A Question of Honor? The Labor Market Advantage of Academic Signaling

Mael Astruc-Le Souder, Olivier Bargain & Gedeão Locks*

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Abstract

As holding a Master's degree becomes the norm, students can differentiate themselves in terms of academic achievement by graduating with honors. We measure the advantage that this signal provides in the labor market by exploiting the fact that honors are awarded at regular thresholds of the final GPA in France. We combine administrative records from Sorbonne University and an employment survey of its alumni for graduation years 2015-2018. RDD estimates show that graduates with honors enter the labor market more quickly, i.e., the search time is reduced by around a quarter. The effect is driven by sectors where formal skills are highly valued—such as law and economics—making academic signaling most effective. Potential wage impacts are short-lived (i.e., less than a year), but honors students are significantly more likely to obtain a permanent contract within a year.

Key Words : regression discontinuity; returns to education; honors.

JEL Classification : J23, J24, J31, I23, I28.

* Astruc-Le Souder and Bargain are affiliated with the Bordeaux School of Economics (France). Bargain is visiting researcher at Princeton University (US) and affiliated with the *Institut Universitaire de France* (France) and IZA (Germany). Lock is affiliated with the DIW Berlin (Germany). This study has received financial support from the French State in the framework of the Investments for the Future program *IdEx université de Bordeaux / GPR HOPE*. Usual disclaimers apply. Corresponding author: Olivier Bargain, Bordeaux School of Economics, Bordeaux University, rue L. Duguit, 33608 Pessac, France. Email: olivier.bargain@u-bordeaux.fr

1. Introduction

Returns to education probably include a mix of human capital accumulation (Becker 1964) and the signal of workers' inherent productivity (Spence 1973). Empirical studies have tried to quantify the overall returns of different types of diplomas (i.e. high school, undergraduate or Master's degrees), which can be interpreted as the *extensive* margin of educational achievements.[1] Yet it has become equally important to study the *intensive* margins and in particular the heterogeneous performances among students with similar lengths of study.[2] A higher Grade Point Average (GPA) is likely to signal both better progress in learning and better innate abilities (we use *signal* in this broader sense from this point onwards). As we shall see, the labor economics literature on this subject is fairly limited, especially concerning Master's degrees, which motivates our work.[3] With the Master's degree becoming the new standard, employers may increasingly rely on GPA or other means of screening academic results to sort applicants from ever-larger cohorts of graduates.

In this context, we can question the educational policies aimed at making this signal more effective. Signaling often operates in a simplified way through a discretized system of letters (Tan, 2023), college honors (Bratti et al. 2008; Khoo and Ost 2018) or degree classes (Feng and Graetz 2017; di Pietro 2010). These distinctions are usually awarded when GPAs exceed certain thresholds. As such, they represent a coarse measure of academic achievement, which decreases the transaction costs for employers who investigate about job candidates.[4] Thus, honors are widely used in the academic system of many Western countries, from primary education to Masters level, anchoring common references. If academic achievements, as signaled by honors, have a real labor market return because they indicate both acquired skills and talent to potential employers, students have an incentive to work hard to earn honors, which should in turn reinforce the information content of honors and their validity as a

[1] Exploiting discontinuity around the passing cutoff, several studies have examined the labor market impact of holding a high-school degree (Clark and Martorell 2014; Jepsen et al. 2016; Mazrekaj et al. 2019; Tyler et al. 2000), being admitted to university (Grubb 1993; Jepsen et al. 2014; Kane and Rouse 1995) or choosing an economics major (Bleemer and Mehta, 2022).
[2] Another intensive margin is college quality, i.e. attending a more or less selective college (see Dale and Krueger, 2002, Black and Smith, 2004, and Long, 2008, among others).
[3] The closest studies to ours, discussed hereafter, include Tan (2023), Freier et al. (2015) and Baert and Verhaest (2021) on all university degrees, in Singapore, Germany and Belgium respectively, and Toft Hansen et al. (2021) on Master's graduates specifically. Several studies in psychology, sociology and business administration are more correlational and point to a positive association between grades and students' employability (Baert and Picchio 2021; Di Stasio 2014; Neyt et al. 2020, 2022; Pinto and Ramalheira 2017; Thoms et al. 1999).
[4] Indeed, the direct use of GPAs would entail higher information costs for recruiters in order to interpret these scores and the context in which they are given.

screening device for recruiters.

We propose testing whether academic honors significantly impact the labor market outcomes of Master's graduates. Our study leverages a unique aspect of the French education system: the discontinuous awarding of honors. In France, academic institutions grant honors (*mentions*) solely on the basis of students' final cumulative GPA, without considering other factors like rankings or extracurricular activities. The GPA scale ranges from 0 to 20, with a score above 10 required to pass and higher distinctions given for scores above 12 ('Honors'), 14 ('High Honors'), and 16 ('Highest Honors'). These thresholds, unchanged for over fifty years, resemble Latin Honors in the US. Crucially, this setup is ideal for a regression discontinuity design (RDD), allowing us to determine the specific effects of different honor levels on employment prospects.

To evaluate this, we use two datasets on Master's graduates from *Université Paris 1 Panthéon-Sorbonne* (`*Sorbonne'*), one of France's largest public universities with 50,000 students. We analyze administrative records of students' GPAs in law, business administration, economics, and political sciences—fields where academic achievement is particularly valued in the labor market (Walker and Zhu 2011). In addition, we use data from an original survey on the employment outcomes of Sorbonne alumni, including time to secure the first job, salary levels, and contract types. The RDD estimates compare students with very similar final GPAs around thresholds that determine honors. Thus, what we are measuring is the effect of the academic performance signal as provided by the honors system. Our approach should make it possible to assess the effectiveness of honors as a broad selection device used to differentiate large cohorts of Master's graduates.

Our results can be summarized as follows. RDD estimates indicate some effectiveness in terms of hiring speed. We find that graduating with honors reduces the time to find a first job by 23%, which is about 1.5 month faster, compared to the mean duration. The signaling effect peaks after 4 months, with High Honors graduates around 24-30% (across specifications) more likely to be in employment. It declines as the bulk of alumni become employed, i.e. within a year. This result may point to a general effect of honors or, alternatively, an effect triggered by the types of organizations that are mostly interested by academic performances (rather than non-cognitive skills, for example) and use honors information to improve matching in their recruitment process. In any case, it is reasonable to think that employer learning about productivity occurs quickly after labor market entry and relies on a variety of factors so that the informational effect of honors eventually disappears (Lange and Topel 2006, Habennalz, 2006, Lange 2007, Khoo and Ost 2018, Ablay and Lange, 2023). Consistently, we find no effect of honors on wages after a year post-graduation. A remarkable long-term outcome is the sustained initial career boost. After one year, the likelihood of securing a permanent contract is significantly higher for honors graduates, by about 18-22% (across specifications). Results are robust to the usual manipulation tests and sensitivity checks (i.e. on the specification of the smooth function of GPAs, sample choice, bandwidth definition, and accounting for specific features such as jury points). Our detailed analysis reveals that this effect on employment speed primarily stems from the 'High Honors' category and is most pronounced in fields where academic prowess is crucial, such as law and economics. This underscores the effectiveness of academic honors as a signal of achievement in these sectors.

The contribution of the paper is manifold. First, to the best of our knowledge, this is one of the rare quasi-experimental assessment of labor market returns to honors for Master's level students. As argued above, considering Master's degree students is important because it represents a large and growing portion of the student population in rich countries. The profusion of Master's level training means that companies and administrations will increasingly need selection mechanisms to choose new recruits from the pool of graduates. The literature so far is very limited. Baert and Verhaest (2021) use fake resume and estimates the impact of honors, among other attributes, on job interview invitations in Belgium. They suggest heterogeneity results comparing Bachelor and Master's graduates and find larger benefits from honors for the latter.[5] Beyond experiments, quasi-experimental evidence is rare and based on specific mechanisms. Toft Hansen et al. (2021) exploit a large change in grades scaling in Denmark in 2007 – which is quite different from honors – and explore the effect on earnings for Master graduates. Freier et al. (2015) study the role of honors on earnings in Germany. Their approach is based on the comparison between two disciplines (law and medicine), only one of which is awarding honors, so the interpretation of their estimate is very different from ours and is specific to law students (relative to medicine). Tan (2023) looks at the effect of letter grades in Singapore, which are also a discretization of GPA that lend itself to RDD analyses. Unlike us, however, this study focuses on the signal effect of each course, both on income and, in the shorter term, on class choice and future grades.

We contribute more generally to the literature on the labor market outcomes of academic distinctions

[5] A discrete choice experiment is suggested in Humburg and van der Velden (2015), but focusing on the labor market impact of interpersonal skills and professional experience during studies, with similar heterogeneity between Bachelor, Master and PhD graduates.

and other differentiating features among university students.[6] The literature on honors, mainly from the UK and US, finds a positive effect on earnings at the undergraduate level (e.g. Feng and Graetz 2017; Naylor et al. 2016; Walker and Zhu 2011, for the UK), which disappears over time (see Khoo and Ost 2018 for the US). If any, the effect seems to vanish faster for Master's graduates, as we find no significant wage impact after a year with our data.[7] Our results also consolidate past findings regarding the impact of honors on the employment probability after graduation. In particular, di Pietro (2010) finds similar results for the UK but can track graduates for 6 months only. We follow French graduates for 2 years, but similarly conclude that the increased job-finding rate fades out rapidly, i.e. within a year and even after 6 months in some specifications. As mentioned, experimental evidence in Baert and Verhaest (2021) corroborates our quasi-experimental results by showing that honors increase the probability to obtain job interviews.

