university. If we were to estimate this relationship via OLS our results would be biased, as unobserved factors that we cannot account for may jointly affect the decision to study abroad and labour market outcomes later on. From a policy perspective, it is important to analyse how selection into the Erasmus programme occurs, in order to say something about the causal impact that these types of programmes can have on students' outcomes. Answering this question is important for the EU institutions in order to comply with the current EU Better Regulation agenda.[1] for designing more effective and efficient programmes, but also to increase the quality of the evaluations[2].

This paper provides novel evidence on the causal effect of studying abroad with an Erasmus scholarship on students' academic outcomes using rich administrative data from the University of Bologna, the oldest university in Europe and one of the biggest public universities in Italy. We use data on all Erasmus applications done between academic years 2013-2014 and 2019-2020 from students enrolled at the University of Bologna.

Students that apply to Erasmus programmes are ranked based on a score calculated using different criteria (average grade, number of credits, etc), and the available scholarships are awarded based on this ranking. Thus, to estimate the effect of studying abroad with an Erasmus programme

[1]For more information on the EU Better regulation see: https://ec.europa.eu/info/law/law-making-process/planning-and-proposing-law/better-regulation-why-and-how_en.

[2]The Commission has established the Regulatory Scrutiny Board, an independent group of Commission officials and experts from outside the Commission. Its role is to check the quality of all impact assessments and major evaluations that inform EU decision-making.

on academic outcomes we use a Regression Discontinuity Design (RDD), where the cut-off score is given by the last student in the ranking who receives the scholarship. Students can reject a scholarship offer, this we use a fuzzy RDD design as not all students who are assigned the scholarship actually participate to the Erasmus programme. We focus on analysing the causal effect of participating to the Erasmus program to outcomes measuring academic performance, i.e. time to graduation and final graduation grade. We contribute to the literature in at least three different ways. First, to the best of our knowledge this is the first paper that uses administrative data on both Erasmus applications (which allow to study selection into programme participation) and students' outcomes at graduation (which are more precise compared to surveys and allow to look at the short-run effects of studying abroad on the probability to drop out from the university, time to graduation and final grade). Analysing the effects of studying abroad the probability of graduating on time (including the probability of dropping out) is of great importance in the Italian context, where both the drop-out rate and duration of studies is among the highest in Europe (Schnepf 2017). These outcomes are important to look at as they act as intermediate outputs that could explain labour market outcomes later on. If studying abroad increases time to graduation, this could translate in possible income losses for Erasmus students, and should be taken into account for estimating the impact of mobility on future wages. A similar reasoning applies to the impact of Erasmus participation on final graduation grades. If mobility leads to worse graduation results, mobile student would need to offset this negative impact in different ways.
Second, we provide quasi-experimental evidence using a fuzzy RDD approach, complementing the limited evidence on the causal effects of studying abroad. The two papers closest to ours in terms of methodology are Oosterbeek and Webbink 2011 and Parey and Waldinger 2010, although our paper differs in several ways.

Oosterbeek and Webbink 2011 use data on applications for a scholarship targeted at talented students who complete an undergraduate programme in the Netherlands to estimate the causal impact on the probability to live abroad later on. Applicants ranked above the cut-off receive a scholarship whereas those below the cut-off do not. This setting allows to apply an instrumental variable analysis using the cut-off in scholarship assignment, to then estimate the impact of mobility on the probability to live abroad after programme completion. Final results show that receiving a scholarship increases the probability to study abroad from 72% to 97% and increases the number of months spent studying abroad from 10 to 15 months. Being awarded the scholarship also lowers the probability that an applicant lives in the Netherlands during the early years of his/her working career by 30 percentage points. Our paper differs in several ways. First and foremost, the programme itself is different from the Erasmus mobility programme, as students go abroad for about a year after completing the undergraduate degree. Hence the main objective is to foster enrolment in post-graduate studies such as Master's studies, which is not necessary the same for Erasmus. Although the authors are the first to use data on applications the working sample is very small (847 applicants and 335 scholarships) and becomes even smaller when restricting the analysis to students just above and just below the cut-off, on which the local effect is identified. Finally, the authors had to trace these students using their addresses in order to submit online questionnaires (with low response rate), to collect data on the outcomes after programme completion. Our paper is also closely related to Parey and Waldinger (2010) who provide the first causal evidence on the effect of going on Erasmus on the probability to work abroad. The analysis is based on a nationally representative longitudinal sample of students who complete their undergraduate education in Germany in specific academic years. The data allow to follow up students 1 and 5 years after graduation (response rate is 25% 5 years after graduation). Differently from us, the authors observe Erasmus participation ex-post, without having the possibility to address selection into treatment. Their identification strategy exploits the introduction and expansion of the Erasmus programme in 1987 and the fact that in Germany different departments adopted it at different times. Using instrumental variables they find that studying abroad increases an individual's probability of working in a foreign country by about 15 percentage points. Differently from Parey and Waldinger (2010) we use data on applications to the Erasmus programme and we employ a different identification strategy that exploits the scholarships allocation mechanism. Moreover we concentrate on a different set of outcomes measuring students' academic performance.

Additional papers that tackle the selection issues related to studying abroad are: Messer and Wolter (2006) who examine the effect of International student mobility on commencement of a postgraduate project and salary in Switzerland; Salisbury et al. (2013) who look at cultural competences in the US; Rodriguez et al. (2013) and Jacob et al. (2018) analyzing the impact on labour market outcomes across European countries; Sorrenti (2017) on language proficiency for students departing from Italy; Di Pietro (2015) on employment outcomes in Italy; Petzold (2017a) and (2017b) on employers' hiring practices in Germany; Netz and Grüttner (2018) on salary in Germany; Waibel et al. (2018) on occupational attainment and Schnepf and d'Hombres (2019) on employment and uptake of postgraduate studies in the UK and Italy.

Finally, the value added of this study regards its in-depth examination of heterogeneous effects, according both to characteristics of students and of the Erasmus programme, including length and country of destination.