The rest of the paper is structured as follows: section 2 explains the institutional background, section 3 describes our data and empirical strategy, section 4 presents our main results, robustness checks and heterogeneity analysis. Section 5 concludes.

2. Institutional background

2.1 Honors

In France, the grading scale ranges from 0 to 20, with the grade of 10 as the threshold to pass an exam (or, with the final GPA, to obtain a degree). French higher education institutions award academic honors based on regularly spaced thresholds of the final GPA at 12, 14 and 16. These are strict thresholds: they do not take into account percentile rankings or extra-curricular activities. This classification system is a tradition widely adopted by universities (exceptions are mentioned and treated hereafter). In the 1960s, a letter honor system, similar to the standardized US system at the time (or the Singaporean system today, cf. Tan, 2023), was proposed but not adopted (Schneider and Hutt, 2014). The French grade system was finally supplemented by honors in 1971 for high school and university diplomas (Gimmonet, 2007).

Honors are defined as follows: (i) *mention assez bien* (`quite good' distinction) is awarded if the final

[6] Beyond honors, the literature has investigated the labor market returns to other experiences such as acting as leader of a student union (Lundin et al. 2021), professional experience during studies and internship (Baert and Verhaest 2021; Humburg and van der Velden 2015) or international mobility experience (De Benedetto et al. 2023).

[7] Among rare studies at the Master's level, Freier et al. (2015) find an earnings effect of honors for Germany, which also fades away.

GPA is equal to or higher than 12 and less than 14 on the 0-20 scale, (ii) *mention bien* (`good') if the GPA is above 14 and below 16, (iii) *mention très bien* (`very good') if the GPA is above 16. These honors broadly correspond to the *cum laude*, *magna cum laude*, and *summa cum laude* in the North American systems of Latin honors. According to Campus France, the French Agency for the promotion of education abroad, the translation of past transcripts used when French students study in the US is 'Honors', 'High Honors', and 'Highest Honors' respectively. This system of honors with regular cutoffs has been in use for half a century in France, from secondary school exams to those for the Master's degree. Few exceptions exist, which correspond to alternative honors cutoffs at 13, 15 and 16, and which we shall discard in our empirical work.

3.2 Master's degrees

As motivated above, very few studies address the role of academic achievements at Master's level. This is however a critical aspect given the need for students to stand out from the crowd as the number of Master's programs increases. Master is often described as the "new bachelor", because the proportion of Master graduates is similar to the proportion of bachelor graduates in the 1960s for most OECD countries.[8] In the US and France, respectively 44% and 54% of bachelor students advanced to a Master's program in 2018, compared to 35% and 39% in 2000 (OECD, 2022).

More specifically, European countries have implemented a profound harmonization of their education system through the `Bologna Process', started in 1999 and achieved by 2010. It has aimed at ensuring comparability in the standards and quality of higher-education qualifications, with a system of transferable credits and a uniform three-cycle higher education system (a 3-year bachelor level followed by 2-year master's degrees and the doctorate level). For France, the administrative dataset we use was provided by the *Université Paris 1 Panthéon-Sorbonne*, the oldest university in the country and one of the largest, with about 50,000 students. Sorbonne offers a variety of Master's degree programs in Economics, Law, Philosophy, Geography, Humanities, Cinema, Plastic Arts, Art history, Political Science, Mathematics, Business, and Social sciences. As in most universities in France, there are two types of Master's degrees: the `research' and `professional' tracks. The professional Master's represents the bulk of Master programs and prepares for all types of jobs in firms or administrations. In principle, research Master's programs are additionally aimed to prepare students for a PhD or research-based

[8] See contextual discussions in Glazer-Raymo (2005), Schneider and Klor de Alva (2018), Carnevale et al. (2015), Blagg (2018) and https://www.vox.com/2014/5/20/5734816.

activities (high-level consultants or analysts, careers in international organizations, etc.). However, this dichotomy is no longer relevant, given the diversity of the professions practiced by students from research Master's. Nevertheless, we will consider potential heterogeneity between these two types of Master's.

3. Data and Empirical Strategy

3.1 Data

Data sources and variables. We use two datasets on graduates from Sorbonne: the administrative records with information on students' GPAs combined to a survey conducted by the ORIVE (the *Observatory of Results, Professional Integration and Student Life*) two years after students' graduation. The combined data contains administrative information on the student's discipline, the type of Master's (research or professional), the year of graduation, the grades – and in particular the final GPA obtained at the end of the Master's, and honors. From the employment survey, we use information on the date of the first job, and on employment characteristics 1 and 2 years after graduation, namely the labor market status, wage levels and the contract type. The sample comprises 6,635 students in Business, Economics, Law and Political Sciences who graduated between 2015 and 2018 from a Master program at Sorbonne.[9] The disciplines included in our analysis are similar to the ones used in Bratti et al. (2008) and Walker and Zhu (2011) and, according to these studies, represent the sectors of activities where academic signaling might be most effective.

Selection. Since we are interested in the effect of honors defined around the 12, 14 and 16 cutoffs, we use broad bandwidths of ± 1 in our baseline estimations, i.e. groups of students with grades between 11 and 13, 13 and 15, 15 and 17 respectively. In this way, we discard 8% of our initial sample at the tails.[10] While these regular segments make sense for a harmonized treatment of the different cutoffs, we also replicate estimations using optimal bandwidths in the sensitivity analyses thereafter. Note that our baseline sample also excludes those who continue their studies after graduation (e.g. those who start a new Master's program, enter a PhD program, or prepare and attend competitive exams to enter

[9] Detailed disciplines include Business administration, the University School of Management (IAE), Economics, different Law degrees (Public, Private and International law) and Political sciences. We regroup them as indicated. In the data, the field of business administration has the highest number of students (nearly 40% of the dataset), followed by Economics (25%), Law (22%) and Political Science (14%).

[10] We exclude observations especially at the lower end, just above the 'pass threshold'. Robustness checks show that this does not change our conclusions.

the public sector), i.e. an additional 38%. Finally, we take out respondents from a minority of the Master's programs in Law that happen to use different honors cutoffs, as mentioned before (this corresponds to 7% of the initial sample). This leaves us with a final dataset of 3,166 individuals.

Table A.1 in the Appendix provides descriptive statistics for our sample, which includes statistics for the available outcomes and for some individual characteristics (used as control variables). Looking first at the overall sample (column 1), and regarding outcomes of interest, we find that students took 6.2 months on average to secure their first job. One year following their graduation, 80% of them held a job, against 94% two years post-graduation. Net wages a year after graduation were approximately €2,265 per month, and €2,501 after two years. Regarding individual characteristics, the average age of the former students in the sample is 26.5 years and there is a slight majority of women (57.6%). Most of the alumni were born in France (74%), with the next largest group coming from Africa (10%). The majority were enrolled in a `professional' Master's programs (90%) and the rest in a `research' Master's. The subsequent columns show statistics by relevant GPA intervals (columns 2-5). We also provide tests of the mean differences between short intervals around cutoffs (columns 6-8). Differences in outcomes reflect the results discussed hereafter and notably a faster hiring in the intermediate group. Regarding individual characteristics, there is no fundamental differences between students at different levels of academic achievement (we provide more specific balance tests around GPA cutoffs in our robustness checks). Finally, Figure A.1 represents the distribution of GPAs in the sample while indicating honors cutoffs. We do not see any discontinuity in the density of GPAs (specific McCrary tests are presented hereafter). GPAs are relatively concentrated between 12 and 15. Most individuals received lower/intermediary honors: 53% obtain a GPA between 12 and 14 (and hence the 'rather good' honors). Then, 34% are between 14 and 16 ('good'), only 2.7% got a GPA above 16 (`very good') while the rest is below 12. Note that a minority of students attend a second examination session to re-sit some of the exams they did not pass or could not attend during the regular session, but this feature of the exam system is neutral for our analysis. [11]

[11] These cases essentially correspond to re-sit obligations due to systems of compensation between blocks of subjects, but rarely to voluntary choices by students who would like to increase their GPA to obtain honors. Precisely, second sessions concern only 270 students in our sample, and only 4.7% of them obtained Honors (i.e. reached the 12 cutoff) thanks to the re-sit. After verification, we find that excluding this group (or all those attending second section) does not affect our results. Second sessions concern only 90 students near the High Honors, which we focus on hereafter, and all of them already had a final GPA above 14 before the retake exams.

3.2 Empirical Strategy

To estimate the causal impact of honors on labor market outcomes, we use a regression discontinuity design (RDD) exploiting the attribution of honors based on evenly spaced cutoffs. As noted by Lee and Lemieux (2010), treatment assignment is as-good-as-random for observations close to the discontinuity, which means that crossing the GPA cutoff affects labor market outcomes only by changing the honors received, but not the talent and effort put by students during their exams. More generally, we assume that students are quasi-identical around the cutoffs (local continuity assumption) and test it in the empirical section. We interpret the potential impact of honors as the pure effect of signaling the candidate's quality to employer on employment probability and future wages. Formally, we estimate the following regression:

$$Y_i = \alpha + \beta\, T(S_i) + \ \theta(S_i) + \gamma\, X_i + \delta_{year} + \varepsilon_i \qquad (1)$$

where Y_i will be alternative outcomes for a former student i. The main outcomes concern employment probability. We first use a binary variable equal to one if the person has already found a job after *t=1, 2,… 27* months post-graduation (and zero otherwise). We simply run a linear probability model for each of these periods. Alternatively, we run a single estimation where Y_i is the number of months needed to find the first job after graduation. For the latter approach, we have also experimented with RDD embedded in duration models and results are very similar (unreported). Finally, we use information on other labor market outcomes, namely the wage level and a dummy for holding a permanent contract, measured exactly one and two years after graduation.

Explanatory variables include different functions of the running variable S_i, which is the final GPA of an individual i. The original GPA aims to capture the genuine level of the student. The local continuity assumption requires that $\theta(S_i)$ is a smooth function of the running variable. There is actually no reason for labor market outcomes to vary abruptly at GPA cutoffs other than the pure effect of honors. We have actually checked that there were no other requirement or policy based on specific cutoffs of GPAs that employers in public and private sectors may have implemented, at least for the careers corresponding to the disciplines in our sample, i.e. law, economics, business administration, political sciences (Vincens and Johnston, 1995). RDD estimations usually rely on a large sample strategy, i.e. using observations both close and further away from the cutoff. In that case, we will systematically suggest a variety of alternative parametric functional forms for $\theta(S_i)$ in order to balance the trade-off between precision and bias (Lee and Lemieux, 2010). In alternative approaches, we will focus on local observations in two ways: by using automatic bandwidth selection (Calonico et al., 2014) or non-parametric estimations.

Model (1) can be estimated for each specific honor (either at 12, 14 or 16 cutoffs) separately. In this case, the treatment variable $T(S_i)$ is a dummy equal to 1 if the student's final GPA S_i is above the cutoff or 0 if it is below, within a bandwidth of ± 1 corresponding to the relevant interval (for instance the 13-15 interval for the 'High Honors' cutoff at 14). We can also estimate the effects of the three honors simultaneously. In this case, $T(S_i)$ is replaced by three variables $T_k(S_i)$ for honors k=1,2,3, corresponding to cutoffs 12, 14 and 16 respectively. Smooth functions are also adapted: for instance, instead of a linear spline specification in the single-cutoff case, $\theta(S_i)$ becomes a piecewise linear function with different linear segments for each interval 11-12, 12-14, 14-16, 16+. Finally, it is possible to estimate the overall effect of honors. In this case, $T(S_i)$ is a dummy indicating if the GPA is above the closest cutoff, using normalized GPAs around centered cutoffs with bandwidths of ± 1 (for instance, GPAs of 14.3 and 16.3 will both become a normalized value of 0.3).

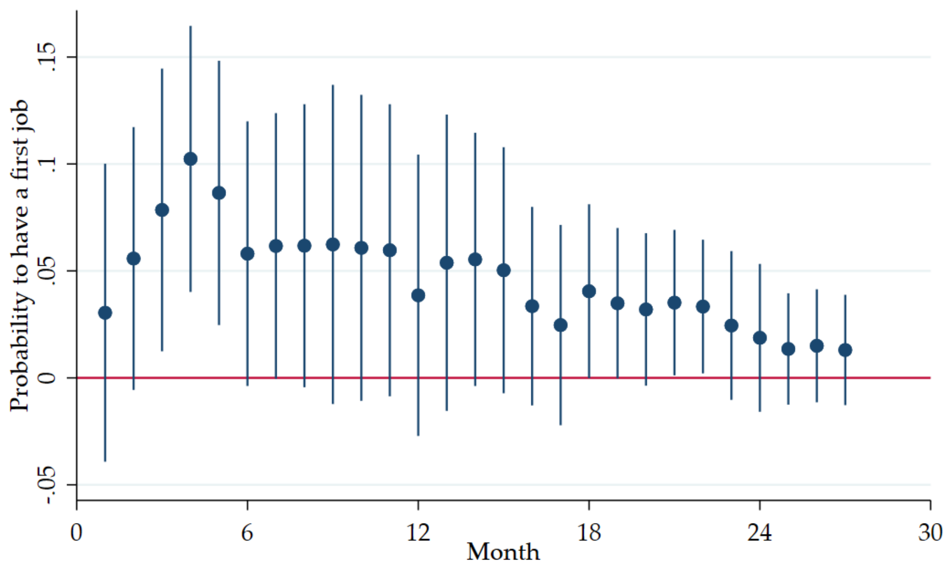
To improve precision, we include a few controls, denoted by the vector X_i of individuals' characteristics (age, gender and continent of birth). For all the estimations, we pool the different years available in the data to maximize sample size (as requested for RDDs), but control for business cycles, cohort effects and their potential implications for labor market outcomes through the set of coefficients δ_{year} for the different year dummies. We also cluster our results by cohort-country of origin (very similar results are obtained when clustering by cohort only).

4. Results

4.1 Baseline Results: Honors and Labor Market Outcomes

We now present our baseline RDD estimations. They are carried out on our selection, as described in the data section, while excluding marginal cases that receive specific treatments in our sensitivity analyses thereafter. Precisely, we use the final GPA (before potential jury points) and exclude students who received jury points (5.7% of the selected sample). We focus here on the bulk of the alumni for whom the final GPA has directly and deterministically led to the award of honors or not (i.e. for whom we have a sharp RDD). We start with the first labor market outcome, namely the time spent to find a job. We first consider the *overall effect* around all the cutoffs simultaneously by using normalized GPAs, i.e. centered around their closest cutoff that is normalized to zero, and a bandwidth of ±1. Precisely, we run RDD estimations of the probability to hold a first job for each period *t=1, 2,… 27* months post-graduation, using local polynomial regressions. Figure 1 presents the estimates of the overall honors effect at each period, with 95% confidence bounds. We observe a significant effect in the short run, which peaks at around four months after graduation. At the peak, the probability to have found a job increases by 10 percentage points. Given that 54% of the alumni are employed after 4 months, this estimate means a 18.5% relative increase in the employment probability. This result confirms the effectiveness of the honors system to signal the quality of job candidates and accelerate matching on the labor market of graduates from legal and economic/business disciplines. According to the graph, the impact diminishes as the stock of former students still to find a job drops (recall that 80% of them find their first job within a year).

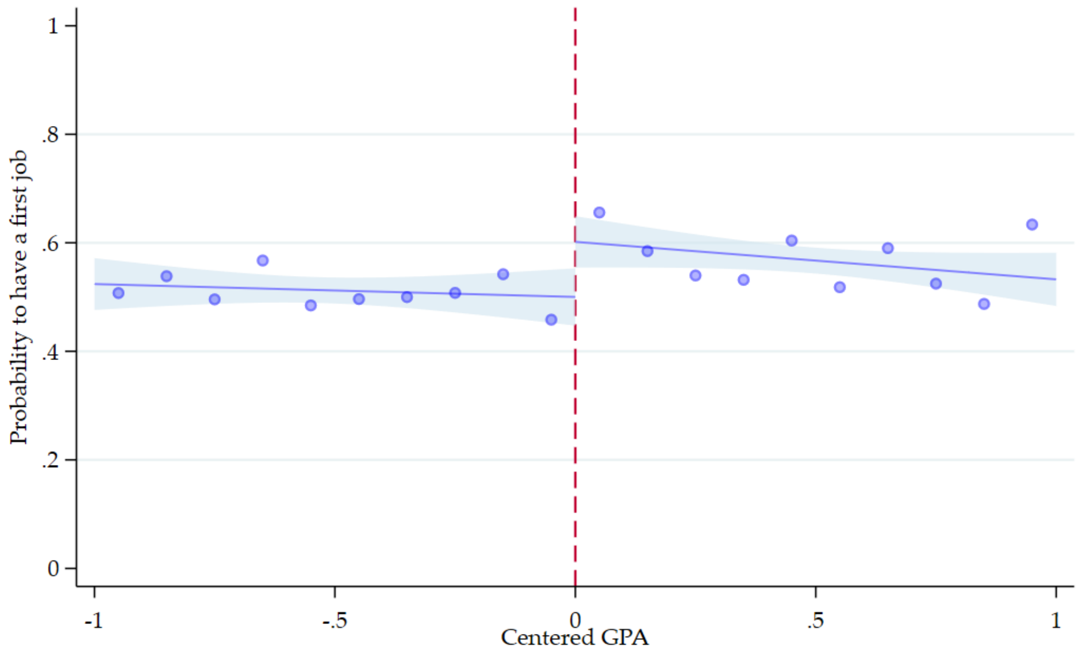
Figure 1: RDD estimates of employment probability at different months post-graduation (normalized GPA around centered cutoffs)



Notes: This graph summarizes the results of 27 independent RD estimates of the honors' impact on the probability to have already found a first job at a given month after graduating. The dots present the estimated coefficient for each month. The vertical bars show the 95% confidence intervals. These estimations use all the honors by normalizing the cut-offs to 0 and centering the GPA around the closest cutoff with a bandwidth of ± 1. These estimations use a local polynomial for the smooth function of the running variables. Controls include age, gender, continent of birth and a cohort fixed-effect. Estimations clustered by cohort and country of origin group

Before exploring the sensitivity of these results to different specifications, we focus on the effect of honors at 4 months after graduation. As before, the GPAs are centered on the closest cutoff that is normalized to zero. With linear trends on both sides of the cutoff, the classic RDD graph of Figure 2 confirms that receiving honors increase the probability of employment at 4 months by around 20%.