Our first findings document that, overall, both bachelor and master students who participate to an Erasmus programme have on average slightly higher probability of graduating on time and final graduation grade relative to students who don't participate to Erasmus. Results from the RDD estimation show that the causal impact of studying abroad through an Erasmus programme is, on average, zero on the probability of graduating on time and positive on the final graduation grade for bachelor students only.

The effects on the final graduation grade for bachelor students is heterogeneous across different both students' and programme's characteristics: it is slightly stronger for females and remarkably stronger for students of STEM (science, technology, engineering and mathematics); the effect is also stronger for programmes of shorter durations and in destination countries with an overall relatively lower quality of higher education.

The remainder of the paper is organised as follow. Section 2 describes the functioning of the selection process for participating to the Erasmus programme at the University of Bologna and the data used for the empirical analysis. Section 3 discusses how the regression discontinuity design is implemented in order to estimate the causal impact of participating to the Erasmus programme. Section 4 presents and discuss the first preliminary results and summarizes the future steps.

2 Institutional background and data

2.1 The Erasmus programme at the University of Bologna

At the beginning of every calendar year, the university of Bologna publishes a call for applications for taking part to the Erasmus programme in the following academic year. Each department has different agreements with several host institutions. Students in each department can apply to the specific exchange study programme at a specific host institution. The number of scholarships available for each specific program depends on the agreements between the departments of University o Bologna and the different departments of the host institutions. Students are eligible to apply if they have at least a level B2 certification for the language spoken in the destination country and a study plan for their period abroad. Once students apply, they are assigned a score -from 0 to 100- based on their academic career and the quality of their application. More specifically: up to 60 points are assigned based on the average grade and the number of exams credits accumulated up to the application year; the remaining 40 points are assigned by the professor managing the exchange program based on the quality of the student's study project, the motivation letter and language proficiency. Until 2018, each student could apply to a maximum of two specific programs within his department. After the first ranking was published and the first assignment of scholarships was completed, a second round of applications was launched to fill possible vacant places. The potential outcomes of the application, resulting from the ranking, are: *vincitore*, i.e. the student is assigned the scholarship; *idoneo*, i.e. the student fulfils the minimum requirements (measured by the score) to participate in the Erasmus programme but his ranking position is below the number of available scholarships.

All students applying to a specific programme are ranked based on this score and the available scholarships are assigned to the highest ranked students.

After the results of the rankings are published, students have approximately one week to decide whether to accept the scholarship.[3] Then - based on these decisions - scholarships are reallocated to the next students in the ranking until reaching the last *idoneo* student. If some places remain unfilled after this process, a second round of applications is launched and the whole process is repeated. Each student can apply several times along his career and across different study careers (e.g. bachelor and master), and he can receive one or more Erasmus scholarships even within the same course of study, with the only limitation that the cumulative duration of his period abroad does not exceed 12 months (or 24 months for single cycle degrees).

[3] Students can also decide to renounce to the scholarship after having accepted it, at a later stage. Another possibility is that the student accepts the scholarship but he is then rejected by the host institution, because for example he didn't fulfil specific requirements from the host institution (e.g. specific deadlines, etc.)

2.2 Data and summary statistics

In order to estimate the causal impact of taking part to the Erasmus programme, we use administrative data on all the applications to *Erasmus - studio* made between academic years 2013/2014 and 2019/2020 from students who enrolled at the University of Bologna between academic years 2007/2008 and 2018/2019.[4] We focus on bachelor and master student whose career, as of end of 2019 (the time at which data are extracted) should have already been concluded, according to the legal duration of their study course (78% of the sample). We further restrict to students who have graduated, excluding those who dropped-out (1.3% of the sample) and those who are still enrolled with delay(17%).[5]

Overall in the period considered we have roughly 3,900 specific programmes and 16,500 applications from approximately 6,000 bachelor and 4,000 master students. Table 1 displays some summary statistics for the two samples of applicants.

The average number of applications by a student along his entire career is 1.8 for bachelor/single cycle students and 1.5 for master students. Within the same academic year -when students can only submit maximum two applications in the first round and maximum one in the second round- slightly more than one half of students submits two applications in the bachelor sample and one application in the master sample. Of all students in each sample, approximately 60% ever takes up an Erasmus program along his career, while only a very small percentage participates to an Erasmus program twice (or three times), namely 0.8% of bachelor students and 0.2% of master students. 59 and 66% of respectively bachelor and master students apply for scholarships of duration between 1 and 6 months. The most popular destination country is Spain, followed by UK and France, and Germany.

Panel B reports average characteristics for the "treated" and "non-treated" groups, i.e. respectively students participating to the Erasmus programme at least once over their career and students who never participated. Females and students who moved from another Italian region

[4]These data were made available by the statistical office of the University of Bologna together with the office responsible for the management of exchange programmes. We thank in particular Camilla Valentini - responsible of the Programming and Support to Evaluation Area-; Danilo Cinti - responsible of the data warehouse office- and Carmela Tanzillo - responsible of the office managing European exchange programmes.

[5]Table B1 in the Appendix reports the results of the estimation of the causal effect of participating to the Erasmus programme on the probability of graduating on time in the entire sample of students whose career should have already been concluded, showing that there is no effect.

to study at the University of Bologna appear to be slightly more represented in the Erasmus participants group respectively in both samples and in the bachelor sample only. On average, both bachelor and master students who participated to an Erasmus programme at least once during their career accumulated a smaller number of exams and ECTS at the moment of their application. Finally, in both samples, Erasmus participants have a slightly higher probability of graduating on time and a higher final graduation grade.

3 Empirical strategy

The main identification issue that needs to be tackled when estimating the causal effect of participating in the Erasmus programme on later outcomes is that students are not randomly assigned to the "treatment".

Our starting population is composed of students who applied for the Erasmus scholarship at least once. We treat separately the sub-populations of bachelor students and master students, such that different careers of the same student are considered as being independent. Within a study career, students can participate to different calls for applications in different academic years: for each student we focus on the first academic year of participation to a call for applications; one can indeed think that every subsequent participation to other calls is partly affected by the outcome of the first participation.