Figure 2: RDD estimate of the employment probability at 4 months after graduation (centered cutoffs)



Notes: This illustrates the RD estimates of the honors' impact on the probability to have already found a first job four months after graduating. The horizontal axis corresponds to the centered GPA obtained by normalizing the cut-offs to 0 and centering the GPA around the closest cutoff with a bandwidth of ±1. This graph uses a linear spline for the smooth function of the running variables. The shaded area represents the 90% confidence interval of the fitted values with the linear estimations. The bins represent the average probability to have a first job for individuals grouped by GPA with 0.1 cuts. Observations: 1498 below the cutoffs and 1526 above the cutoffs.

Table 1 reports the estimated treatment effect of receiving an honors degree at the Master's level on the probability to have already found a first job after four, six, eight, ten, and twelve months after the graduation. We report estimates with different smooth functions for the parametric model, as well as the estimates for local polynomial regressions, which correspond to the point estimates at 4, 6, 8, 10 and 12 months on Figure 1. As noted before, these baseline results on employment indicate a robust effect on job status at the 4-month mark. Given statistical noise, estimates of the parametric model necessarily vary across specifications of the smooth function of the running variable, with estimates ranging from 8.7 to 12 percentage points. This translates into a relative employment effect between 16% and 22%. The next columns confirm that the honors effect fades rapidly. Only two or three specifications still show significant effects after 6, 8 or 10 months post-graduation, while all the specifications agree on a nil effect after a year.

Table 1: RDD estimates of the employment probability at various months after graduation (centered cutoffs)

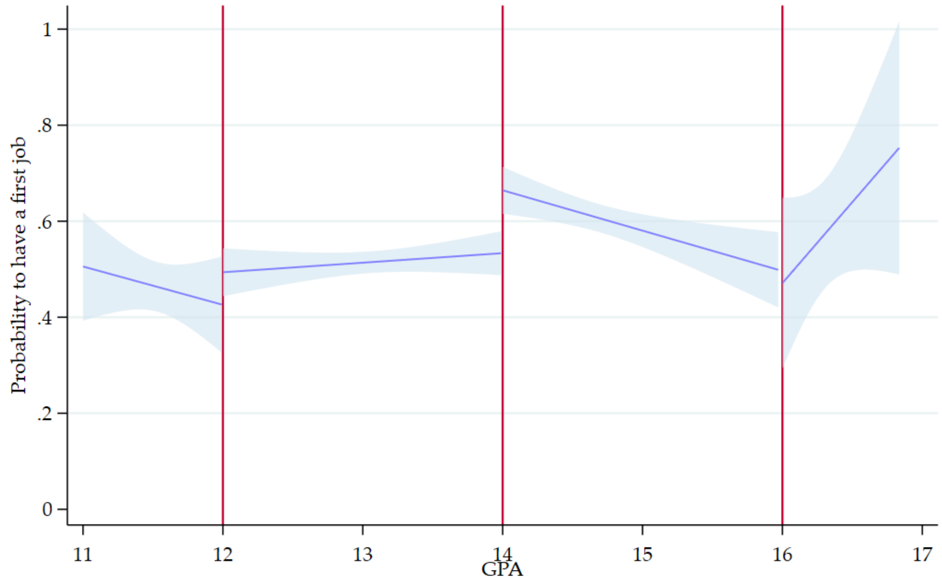
	4 months	6 months	8 months	10 months	12 months
Linear Spline	0.087***	0.047	0.054*	0.070**	0.044
	(0.028)	(0.033)	(0.031)	(0.031)	(0.028)
Quadratic spline	0.12***	0.058	0.057	0.030	0.017
	(0.038)	(0.050)	(0.049)	(0.060)	(0.059)
Cubic	0.052***	0.029*	0.019	0.025	0.0092
	(0.014)	(0.016)	(0.012)	(0.017)	(0.015)
Quartic	0.062***	0.037**	0.025*	0.029*	0.012
	(0.015)	(0.017)	(0.013)	(0.016)	(0.015)
Local polynomial	0.10***	0.058*	0.062*	0.061*	0.039
	(0.032)	(0.032)	(0.034)	(0.036)	(0.034)
Obs.	2,401	2,401	2,401	2,401	2,401

Notes: This table presents the RD estimates of the honors' impact on the probability to have already found a first job at various months after graduation. Reported coefficients are based on Equation 1. Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and a different outcome per column. These estimations use all the honors by normalizing the cut-offs to 0 and centering the GPA around the closest cutoff with a bandwidth of ± 1. Controls include age, gender, continent of birth and a cohort fixed-effect. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

While the previous exercise aimed to convey an overall message about the impact of honors, we also examine specific effects around the different cutoffs. Figure 3 illustrates them graphically at the 4-month post-graduation, employing piecewise linear splines. The impact at the 12-cutoff is small and not significant. This is not very surprising since 90% of the former students had received a final GPA above that score, so it cannot really be a tool of differentiation on the labor market. The framing “rather good” is also relatively explicit about the fact that this score does not reflect a truly significant achievement. The impact around the 14-cutoff is significant and large. This award makes the employment probability jump from around 54% to 67%, i.e. a 13 percentage points increase (+24%). Clearly, this honors level drives the overall effect characterized before, which is not so surprising. First, it is not underpowered, as it concerns a rather large number of students (34%). Second, an award framed as 'High Honors' is symbolically stronger and reflects a higher academic performance. Finally, the impact around the 16 cutoff is nil. It may primarily be due to the limited number of observations above this cutoff (2.7% of the sample), which poses a challenge for RDDs. Moreover, the small size of the group obtaining this distinction makes it difficult to interpret the corresponding effect given the possibly very specific nature of this group in the sample.[12]

[12] The graph also shows increasing trends within each interval as expected. The exception between 14 and 16, i.e. a declining trend, might be due to selection: those with better GPA have better economic background and can wait longer to look for a

Figure 3: RDD estimate of the employment probability at 4 months after graduation (multiple honor cutoffs)



Notes: This illustrates the RD estimates of the honors' impact on the probability to have already found a first job four months after graduating. The horizontal axis corresponds to the GPA obtained. This graph uses a piecewise linear spline smooth function of the running variables with three different treatment variables corresponding to the three cutoffs. The shaded area represents the 90% confidence interval of the fitted values with the linear estimations. Observations: 310 pass, 1649 Honors, 995 High Honors and 70 Highest Honors.

Table 2 reports the detailed results of the joint estimation of the potential effects at the different cutoffs (12, 14, and 16). We also examine the robustness of the findings across different smooth functions of the final GPA. The table confirms that our overall effect is driven by High Honors (the 14-cutoff). The effect for this intermediary honors is strongly significant at four months post-graduation, with larger and more precise estimates than when we grouped the three centered cutoffs. It ranges from 9 to 16 ppt across specifications (from +17 to +20% in relative terms). The effect at 14 also seems more persistent than the overall effect but this depends on the specification and it becomes insignificant after one year in a majority of specifications.

better match on the labor market. Recall also that we exclude those who continue their study after the Master's, while there might be positive selection into PhD education.

Table 2: RDD estimates of the employment probability at various months after graduation (multiple cutoffs)

		4 months	6 months	8 months	10 months	12 months
Piecewise linear	12	0.090	0.046	0.046	0.042	0.029
		(0.066)	(0.061)	(0.053)	(0.042)	(0.036)
	14	0.088***	0.068***	0.049**	0.061**	0.043**
		(0.031)	(0.022)	(0.022)	(0.026)	(0.020)
	16	-0.13	-0.12	0.097	0.039	0.033
		(0.15)	(0.14)	(0.094)	(0.092)	(0.069)
Piecewise quadratic	12	0.00051	-0.085	-0.081	-0.072	-0.060
		(0.086)	(0.082)	(0.11)	(0.097)	(0.093)
	14	0.11***	0.087***	0.074**	0.093**	0.064**
		(0.026)	(0.026)	(0.031)	(0.034)	(0.025)
	16	-0.081	-0.11	0.22**	0.17*	0.16**
		(0.18)	(0.15)	(0.090)	(0.086)	(0.067)
Cubic	12	0.042	-0.014	0.0052	0.013	-0.0060
		(0.056)	(0.050)	(0.054)	(0.045)	(0.040)
	14	0.12***	0.082**	0.051**	0.075**	0.037
		(0.028)	(0.029)	(0.023)	(0.035)	(0.033)
	16	0.12	0.072	0.17*	0.096	0.092
		(0.14)	(0.12)	(0.095)	(0.081)	(0.063)
Quartic	12	0.057	-0.0029	0.010	0.017	-0.0032
		(0.058)	(0.054)	(0.057)	(0.047)	(0.040)
	14	0.15***	0.11***	0.063**	0.085**	0.044
		(0.030)	(0.028)	(0.026)	(0.036)	(0.036)
	16	-0.059	-0.065	0.11	0.042	0.059
		(0.18)	(0.16)	(0.12)	(0.12)	(0.099)
Local polynomial	12	0.019	-0.084	-0.045	-0.039	-0.012
		(0.12)	(0.12)	(0.14)	(0.12)	(0.11)
	14	0.16***	0.12**	0.10*	0.089	0.030
		(0.051)	(0.058)	(0.062)	(0.092)	(0.085)
	16	-0.27	-0.20	0.0051	-0.020	0.040
		(0.23)	(0.17)	(0.13)	(0.14)	(0.15)
Obs.		2,401	2,401	2,401	2,401	2,401

Notes: This table presents the RD estimates of the honors' impact on the probability to have already found a first job at various months after graduation. Reported coefficients are based on Equation 1. Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and a different outcome per column. These estimations use all the honors with three treatment variables with a bandwidth of ± 1. Controls include age, gender, continent of birth and a cohort fixed-effect. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1

Note that simultaneous estimates of the different honors classes in Table 2 (similarly to Figure 3) necessarily rely on larger bandwidths. For instance, all the observations between 12 and 16 are implicitly used to identify the coefficient at the 14 cutoff, hence an effective bandwidth of ± 2 around that cutoff. For a focus on honors at 14, we run RDD estimations on observations around this threshold and with our baseline bandwidth of ± 1. Results are reported in Table A.2, again for various smooth functions. Once again, the estimated benefit of honors peak at 4 months after graduation and fades out within a year time. Estimates are slightly larger in this series of estimations for spline and cubic specifications, which are more sensitive to the bandwidth and the sample used around the cutoff. Not surprisingly, however, results are very similar to Table 2 for flexible specifications and in particular for local polynomial regressions. High Honors increase the probability of being employed at four months after graduation by 13-16 ppt (i.e. +24% to +30% more than the average employment probability). We also represent these results visually in

Figure A.**2**, focusing on the 14 cutoff for local polynomial regressions at detailed points in time. It confirms that estimates are larger than when grouping the different honors, at any point post-graduation.

4.2 Robustness Checks

We subject our baseline results to extensive robustness checks to confirm their validity. These checks include replications of the RDD with an optimal bandwidth, balance tests to verify the similarity of students around the cutoffs, density tests to detect manipulation of the running variable (Cattaneo et al., 2019), placebo tests, and selection in survey responses. Logically, given the previous results, we are focusing mainly on High Honors.

Optimal bandwidths. We first examine this 14-threshold using a RDD with optimal bandwidth (Calonico, 2014, Cattaneo et al., 2019, 2020). This approach evaluates the optimal position between wide and narrow bandwidths, which can be seen as a trade-off between precision and accuracy. Namely, a wide bandwidth uses more observations and is therefore more precise but possibly less accurate since the observations far from the cutoff may not respect the local continuity assumption. A narrow bandwidth is just the opposite, with a more credible assumption of similarity around the cutoff for close observations but more noise and less precision.[13]

Results are reported in Table 3**.** With an optimal bandwidth, the impact of High Honors on the employment probability is relatively close to what we have found with a ± 1 bandwidth, but estimates are now much more similar across specifications, as expected. At four months post-graduation, we obtain a gain in employment probability of 14-15 ppt (+26% to 28%) across various polynomial models. Again, the advantage of graduating with High Honors is effective for the bulk of alumni who find a

[13] Another way to see the tradeoff is the following: an excessively wide bandwidth could dilute the effect by incorporating too many dissimilar observations; an overly narrow one might lead to overfitting the model to the data.

job within half a year, then quickly disappears.

Table 3: RDD estimates of the employment probability at various months after graduation (14-cutoff with optimal bandwidths)

	4 months	6 months	8 months	10 months	12 months
Linear Spline	0.14***	0.097	0.083**	0.11***	0.057
	(0.037)	(0.065)	(0.037)	(0.037)	(0.059)
Quadratic spline	0.15***	0.17	0.089*	0.081	0.014
	(0.054)	(0.066)	(0.052)	(0.085)	(0.084)
Cubic	0.14***	0.17**	0.089**	0.093	0.051
	(0.050)	(0.081)	(0.041)	(0.062)	(0.067)
Quartic	0.14***	0.17**	0.090**	0.094	0.054
	(0.051)	(0.080)	(0.041)	(0.063)	(0.067)
Local polynomial	0.14***	0.13***	0.088***	0.099***	0.043
	(0.035)	(0.045)	(0.031)	(0.037)	(0.056)
Optimal bandwidth	0.83	0.56	1.00	1.04	0.71
Obs. Left	607	386	733	766	520
Obs. Right	490	370	549	563	440

Notes: This table presents the RD estimates of the honors' impact on the probability to have already found a first job at various months after graduation. Reported coefficients are based on Equation 1. Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and a different outcome per column. These estimations focuses on the 14/20 cutoff with an optimal bandwidth precised at the bottom of each column. Controls include age, gender, continent of birth and a cohort fixed-effect. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Manipulation tests. We address concerns about students who may be manipulating their GPA to barely pass the honors threshold. Since the threshold levels are widely known, students might adjust their efforts to land just above them and receive the honors. Given the large number of exams in each Master's program, however, and the uncertainty about professors' grading style, exam difficulty, etc., it is unlikely that students are able to adjust their final average score so precisely. The distribution of final GPAs is more likely to reflect a combination of talent and effort on the part of each student, leading to final marks that may be well below or above the threshold of the distinction students are targeting. We provide a series of checks. First, Figure A.3 in the Appendix shows GPA density at every level, considering in turn the three different honors thresholds. Visual inspection of the confidence bounds suggests the absence of discontinuity at the cutoffs that would occur in case of GPA manipulation. We also implement McCrary tests as refined by Cattaneo et al. (2019), who formally test for discontinuities in the density of the running variable at the cutoff. On each graph, we report the p-values both for the classic test (McCrary, 2008) and for the test with optimal bandwidth. We do not reject the hypothesis of equal density around each cutoff (in particular for the 14-cutoff, we obtain p-values of 0.86 and 0.93

respectively). More qualitatively, we also check that students are similar just around the cutoffs. Table A.3 in the Appendix provide balance tests, which ensure that students on either side of the GPA cutoffs are indeed comparable along standard characteristics available in the data and used as control in the empirical model. We can also check, for all the covariates at once, that there are no jump by some of them that would shift the outcome discontinuously. To do so, we predict the outcome using these control variables only, then run the RDD on the predicted outcomes. Table A.4 reports the estimates of the latter step and confirms that there are no significant change in individual characteristics that would trigger discontinuous jump of the outcomes at the different thresholds.

Jury points. In France, "jury points" refer to additional points awarded by the examination board. They are a form of academic discretion that allows the board to *marginally* adjust results upwards, in order to more accurately reflect a student's overall performance. These points are usually given to account for exceptional circumstances (such as health issues) and/or provide some form of compensation (such as a student's active participation and engagement in the course). In our broader sample, 77 individuals have received jury point (5.7% of the selected sample and 6.4% of the selected sample without retake exams). Their final GPA was just below 14 and was marginally increased by these points so that they were able to obtain High Honors (the adjustment represents +0.12 points on average, and a median adjustment to the final GPA of +0.09). In Table 4, focusing on the employment effects at four months post-graduation, we first reproduce our baseline effect of High Honors (column 1) and compare it with RDD estimates on the sample augmented with these students (column 2). Results barely change. Then, we notice that in the latter case, the RDD becomes fuzzy: some students have a final GPA below the cutoff but eventually receive honors. In that sense, they can be identified as "always-takers". This aligns with the idea of high-achieving students narrowly missing the honors cutoff, possibly due to special circumstances like health issues, and receiving systematic compensation from the jury. Similar situations are reported in Feng and Graetz (2017) for the grading system at the London School of Economics. Yet, in their case, there were two-way potential adjustments (both upward and downward). In contrast, the adjustments at Sorbonne and in France more generally are only one-way (upward), so the "never-taker" scenario (students above the threshold who would not receive honors) does not exist. Given the (one-way) fuzzy design, the estimates discussed above (column 2) are an intention-to-treat (ITT), which requires scaling by 1/(1-6.4%), i.e. a very small increase of 6.8%, to obtain the local average treatment effect (LATE). Estimates in Table 4 (column 3) reflect this marginal adjustment.[14]

Table 4: RDD estimates of the employment probability at 4 months after graduation - 14 cutoff with alternative samples

	Baseline	Including receivers of jury points (ITT)	Including receivers of jury points (LATE)	Jury points + optimal donut-hole
Linear Spline	0.13***	0.12***	0.13***	0.13***
	(0.034)	(0.038)	(0.038)	(0.030)
Quadratic spline	0.16***	0.17***	0.18***	0.18***
	(0.054)	(0.051)	(0.051)	(0.060)
Cubic	0.15***	0.15***	0.16***	0.16***
	(0.046)	(0.044)	(0.044)	(0.045)
Quartic	0.15***	0.15***	0.16***	0.16***
	(0.046)	(0.046)	(0.046)	(0.044)
Local polynomial	0.14***	0.14***	0.15***	0.14***
	(0.033)	(0.028)	(0.028)	(0.039)
Obs.	1,285	1,362	1,362	1,276

Notes: This table presents the RD estimates of the honors' impact on the probability to have already found a first job 4 months after graduation. Reported coefficients are based on Equation 1. Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and a sample per column. Column 1 coressponds to the baseline sample, excluding students who received a bonus. Column 2 includes the students who received a bonus. Column 3 excludes the students the students who received a bonus and the ones just below the cutoff who did not receive bonus. These estimations focuses on the 14/20 cutoff with a bandwidth of ± 1. Controls include age, gender, continent of birth and a cohort fixed-effect. Column 2 and 3 include a dummy variable controling for students who received the honors thanks to the bonus. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Another observation is that adding these students makes that local continuity is no longer guaranteed because we move them from below the cutoff to a GPA of 14 exactly, reducing the mass just below the 14-cutoff. Therefore, we perform a `donut RDD' (Barreca et al., 2016) by excluding a small fraction of students just below the cutoff. This donut hole is optimally determined by increasing its size in a stepwise manner until we pass the McCrary test (i.e. until we can reject a difference in density on both sides of the donut hole). Results in Table 4 (column 4) show again very little difference with the baseline.