For each specific exchange programme, all applicants are ranked based on the score obtained for their applications and the allocation process takes place as explained in the previous section. We observe the ranking with the final outcome of this process.

In our design, the last student within each ranking who accepts the Erasmus scholarship determines the cut-off score. For each student we construct the running variable as her score normalised to the cut-off score, i.e. the difference between the individual score and the cut-off value divided by the cut-off value. Thus, the running variable is equal to zero for the last student in the ranking accepting the scholarship, and takes a positive (negative) value for those higher (lower) ranked.

In this setting, all the applicants with a score above the cut-off have received the offer of the scholarship whereas all those with a score below the cut-off have not received the offer, but being above or below the cut-off score does not exactly determine the treatment status (participating in the Erasmus programme and studying abroad).

We define an individual being 'treated' if she ever participated to the Erasmus programme over her study career. Within the same academic year, for students with more than one specific programme application we take the running variable with the maximum value. Applying to several specific programmes in the same call for applications -which equals different destinations- entails an implicit -non observable- ranking from students based on preferences. Whether the maximum of the running variables is above or below the cut-off is a proxy of the probability of studying abroad through the Erasmus programme.

By definition, being the cut-off value equal to the score of the last student receiving a scholarship, all the students at the cut-off point (with the running variable equal to zero) are treated. Above the cut-off, non-compliance is given by students who reject all offers received and students who renounce to the scholarship at a later stage. Below the cut-off, non-compliance is given by students participating in an Erasmus programme as outcome of applications done in subsequent years of their career. Thus, we have that:

$$\lim_{x \to 0^+} E[T|X = x] = 1,$$

where X is the running variable, T is the treatment status.

The identifying assumption is that individuals do not have precise control over the received score, i.e. "no manipulation", and being the last student receiving the scholarship or the first excluded can be considered "as good as random'. In practice, this means that on average, treated and control units around the cut-off have similar observable and unobservable characteristics (e.g ability, motivation, etc).

Given that each ranking has its own cut-off score, normalising the running variable according to the score of the last scholarship available generates a bulk of values exactly equal to zero. This will produce a discontinuity in the distribution of the running variable that translates in a failure in the standard test of manipulation of the running variable (McCrary, J., 2008). For this reason, only *within-ranking* variability is exploited, by including in the analysis ranking fixed-effects.[6]

[6]Figure B1 in the Appendix shows the discontinuity in the distribution of the running variable at the cut-off (left panel). The right panel shows that the distribution of the residuals of the running variable after the inclusion of

We estimate the causal effect of participating in the Erasmus programme on students' academic outcomes, namely time to graduation and final grade, via instrumental variable. In our setting, the discontinuity in the probability of participating in the programme given by the normalised score is used as an instrument for the treatment status.

Our equation of interest is:

$$Y_{ir} = \beta_1 T_{ir} + \beta_2 f(\tilde{x}_{ir}) + \mu_r + \epsilon_{ir} \tag{1}$$

where Y_{ir} is the outcome of student i that participated at ranking r. T_{ir} is the treatment variable, which takes value 1 if the student has ever studied abroad through an Erasmus programme in her career. $\tilde{x}_{ir}$, is the running variable, i.e. is the normalised score centered at the cutoff point of the ranking r. $f(\cdot)$ is a polynomial in the running variable, which represents the relationship between the running variable and the outcome. μ_r are ranking fixed-effects. ϵ_{ir} is an individual specific error term. The excluded instrument used in 2SLS is a dichotomous indicator for having a score $Z = \mathbf{1}(x > 0)$.
The corresponding first stage equation reads as follows:

$$T_{ir} = \gamma_1 Z_{ir} + \gamma_2 f(\tilde{x}_{ir}) + \mu_r + \eta_{ir}, \tag{2}$$

where Z_{ir} is the instrument for T_{ir} and η_{ir} is an individual error term. In the analysis, we compute the results both using linear and quadratic polynomials of the running variable, using uniform and triangular kernels and with different bandwidths. Standard errors are clustered at ranking level. Our first results are discussed in Section 4.

4 Results

In this section we discuss the first preliminary results of our fuzzy RDD strategy. In particular, we present and discuss the first stage results and the reduced form results for three academic career outcomes, namely (i) the probability of graduating on time, (ii) a career delay index, and (iii) final graduation grade. The first outcome measures the probability of having graduated within the last

ranking fixed effects is instead not discontinuous at the cut-off.

academic year of the legal duration of the career; the second one is an index constructed as number of years between the 1st of October of the academic year of enrolment and the date of graduation, divided by the legal duaration of the career.

Figure 1 is a graphical representation of the first stage, i.e. the relationship between the running variable and the treament variable. We use a quadratic specification and do not condition on other covariates. The figure shows a clear big jump in the probability of participating to the Erasmus programme due to the scholarship assignment mechanism, both for the sub-sample of bachelor students -panel (a)- and of master students -panel (b).

Table 2 reports the results of the estimation of the first stage equation. We estimate different specifications with varying polynomial order and kernels, for three increasingly narrower bandwidths around the cut-off. Having a score above the cut-off increases the probability of participating to the Erasmus programme by approximately 71 to 75 pp for bachelor, and 83 to 90 pp for master students.The results are significant at the 1% level and are robust across specifications.

We run a series of estimations to check that there is no jump at the cut-off for pre-treatment variables, namely the number of exams and of ECTS (European Credit Transfer and Accumulation System) the students accumulated until the calendar year before the year of application, a dummy for being female and a dummy for having moved region to study at Bologna university. Table 3 reports the results of these estimations showing that the selected pre-treatment variables are balanced around the cut-off.

Figure 2 plots the three outcomes as a function of the score received in the ranking normalised to the cut-off point, for the sub-samples of bachelor -top panel (a)- and master students -bottom panel (b). Here we do not observe clear big jumps at the discontinuity point.