Placebo checks. We implement a placebo test using GPA thresholds not associated with the assignment of academic honors in France. We choose placebo cutoffs close to the main actual cutoff of interest, namely at 13.5 and 14.5. We implement these tests by running RDD estimations for different

[14] Strictly speaking, the LATE assesses the impact of honors on "compliers", namely those who do not get honors if their GPA is below 14 and receive honors with a GPA above 14. They can be interpreted as the bulk of students who, if they had failed to obtain honors, would not be `saved' by the jury point system. They constitute 91.6% of the sample below the 14 GPA mark.

smooth functions using a bandwidth of ±1. Results in Table A.5 shows no statistically significant treatment effects at these placebo thresholds, for the baseline sample or the `complete' sample (i.e. re-introducing students who received jury bonus). This reinforces the idea that our actual effects are not due to random discontinuities. In contrast, we have seen that the treatment effect was significant at the actual GPA cutoff of 14 for High Honors.

Non-respondents and selection. A frequent issue with any type of survey is the representativeness of those who actually participate to it. In the present case, 49.2% of the alumni of the 2015-2018 cohorts have responded to the survey. The issue of potential selection of those in the survey is rarely treated due to the lack of information about the non-respondents. Interestingly, we avail of the administrative information for the complete cohorts. In particular, we can check potential GPA differences between respondents and non-respondents. Figure A.4 shows the GPA distributions for the two groups. They actually look very similar. Yet, the mean GPA of respondents (14.0) is slightly larger than for non-respondents (13.5), and significantly so (the p-value of the difference test is close to 0). Beyond the question of the overall representativeness of the respondents, a more critical aspect for a valid causal analysis is whether non-respondents are distinctive in unobservable factors that correlate with the receipt of honors. Precisely, we need to check that there is no discontinuity in the response rate around the honors cutoffs. In Figure A.5, we show the rate of survey respondents by GPA levels in our grand sample, using a piecewise linear representation of the trends in each interval between honors cutoffs. We observe a positive correlation between academic success and response rates (better students may be more proud and willing to take the survey) but, most importantly, this relationship evolves smoothly across the honors thresholds.

4.3 Additional results

From the various specifications (smooth function, bandwidths) and alternative samples used above, we reach a confidence interval of the employment effect of High Honors at four months post-graduation between 0.12 and 0.18, which corresponds to 22%-33% the average first employment rate at four months. We now suggest alternative outcomes and heterogeneous analyses.

Employment, wages and contract type. We provide estimates of additional outcomes in Table 5. We start with an alternative way to measure the employment effect, namely running RDD estimations on the time it takes to find the first job (column 1). We still focus on the 14 cutoff for High Honors. The local polynomial regression yields a very significant effect of around 1.5 month reduction in time to first job. With an average (median) time of 6.2 (4.0) months, this represents a 24% (37.5%) decrease, highlighting the faster matching process enabled by High Honors. Across parametric specifications of the smooth function of GPAs, estimates range from 1.25 to 1.63 months, i.e. a 20%-26% decrease relative to the mean time to first job. This is broadly in line with the previous outcomes on hiring speed.

We then consider wages. Unfortunately, we do not have short-term information. Yet, in the short-run, it seems more important to know if someone has earnings or not (our primary outcome), while in the longer-run, when everyone is employed, the relevant question becomes whether academic achievements alter earnings levels. Interestingly, we do have information on wages at one and two years after graduation. We report estimates of the RDD on log wages in Table 5 (columns 2 and 3). It shows no effect.[15] This suggests that while High Honors facilitate quicker job placement, they do not appear to influence wage levels. It is reasonable to assume that productivity depends on a variety of other factors and quickly become apparent after entering the labor market (Lange and Topel 2006, Lange 2007), so that potential wages effects of honors eventually disappears (Khoo and Ost 2018).[16] More generally, returns to degrees, honors or similar credentials reveal information frictions in the labor market, and these returns certainly decrease with experience and the speed of employer learning (Graetz 2021, Ablay and Lange, 2023).

Finally, we examine whether former students of Sorbonne hold a permanent contract one or two years after graduation (columns 4 and 5 of Table 5). We find a positive and statistically significant effect on the likelihood of securing an open-ended contract after one year. The local polynomial regression yields an estimate of 0.13, which corresponds to a relative increase of 18.3% in the changes of holding a secured position. Parametric estimations range from 0.13 to 0.16, i.e. a relative 18.3%-22.5% effect. This effect persists after two years with an average effect of 9 ppt (11.3%). That graduates with High Honors are more likely to secure a permanent employment contract within the first year after

[15] Results are very similar when log wage estimations control for Heckman-type of correction for selection into labor market participation.

[16] Nonetheless, past studies find a short-term effect on earnings for honors in bachelor degrees (e.g. Khoo and Ost 2018). Several factors might at play to explain why a potential honors effect on earnings would live less than a year in France or would not exist or be detectable. First, Master's graduates might be more likely to have gained professional experience, done internships, experienced international mobility, etc., in other words, cumulated other skills that have become equally important as academic achievement for earnings profiles (Baert and Verhaest 2021; Humburg and van der Velden 2015; De Benedetto et al. 2023). Second, having a Master's, compared to a Bachelor, is already a signal for employers – especially if from a reputed university (Bordon and Braga 2020) – so that earnings variation among Master's students through honors may count at a more marginal level. Third, the French wage distribution is quite compressed, which limit the detectable variation between employees at an early career stage (Verdugo, 2014).

graduation may be a direct consequence of obtaining a first job more quickly. Another interpretation would be a long-term benefit of honors but this is more unlikely. We rather see it as faster hiring, combined with being a good candidate, enabling honors graduates to get permanent contracts more quickly, i.e. a mechanically faster progression in the career.

Table 5: RDD estimates of other labor market outcomes (14 cutoff)

	Time to find a job	Wages		Permanent contract	
		+1 year	+2 years	+1 year	+2 years
Linear Spline	-1.63**	-0.0033	0.013	0.13***	0.089***
	(0.68)	(0.049)	(0.044)	(0.044)	(0.031)
Quadratic spline	-1.25*	-0.034	-0.064	0.16*	0.086
	(0.72)	(0.073)	(0.052)	(0.084)	(0.066)
Cubic	-1.42**	-0.023	-0.035	0.16**	0.096**
	(0.68)	(0.060)	(0.050)	(0.071)	(0.042)
Quartic	-1.43*	-0.023	-0.034	0.16**	0.098**
	(0.70)	(0.059)	(0.050)	(0.070)	(0.041)
Local polynomial	-1.48***	-0.013	-0.016	0.13***	0.088**
	(0.54)	(0.042)	(0.035)	(0.050)	(0.038)
Obs.	1,149	624	880	730	1,006

Notes: This table presents the RD estimates of the honors' impact on different labor market outcomes. Reported coefficients are based on Equation 1. Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and a different outcome per column. These estimations focuses on the 14/20 cutoff with a bandwith of ±1. Controls include age, gender, continent of birth and a cohort fixed-effect. Columns (2) and (3) include controls for permanent contracts for the corresponding years. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1

Heterogeneity. The employment impact of a High Honors degree is likely to be heterogeneous across subgroups of our sample. We simply run RDD estimations while interacting the treatment variable with the different factors of heterogeneity (gender, discipline, Master's type). Table 6 displays the results. Honors similarly boost the likelihood of men and women finding their first job 4 months after graduation – this balanced result is in line with some of the past studies but existing evidence is mixed.[17] In contrast, the advantages of honors are not uniformly distributed across the different fields of study. Students in Law, and to a less extent in Economics, seem to benefit most from the High Honors distinction, which is a relatively stable result across the different specifications. These sectors of activities are likely to be those where academic skills matter most so that academic signaling might be most effective, as also reported in previous studies.[18] Finally, our employment effect is driven by

[17] Previous studies do not agree on the heterogeneous effect of honors between genders. While Baert and Verhaest (2021) document a stronger impact on women's job interview rates, Feng and Graetz (2017) find a larger wage premium for men. Pinto and Ramalheira (2017) find similar employability effects for both genders.

[18] Freier et al. (2015) find labor market advantages for law students (relative to medical students) in obtaining honors. Studies from the UK point to stronger returns to A-level in social sciences, law and accounting (Blundell et al., 2000, Walker and Zhu,

professional Master's degrees, most certainly because it represents the bulk of our sample.

Table 6: RDD estimates of the employment probability 4 months after graduation Heterogeneity at the 14 cutoff

	Linear Spline	Quadratic spline	Cubic	Quartic
Men	0.11**	0.15***	0.14***	0.14***
	(0.047)	(0.046)	(0.043)	(0.043)
Women	0.13***	0.17**	0.16**	0.16**
	(0.042)	(0.069)	(0.060)	(0.060)
Business	0.077*	0.11	0.097	0.096
	(0.039)	(0.075)	(0.064)	(0.064)
Economics	0.14*	0.18*	0.16*	0.16*
	(0.077)	(0.093)	(0.087)	(0.088)
Law	0.17***	0.20***	0.19***	0.19***
	(0.052)	(0.065)	(0.057)	(0.056)
Political Sciences	0.039	0.072	0.062	0.061
	(0.062)	(0.078)	(0.070)	(0.070)
Professional	0.13***	0.17***	0.16***	0.16***
	(0.037)	(0.050)	(0.043)	(0.043)
Research	0.052	0.099	0.085	0.085
	(0.10)	(0.12)	(0.11)	(0.11)
Obs.	1,285	1,285	1,285	1,285

Notes: This table presents the RD estimates of the honors' impact on the probability to have already found a first job 4 months after graduation. Reported coefficients are based on Equation 1. Each group of rows corresponds to a different estimation. Each coefficient corresponds to a different treatment variable if equal to 1 if the individual received the High Honors and is included in the subgroup of the variable, with a different smooth function of the running variable per column. These estimations focuses on the 14/20 cutoff with a bandwidth of ±1. Controls include age, continent of birth and a cohort fixed-effect, as well as dummy variables controling for the variable studied. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

5. Concluding Discussion

This study measures the impact of academic honors on labor market outcomes for Master's students using data from one of France's largest public universities, *Paris 1 Panthéon-Sorbonne*. Our results suggest the effectiveness of intermediate honors (High Honors) to signal students' ability and accelerate job matching in their case. Precisely, High Honors significantly reduce the time needed to find a first job by around a quarter, particularly within six months post-graduation. After a year, the distinction becomes less significant as a majority of students have already found their first job. We do not find any effect from honors at lower and upper parts of the skill distribution, since they do not allow screening among students (for the lowest honors) or because tests are possibly underpowered (for the highest honors). Our results are robust to a battery of specification checks. Our main result on

2011, Bratti et al., 2008).

hiring speed stems essentially from labor markets where academic knowledge is probably more valued and hence where the signaling of academic achievement matters most, notably the careers associated with law and economics studies. The benefits of honors possibly decrease as time passes and especially as employers reveal their true productivity on the job – consistently, we find no long-term effects of honors on wages.

A possible limitation is the focus on the University *Paris 1 - Panthéon Sorbonne*. It might indeed be perceived as one of the most famous French Universities so the relative effect of honors would be less important than in other French universities.[19] However, this potential limitation in terms of external validity must be put into sharp perspective. Indeed, Sorbonne is one of the few higher-education institution that people tend to know internationally because it is the oldest French University. Nowadays, it is a large institution (50,000 students), which supplies large cohorts of heterogeneous levels to the labor market and not just elite students. In the eye of recruiters, in particular, there are many other renowned institutions, especially given the prevailing role of the '*Grandes Ecoles*' system (Giret et al., 2011) but also with the presence of universities known for their excellence in specific domains (for instance Toulouse for economics, Assas for law, etc.). Future research should include more universities to better understand how signals from diploma levels, institutional prestige, and honors interact. We also lack data on students' professional and international experiences, which could inform further analysis on how academic skills and field knowledge interact. Additionally, the normative discussion on the honors system is still limited. Notably, honors, as coarse measures of academic performance, influence labor market outcomes and can create disparities among nearly identical students divided by the honors threshold. Beyond labor market effects, the implications for student well-being should also be considered in designing grading systems, offering a new perspective on these issues.

References

Ablay, Mahmut and Fabian Lange. 2023. "Approaches to learn about employer learning. *Canadian Journal of Economics/Revue canadienne d'économique*", 56: 343-356.

Baert, Stijn, and Matteo Picchio. 2021. "A Signal of (Train) Ability? Grade Repetition and Hiring Chances." *Journal of Economic Behavior & Organization* 188: 867–78.

Baert, Stijn, and Dieter Verhaest. 2021. "Work Hard or Play Hard? Degree Class, Student Leadership

[19] Main and Ost (2014) note that it is difficult to generalize results based on a single institution. Bordon and Braga 2020 examine the return to prestige.

and Employment Opportunities." *Oxford Bulletin of Economics and Statistics* 83 (4): 1024–47.

Barreca, Alan I., Jason M. Lindo, and Glen R. Waddell. 2016. "Heaping-Induced Bias in Regression-Discontinuity Designs." *Economic Inquiry* 54 (1): 268–93.

Becker, Gary S. 1964. "Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education." SSRN Scholarly Paper. Rochester, NY.

Black, Dan, and Jeffrey Smith. 2004. "How robust is the evidence on the effects of college quality? Evidence from matching." *Journal of Econometrics*, 121, 99–124

Blagg, Kristin, 2018. The Rise of Master's Degrees: Master's Programs Are Increasingly Diverse and Online, Urban Institute

Bleemer, Zachary, and Aashish Mehta. 2022. "Will Studying Economics Make You Rich? A Regression Discontinuity Analysis of the Returns to College Major." *American Economic Journal: Applied Economics*, 14:2, 1-22.

Blundell. R., Dearden, L., Goodman, A. and Reed, H. 2000. "The returns to higher education in Britain: Evidence from a British cohort", *Economic Journal*, 110: F82-F89.

Bordon, Paola, and Breno Braga. 2020. "Employer learning, statistical discrimination and university prestige." *Economics of Education Review*, 77: 101995.

Bratti, Massimiliano, Robin Naylor, and Jeremy Smith. 2008. "Heterogeneities in the Returns to Degrees: Evidence from the British Cohort Study 1970." SSRN Scholarly Paper. Rochester, NY.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 82:6, 2295–2326.

Carnevale, Anthony P., Ban Cheah, and Andrew R. Hanson. 2015. The Economic Value of College Majors. Washington, DC: Georgetown University, McCourt School of Public Policy, Center on Education and the Workforce.

Cattaneo, Matias D., Rocio Titiunik, and Gonzalo Vazquez-Bare. 2019. "Power Calculations for Regression-Discontinuity Designs." *The Stata Journal* 19 (1): 210–45.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma. 2020. "Simple Local Polynomial Density Estimators," *Journal of the American Statistical Association*, 115:531, 1449–55.

Clark, Damon, and Paco Martorell. 2014. "The Signaling Value of a High School Diploma." *Journal of Political Economy* 122 (2): 282–318.

Dale, Stacy Berg, and Alan Krueger. 2002. "Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables". *Quarterly Journal of Economics*, 117(4), 1491–1528.

De Benedetto, Marco Alberto, Maria De Paola, Vincenzo Scoppa, and Janna Smirnova. 2023. "Erasmus Program and Labor Market Outcomes: Evidence from a Fuzzy Regression Discontinuity Design." SSRN Scholarly Paper. Rochester, NY.

Di Stasio, Valentina. 2014. "Education as a Signal of Trainability: Results from a Vignette Study with Italian Employers." *European Sociological Review* 30 (6): 796–809.

Feng, Andy, and Georg Graetz. 2017. "A Question of Degree: The Effects of Degree Class on Labor Market Outcomes." *Economics of Education Review* 61, 140–61.

Freier, Ronny, Mathias Schumann, and Thomas Siedler. 2015. "The Earnings Returns to Graduating with Honors — Evidence from Law Graduates." *Labour Economics*, 34, 39–50.

Giret, JF., Guegnard, C., Michot, C. 2011. "The Vocationalisation of University Programmes in France: its Consequences for Employability and Mobility". In: Schomburg, H., Teichler, U. (eds) Employability and Mobility of Bachelor Graduates in Europe.

Glazer-Raymo, Judith. 2005. "Professionalizing Graduate Education: The Master's Degree in the Marketplace. " San Francisco: Wiley Periodicals.

Graetz, Georg. 2021. "On the interpretation of diploma wage effects estimated by regression discontinuity designs." *Canadian Journal of Economics/Revue canadienne d'economique* 54(1), 228–258

Grubb, W. Norton. 1993. "The Varied Economic Returns to Postsecondary Education: New Evidence from the Class of 1972." *Journal of Human Resources* 28 (2): 365–82.

Humburg, Martin, and Rolf van der Velden. 2015. "Skills and the Graduate Recruitment Process: Evidence from Two Discrete Choice Experiments." *Economics of Education Review* 49, 24–41.

Habennalz, Steffen. 2006. "More Detail on the Pattern of Returns to Educational Signals", *Southern Economic Journal*, 73(1), 125-135.

Jepsen, Christopher, Peter Mueser, and Kenneth Troske. 2016. "Labor Market Returns to the GED Using Regression Discontinuity Analysis." *Journal of Political Economy* 124 (3): 621–49.