Tables 4 and 5 report the results of the estimation of a reduced form equation respectively for the three outcomes, for both sub-samples. As for the first stage, we estimate the three different specifications, each for three different bandwidths around the cut-off score. Being above the cut-off score does not have a significant effect on the probability of graduating on time and on the career delay index in both samples. When looking at the final graduation grade, the effect of being above the cut-off score is positive and statistically significant at 1% level only for bachelor, whereas the effect is not statistically significant for master students. The result is robust across specifications and bandwidths, and it goes from 0.74 to 1.53 points.

We extend our analysis by looking at heterogeneous effects by gender, field of study, programme duration, gender, and country of destination. Results are reported in Tables 8-9.

For the sample of master students (panels (b) of each table) the non significant effect on all outcomes is homogeneous across different programme and students characteristics. The same is true for the non significant effect on the time to graduation outcomes in the bachelor sample.

The most interesting results are observed for the effect on the final graduation grade of bachelor students. The effect is slightly higher for females (table 6) and much stronger for Erasmus programmes in the scientific and technical fields (STEM) (table 7). Moreover, from table 8 it emerges that only shorter Erasmus programmes, namely of maximum 6 months, benefit students in terms of final grade. Finally, we identify countries that in the QS 2016 Education System Strength Ranking[7] were in the top 10 positions, namely UK, Germany, France and the Netherlands. Interestingly, the positive effect on the final graduation grade is stronger in destination countries with an overall relatively lower quality of higher education.

[7] https://www.topuniversities.com/system-strength-rankings/2016

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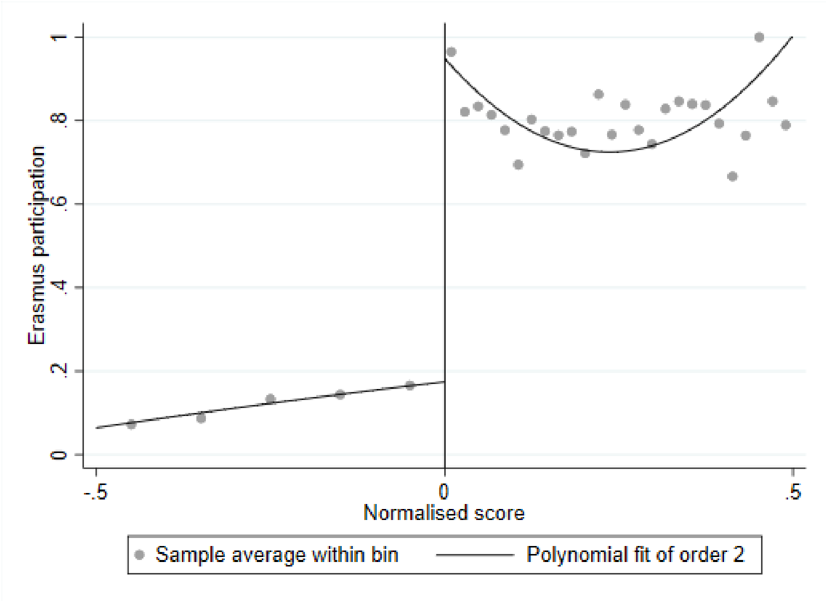
Figures and Tables

Figure 1: First stage plot.

(a) Bachelor



(b) Master

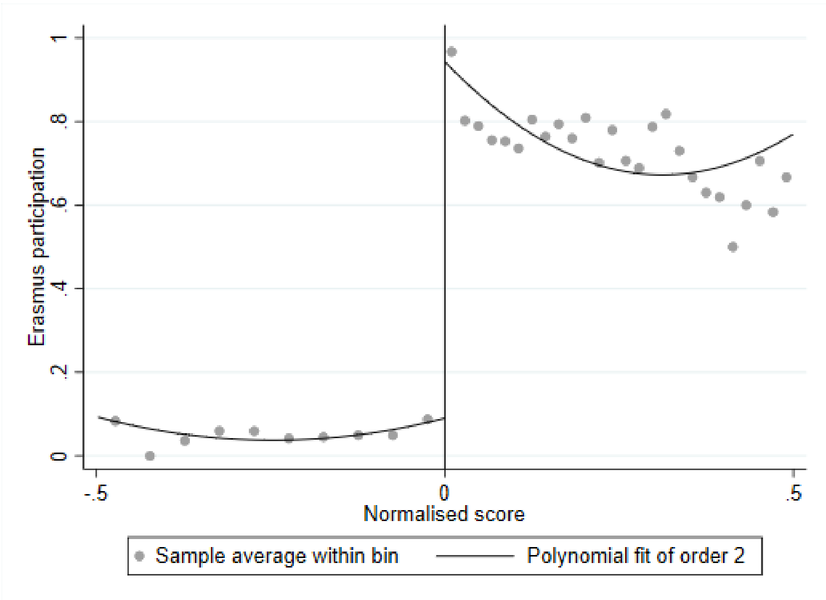
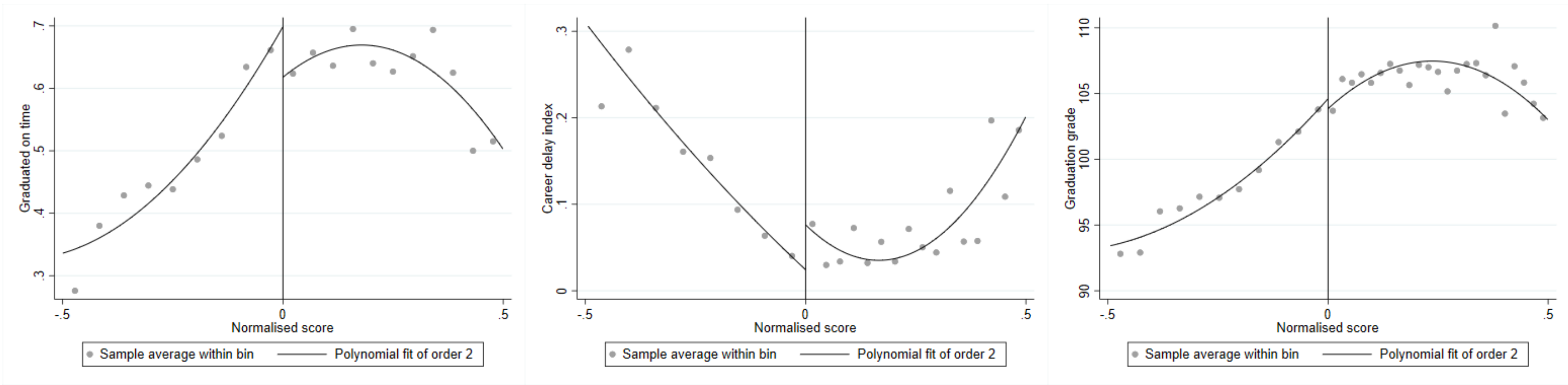


Figure 2: Reduced form plots.

(a) Bachelor

Graduation on time | Career delay index | Final grade



(b) Master

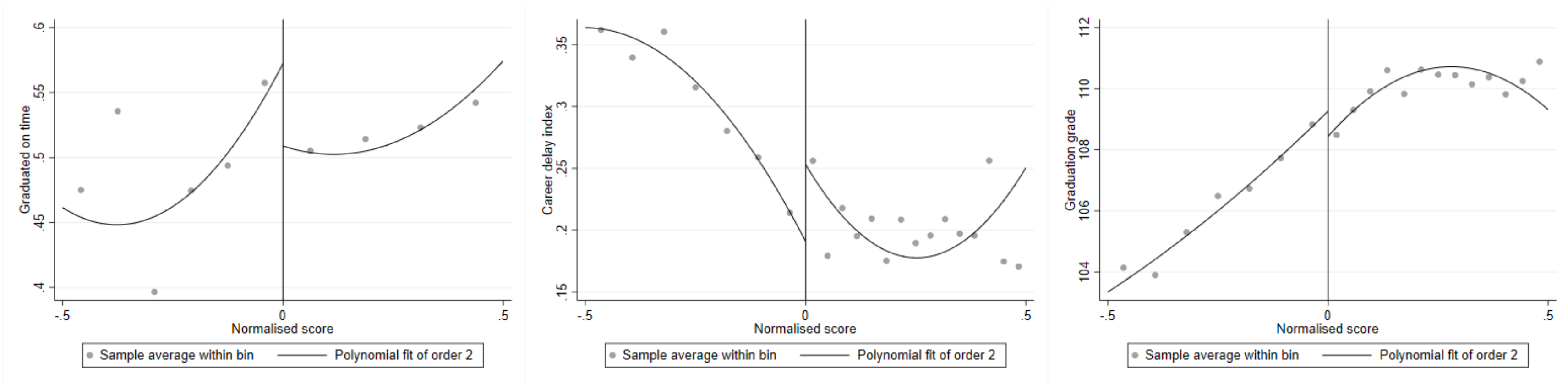


Table 1: Summary Statistics

(a) Descriptives on applications

	Degree Level					
	Bachelor		**Master**		**Total**	
	Col %	No.	Col %	No.	Col %	No.
No. applications						
1	40.6	2,388	49.8	1,956	44.3	4,344
2	46.7	2,741	46.0	1,806	46.4	4,547
3 or more	12.7	746	4.1	162	9.3	908
No. applications-year						
1	45.5	2,671	51.1	2,006	47.7	4,677
2	51.0	2,999	46.5	1,823	49.2	4,822
3	3.5	205	2.4	95	3.1	300
Erasmus participation						
Never	39.6	2,327	42.9	1,682	40.9	4,009
Once	59.6	3,503	56.9	2,234	58.5	5,737
Twice or more	0.8	45	0.2	8	0.5	53
Field of Study						
Education, Arts and Humanities	36.6	2,151	24.9	977	31.9	3,128
Social and behavioural science	35.1	2,060	27.4	1,076	32.0	3,136
Business&Administration and Law	12.0	705	15.1	591	13.2	1,296
STEM	10.0	586	27.5	1,081	17.0	1,667
Health, environment and services	6.3	373	5.1	199	5.8	572
Scholarship duration						
1-6months	58.9	3,461	65.9	2,584	61.7	6,045
7-12months	36.5	2,145	29.0	1,138	33.5	3,283
missing	4.6	269	5.1	202	4.8	471
Destination country						
Spain	20.9	1,230	17.4	681	19.5	1,911
UK	13.4	787	7.8	308	11.2	1,095
France	11.0	644	11.2	441	11.1	1,085
Germany	7.6	449	9.0	354	8.2	803
Netherlands	6.9	403	4.9	194	6.1	597
Other Europe	39.9	2,343	48.7	1,911	43.4	4,254
Other non-Europe	0.3	19	0.9	35	0.6	54
Total	100.0	5,875	100.0	3,924	100.0	9,799

(b) Descriptives by treatment status

	Degree Level							
	Bachelor				Master			
Variable	**Mean**	**S.d.**	**Mean**	**S.d.**	**Mean**	**S.d.**	**Mean**	**S.d.**
	No Erasmus		Erasmus		No Erasmus		Erasmus	
Female	.59	.49	.68	.47	.53	.5	.57	.49
Moved from other region	.52	.5	.55	.5	.65	.48	.65	.48
Number exams at year appl	5.85	4.41	4.48	3.34	.68	1.59	.62	1.59
Number credits at year appl	50.12	36.42	39.34	28.46	5.16	11.88	4.56	11.53
Graduated on time	.84	.36	.91	.29	.79	.41	.79	.4
Career delay index	.09	.23	.06	.19	.25	.28	.24	.25
Final graduation grade	101.48	8.4	104.9	7.14	107.89	5.72	109	4.98
Observations	3,548		2,327		1,682		2,242	

Notes:

Table 2: First stage

(a) Bachelor

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	0.7084***	0.7157***	0.7239***	0.7202***	0.7292***	0.7499***	0.7482***	0.7365***	0.7334***
	(0.0184)	(0.0187)	(0.0221)	(0.0204)	(0.0209)	(0.0256)	(0.0267)	(0.0276)	(0.0360)
Observations	4,669	4,669	4,669	4,161	4,161	4,161	2,742	2,742	2,742
R-squared	0.6510	0.6579	0.6540	0.6589	0.6687	0.6635	0.6669	0.6980	0.6686
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