Jepsen, Christopher, Kenneth Troske, and Paul Coomes. 2014. "The Labor-Market Returns to Community College Degrees, Diplomas, and Certificates." *Journal of Labor Economics* 32 (1): 95–121.

Kane, Thomas J., and Cecilia Elena Rouse. 1995. "Comment on W. Norton Grubb: 'The Varied Economic Returns to Postsecondary Education: New Evidence from the Class of 1972.'" *Journal of Human Resources* 30 (1): 205–21.

Khoo, Pauline, and Ben Ost. 2018. "The Effect of Graduating with Honors on Earnings." *Labour Economics* 55 (December): 149–62.

Lange, Fabian. 2007. "The speed of employer learning." *Journal of Labor Economics*, 25(1): 1–35.

Lange, Fabian, and Robert Topel. 2006. "Chapter 8 The Social Value of Education and Human Capital." In *Handbook of the Economics of Education*, edited by E. Hanushek and F. Welch, 1:459–509. Elsevier.

Lee, David S., and Thomas Lemieux. 2010. "Regression Discontinuity Designs in Economics." *Journal of Economic Literature* 48 (2): 281–355.

Long, Mark, C. 2008. "College quality and early adult outcomes", *Economics of Education Review*, 27/5, 588-602.

Lundin, Martin, Oskar Nordström Skans, and Pär Zetterberg. 2021. "Leadership Experiences, Labor Market Entry, and Early Career Trajectories." *Journal of Human Resources* 56 (2): 480–511.

Main, Joyce B., and Ben Ost. 2014. "The Impact of Letter Grades on Student Effort, Course Selection, and Major Choice: A Regression-Discontinuity Analysis." *Journal of Economic Education* 45 (1): 1–10.

Mazrekaj, Deni, Kristof De Witte, and Sarah Vansteenkiste. 2019. "Labour Market Consequences of a High School Diploma." *Applied Economics* 51 (21): 2313–25.

McCrary, Justin. 2008. "Manipulation of the Running Variable in the Regression Discontinuity Design:

A Density Test," *Journal of Econometrics*, 142:2, 698–714.

Naylor, Robin, Jeremy Smith, and Shqiponja Telhaj. 2016. "Graduate Returns, Degree Class Premia and Higher Education Expansion in the UK." *Oxford Economic Papers* 68 (2): 525–45.

Neyt, Brecht, Dieter Verhaest, and Stijn Baert. 2020. "The Impact of Dual Apprenticeship Programmes on Early Labour Market Outcomes: A Dynamic Approach." *Economics of Education Review* 78: 102022.

Neyt, Brecht, Dieter Verhaest, Lorenzo Navarini, and Stijn Baert. 2022. "The Impact of Internship Experience on Schooling and Labour Market Outcomes." *CESifo Economic Studies* 68 (2): 127–54.

OECD. 2022. *Education at a Glance 2022: OECD Indicators*. Paris: Organisation for Economic Co-operation and Development.

di Pietro, Giorgio. 2010. "The Impact of Degree Class on the First Destinations of Graduates: A Regression Discontinuity Approach." SSRN Scholarly Paper. Rochester, NY.

Pinto, Luisa H., and Diogo C. Ramalheira. 2017. "Perceived Employability of Business Graduates: The Effect of Academic Performance and Extracurricular Activities." *Journal of Vocational Behavior* 99.

Schneider, Jack and Ethan Hutt (2014) Making the Grade: A History of the A-F Marking Scheme. *Journal of Curriculum Studies*, 46, 201-224.

Schneider, Mark, and Jorge Klor de Alva. 2018. "The Master's as the New Bachelor's Degree: In Search of the Labor Market Payoff." Washington, DC: American Enterprise Institute.

Spence, Michael. 1973. "Job Market Signaling." *Quarterly Journal of Economics* 87 (3): 355–74.

Tan, Brandon Joel. 2023. "The Consequences of Letter Grades for Labor Market Outcomes and Student Behavior." *Journal of Labor Economics*.

Thoms, Peg, Rosemary McMasters, Melissa R. Roberts, and Douglas A. Dombkowski. 1999. "Resume Characteristics as Predictors of an Invitation to Interview." *Journal of Business and Psychology* 13 (3): 339–56.

Toft Hansen, Anne, Ulrik Hvidman, and Hans Henrik Sievertsen. 2021. "Grades and Employer Learning." SSRN Scholarly Paper. Rochester, NY.

Tyler, John H., Richard J. Murnane, and John B. Willett. 2000. "Estimating the Labor Market Signaling Value of the GED." *The Quarterly Journal of Economics* 115 (2): 431–68.

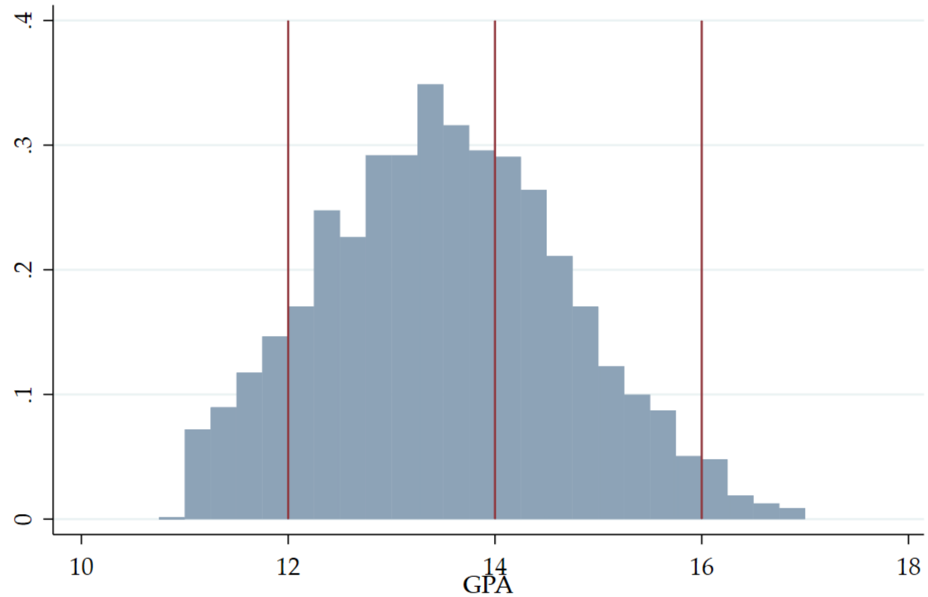
Verdugo G. 2014. "The great compression of the French wage structure, 1969–2008", *Labour Economics*,28,131–144.

Vincens, Jean and Ann Johnston. 1995. "Graduates and the Labour Market in France", *European Journal of Education,* 30, 2, Higher Education and Employment, 133-156

Walker, Ian, and Yu Zhu. 2011. "Differences by Degree: Evidence of the Net Financial Rates of Return to Undergraduate Study for England and Wales." *Economics of Education Review*, Special Issue: Economic Returns to Education, 30 (6): 1177–86.

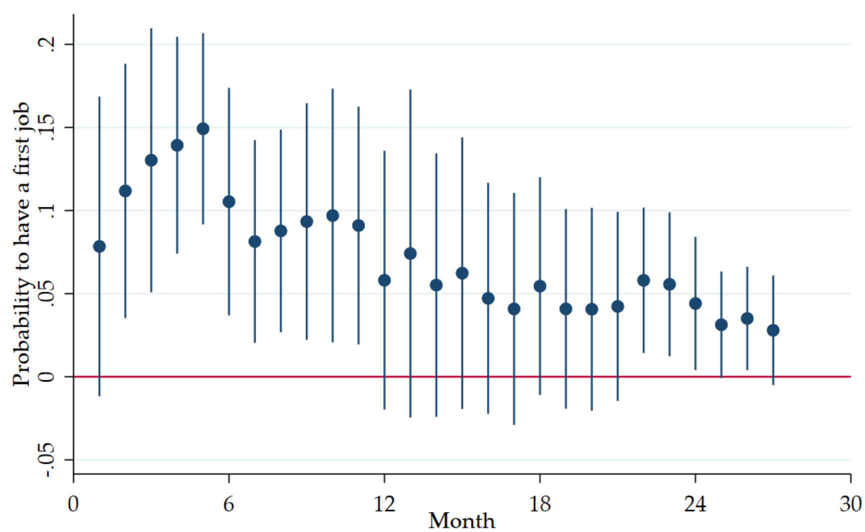
Appendix

Figure A.1: Distribution of GPA



This graph presents the distribution of respondants' GPA. Our sample is composed of 3166 respondants with GPAs between 11/20 and 17/20. Within these students, 311 passed without receiving the honors, 1689 received the Honors 1081 received the High Honors and 85 received the Highest Honors.

Figure A.2: RDD estimates of employment probability at different months post-graduation (14 cutoff)



Notes: This graph summarizes the results of 27 independent RD estimates of the honors' impact on the probability to have already found a first job at a given month after graduating. The dots present the estimated coefficient for each month. The vertical bars show the 95% confidence intervals. These estimations focuse on the 14 cutoff with a bandwidth of ± 1. These estimations use a local polynomial for the smooth function of the running variables. Controls include age, gender continent of birth and a cohort fixed-effect. Estimations clustered by cohort and country of origin group

Figure A.3: Density checks around the different cutoffs