(b) Master

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	0.8631***	0.8618***	0.8696***	0.8568***	0.8671***	0.8867***	0.8940***	0.8748***	0.8330***
	(0.0190)	(0.0194)	(0.0220)	(0.0206)	(0.0217)	(0.0260)	(0.0306)	(0.0314)	(0.0450)
Observations	2,941	2,938	2,941	2,508	2,508	2,508	1,519	1,519	1,519
R-squared	0.7433	0.7520	0.7457	0.7524	0.7633	0.7609	0.7690	0.7909	0.7713
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

Notes:

Table 3: Balance checks of covariates

(a) Bachelor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	No. exams	No. exams	No. exams	No. ECTS	No. ECTS	No. ECTS	Female	Female	Female	Moved reg	Moved reg	Moved reg
Above cutoff-score	-0.2514	-0.2582	-0.2883	-2.6954	-2.7602	-3.0065	-0.0328	-0.0341	-0.0374	-0.0167	-0.0170	-0.0184
	(0.2292)	(0.2287)	(0.2386)	(1.9814)	(1.9770)	(2.0653)	(0.0350)	(0.0351)	(0.0373)	(0.0383)	(0.0385)	(0.0413)
Observations	2,742	2,742	2,742	2,742	2,742	2,742	2,742	2,742	2,742	2,742	2,742	2,742
R-squared	0.5947	0.6004	0.6480	0.5846	0.5903	0.6383	0.4073	0.4126	0.4677	0.3816	0.3855	0.4354
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(b) Master

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	No. exams	No. exams	No. exams	No. ECTS	No. ECTS	No. ECTS	Female	Female	Female	Moved reg	Moved reg	Moved reg
Above cutoff-score	-0.1375	-0.1313	-0.1100	-1.2728	-1.2165	-0.9835	0.0083	0.0053	0.0023	0.0300	0.0301	0.0266
	(0.1314)	(0.1314)	(0.1396)	(0.9882)	(0.9845)	(1.0165)	(0.0504)	(0.0507)	(0.0551)	(0.0489)	(0.0493)	(0.0536)
Observations	1,519	1,519	1,519	1,519	1,519	1,519	1,519	1,519	1,519	1,519	1,519	1,519
R-squared	0.6100	0.6118	0.6489	0.5787	0.5802	0.6202	0.4596	0.4651	0.5208	0.4252	0.4301	0.4821
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Notes:

Table 4: Reduced form results - Bachelor

(a) Probability of graduating on time

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	-0.0037	-0.0071	-0.0109	-0.0168	-0.0004	0.0119	0.0318**	0.0242	0.0346*
	(0.0136)	(0.0129)	(0.0167)	(0.0149)	(0.0136)	(0.0175)	(0.0157)	(0.0158)	(0.0205)
Observations	4,669	4,669	4,669	4,161	4,161	4,161	2,742	2,742	2,742
R-squared	0.4319	0.4597	0.4321	0.4421	0.4951	0.4432	0.4962	0.5645	0.4962
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

(b) Career delay index

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	0.0111	0.0123	0.0115	0.0123	0.0055	-0.0037	-0.0101	-0.0110	-0.0181
	(0.0079)	(0.0076)	(0.0099)	(0.0084)	(0.0082)	(0.0103)	(0.0103)	(0.0108)	(0.0128)
Observations	4,669	4,669	4,669	4,161	4,161	4,161	2,742	2,742	2,742
R-squared	0.4837	0.5161	0.4837	0.5001	0.5469	0.5011	0.5461	0.6057	0.5463
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

(c) Final graduation grade

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	1.5313***	1.1570***	0.3204	0.7413**	0.7553**	0.4367	0.9598**	1.1603**	1.1185*
	(0.3307)	(0.3252)	(0.4023)	(0.3522)	(0.3656)	(0.4632)	(0.4630)	(0.4896)	(0.6008)
Observations	4,669	4,669	4,669	4,161	4,161	4,161	2,742	2,742	2,742
R-squared	0.5623	0.5692	0.5677	0.5567	0.5739	0.5570	0.5516	0.6101	0.5517
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

Notes:

Table 5: Reduced form results - Master

(a) Probability of graduating on time

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	-0.0218	-0.0248	-0.0296	-0.0158	-0.0116	-0.0110	-0.0056	0.0084	0.0114
	(0.0243)	(0.0247)	(0.0296)	(0.0272)	(0.0277)	(0.0353)	(0.0371)	(0.0388)	(0.0550)
Observations	2,941	2,938	2,941	2,508	2,508	2,508	1,519	1,519	1,519
R-squared	0.4452	0.4580	0.4454	0.4416	0.4790	0.4416	0.4531	0.5426	0.4538
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

(b) Career delay index

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	0.0062	0.0111	0.0196	0.0117	0.0126	0.0118	0.0020	-0.0059	-0.0257
	(0.0144)	(0.0142)	(0.0177)	(0.0152)	(0.0165)	(0.0220)	(0.0222)	(0.0231)	(0.0329)
Observations	2,939	2,936	2,939	2,508	2,508	2,508	1,519	1,519	1,519
R-squared	0.4952	0.5100	0.4958	0.4946	0.5291	0.4950	0.5195	0.6059	0.5206
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

(c) Final graduation grade

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	0.0755	-0.1506	-0.6555	-0.2943	-0.3127	-0.7154	-0.6639	-0.3753	-0.0701
	(0.3574)	(0.3541)	(0.4177)	(0.3889)	(0.3970)	(0.4772)	(0.5390)	(0.5633)	(0.7427)
Observations	2,941	2,938	2,941	2,508	2,508	2,508	1,519	1,519	1,519
R-squared	0.4561	0.4611	0.4592	0.4487	0.4849	0.4493	0.4682	0.5194	0.4697
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

Notes:

Table 6: Heterogeneity - Gender

(a) Bachelor

VARIABLES	(1) Graduated on time	(2) Graduated on time	(3) Graduated on time	(4) Career delay index	(5) Career delay index	(6) Career delay index	(7) Graduation grade	(8) Graduation grade	(9) Graduation grade
Female	-0.0035	0.0038	0.0259	0.0095	0.0016	-0.0152	1.2427***	0.8347**	1.2043**
	(0.0135)	(0.0142)	(0.0166)	(0.0077)	(0.0082)	(0.0110)	(0.3365)	(0.3758)	(0.5018)
Male	-0.0138	-0.0083	0.0212	0.0173*	0.0130	-0.0035	0.9997**	0.6073	1.0814*
	(0.0156)	(0.0163)	(0.0185)	(0.0098)	(0.0105)	(0.0132)	(0.4003)	(0.4459)	(0.5759)
Observations	4,669	4,161	2,742	4,669	4,161	2,742	4,669	4,161	2,742
R-squared	0.4598	0.4952	0.5645	0.5163	0.5472	0.6060	0.5693	0.5740	0.6102
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(b) Master

VARIABLES	(1) Graduated on time	(2) Graduated on time	(3) Graduated on time	(4) Career delay index	(5) Career delay index	(6) Career delay index	(7) Graduation grade	(8) Graduation grade	(9) Graduation grade
Female	-0.0234	-0.0110	0.0028	0.0118	0.0127	-0.0077	0.0552	-0.0038	0.0119
	(0.0274)	(0.0300)	(0.0411)	(0.0156)	(0.0179)	(0.0246)	(0.3711)	(0.4147)	(0.5800)
Male	-0.0263	-0.0123	0.0144	0.0103	0.0125	-0.0041	-0.3715	-0.6525	-0.7953
	(0.0272)	(0.0309)	(0.0415)	(0.0155)	(0.0179)	(0.0242)	(0.3960)	(0.4404)	(0.6176)
Observations	2,938	2,508	1,519	2,936	2,508	1,519	2,938	2,508	1,519
R-squared	0.4580	0.4790	0.5427	0.5100	0.5291	0.6060	0.4617	0.4863	0.5216
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Notes:

Table 7: Heterogeneity - Field of study

(a) Bachelor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Graduated on time	Graduated on time	Graduated on time	Career delay index	Career delay index	Career delay index	Graduation grade	Graduation grade	Graduation grade
STEM	0.0636	0.0597	0.0754	-0.0288	-0.0270	-0.0473	3.8347***	3.6533***	3.3452***
	(0.0448)	(0.0470)	(0.0507)	(0.0251)	(0.0254)	(0.0297)	(0.9948)	(1.0666)	(1.2604)
non-STEM	-0.0130	-0.0053	0.0207	0.0157**	0.0082	-0.0085	0.9333***	0.5203	1.0095**
	(0.0129)	(0.0137)	(0.0163)	(0.0076)	(0.0082)	(0.0109)	(0.3271)	(0.3700)	(0.4979)
Observations	4,669	4,161	2,742	4,669	4,161	2,742	4,669	4,161	2,742
R-squared	0.4605	0.4957	0.5650	0.5168	0.5474	0.6062	0.5710	0.5761	0.6113
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(b) Master

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Graduated on time	Graduated on time	Graduated on time	Career delay index	Career delay index	Career delay index	Graduation grade	Graduation grade	Graduation grade
STEM	-0.0132	0.0044	0.0256	0.0141	0.0124	-0.0013	0.1271	-0.3775	-0.5875
	(0.0457)	(0.0510)	(0.0689)	(0.0244)	(0.0249)	(0.0311)	(0.5792)	(0.6717)	(0.9846)
non-STEM	-0.0288	-0.0171	0.0028	0.0100	0.0127	-0.0074	-0.2480	-0.2905	-0.3075
	(0.0242)	(0.0277)	(0.0391)	(0.0149)	(0.0179)	(0.0247)	(0.3773)	(0.4102)	(0.5555)
Observations	2,938	2,508	1,519	2,936	2,508	1,519	2,938	2,508	1,519
R-squared	0.4581	0.4791	0.5428	0.5101	0.5291	0.6060	0.4613	0.4849	0.5195
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Notes:

Table 8: Heterogeneity - Erasmus duration

(a) Bachelor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Graduated on time	Graduated on time	Graduated on time	Career delay index	Career delay index	Career delay index	Graduation grade	Graduation grade	Graduation grade
Below 6 months	0.0098	0.0162	0.0416**	0.0055	-0.0008	-0.0148	1.4909***	1.1140***	1.4323***
	(0.0133)	(0.0140)	(0.0174)	(0.0080)	(0.0085)	(0.0114)	(0.3762)	(0.4146)	(0.5529)
Above 6 months	-0.0364*	-0.0302	-0.0053	0.0240*	0.0167	-0.0050	0.6187	0.1574	0.7256
	(0.0215)	(0.0221)	(0.0241)	(0.0127)	(0.0132)	(0.0161)	(0.4630)	(0.5082)	(0.6482)
Observations	4,658	4,150	2,735	4,658	4,150	2,735	4,658	4,150	2,735
R-squared	0.4604	0.4959	0.5655	0.5162	0.5470	0.6056	0.5691	0.5738	0.6097
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(b) Master

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Graduated on time	Graduated on time	Graduated on time	Career delay index	Career delay index	Career delay index	Graduation grade	Graduation grade	Graduation grade
Below 6 months	-0.0102	0.0052	0.0369	0.0065	0.0073	-0.0166	0.0439	-0.0200	-0.0236
	(0.0268)	(0.0302)	(0.0411)	(0.0154)	(0.0183)	(0.0244)	(0.4132)	(0.4588)	(0.6371)
Above 6 months	-0.0589	-0.0512	-0.0534	0.0218	0.0250	0.0172	-0.6083	-0.9987*	-1.1366
	(0.0421)	(0.0447)	(0.0561)	(0.0265)	(0.0262)	(0.0325)	(0.4657)	(0.5157)	(0.7030)
Observations	2,938	2,508	1,519	2,936	2,508	1,519	2,938	2,508	1,519
R-squared	0.4585	0.4796	0.5443	0.5102	0.5293	0.6066	0.4616	0.4859	0.5208
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Notes:

Table 9: Heterogeneity - Country of destination

(a) Bachelor

VARIABLES	(1) Graduated on time	(2) Graduated on time	(3) Graduated on time	(4) Career delay index	(5) Career delay index	(6) Career delay index	(7) Graduation grade	(8) Graduation grade	(9) Graduation grade
Top10 country	0.0019	0.0077	0.0240	0.0120	0.0073	-0.0116	0.9134**	0.4335	0.9141
	(0.0168)	(0.0162)	(0.0148)	(0.0092)	(0.0091)	(0.0102)	(0.4315)	(0.4619)	(0.5577)
other country	-0.0138	-0.0067	0.0243	0.0125	0.0042	-0.0104	1.3370***	1.0022**	1.3617**
	(0.0159)	(0.0174)	(0.0221)	(0.0099)	(0.0107)	(0.0145)	(0.3992)	(0.4461)	(0.6066)
Observations	4,669	4,161	2,742	4,669	4,161	2,742	4,669	4,161	2,742
R-squared	0.4598	0.4952	0.5645	0.5161	0.5469	0.6057	0.5693	0.5741	0.6103
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(b) Master

VARIABLES	(1) Graduated on time	(2) Graduated on time	(3) Graduated on time	(4) Career delay index	(5) Career delay index	(6) Career delay index	(7) Graduation grade	(8) Graduation grade	(9) Graduation grade
Top10 country	0.0284	0.0561	0.0759	-0.0111	-0.0160	-0.0535	0.6468	0.4565	0.2307
	(0.0366)	(0.0402)	(0.0524)	(0.0227)	(0.0269)	(0.0377)	(0.5164)	(0.5693)	(0.7965)
other country	-0.0486*	-0.0404	-0.0188	0.0210	0.0248	0.0132	-0.5088	-0.6397	-0.6191
	(0.0276)	(0.0304)	(0.0420)	(0.0154)	(0.0164)	(0.0217)	(0.4004)	(0.4445)	(0.6043)
Observations	2,938	2,508	1,519	2,936	2,508	1,519	2,938	2,508	1,519
R-squared	0.4592	0.4808	0.5445	0.5106	0.5300	0.6086	0.4626	0.4863	0.5202
Bandwidth	0.5	0.25	0.1	0.5	0.25	0.1	0.5	0.25	0.1
Pol. Order	1	1	1	1	1	1	1	1	1
Kernel:	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Notes:

Appendix

Figure B1: McCrary test

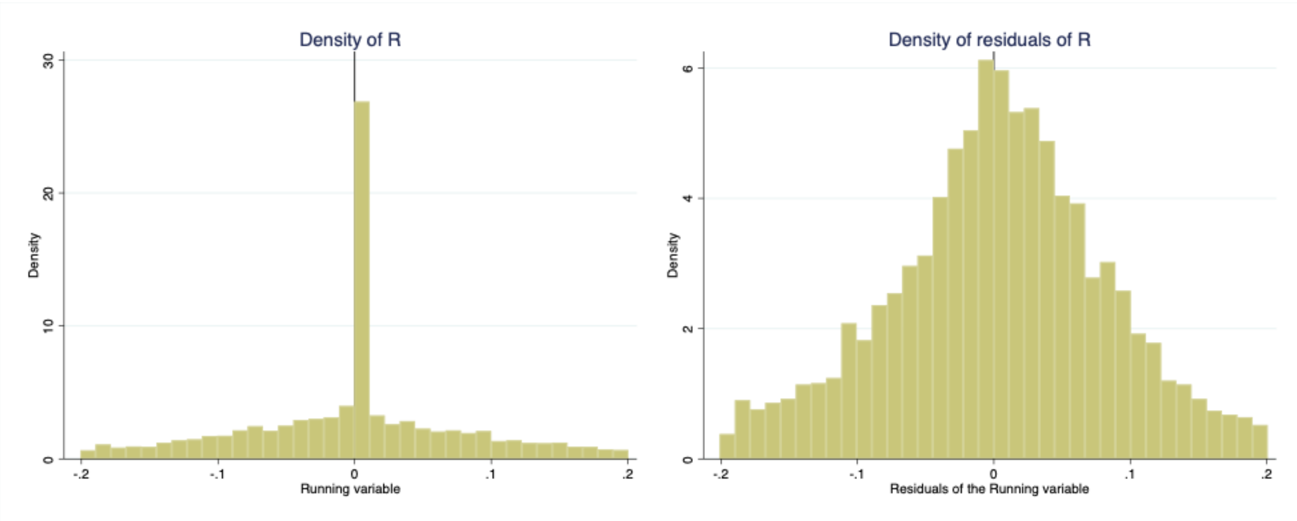


Table B1: Entire sample - Probability of graduating on time

(a) Bachelor

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	0.0039	-0.0024	-0.0120	-0.0140	0.0066	0.0307	0.0548**	0.0400*	0.0440*
	(0.0157)	(0.0154)	(0.0190)	(0.0177)	(0.0169)	(0.0216)	(0.0213)	(0.0210)	(0.0262)
Observations	5,526	5,526	5,526	4,891	4,891	4,891	3,143	3,143	3,143
R-squared	0.4948	0.5159	0.4951	0.5111	0.5508	0.5124	0.5533	0.6151	0.5534
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

(b) Master

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Above cutoff-score	0.0004	-0.0057	-0.0101	-0.0085	-0.0026	0.0050	0.0037	-0.0005	-0.0126
	(0.0232)	(0.0237)	(0.0275)	(0.0258)	(0.0263)	(0.0321)	(0.0350)	(0.0372)	(0.0500)
Observations	4,021	4,018	4,021	3,414	3,414	3,414	2,113	2,113	2,113
R-squared	0.5441	0.5593	0.5443	0.5537	0.5819	0.5539	0.5751	0.6377	0.5753
Bandwidth	0.5	0.5	0.5	0.25	0.25	0.25	0.1	0.1	0.1
Pol. Order	1	1	2	1	1	2	1	1	2
Kernel:	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform	Uniform	Triangular	Uniform

Notes: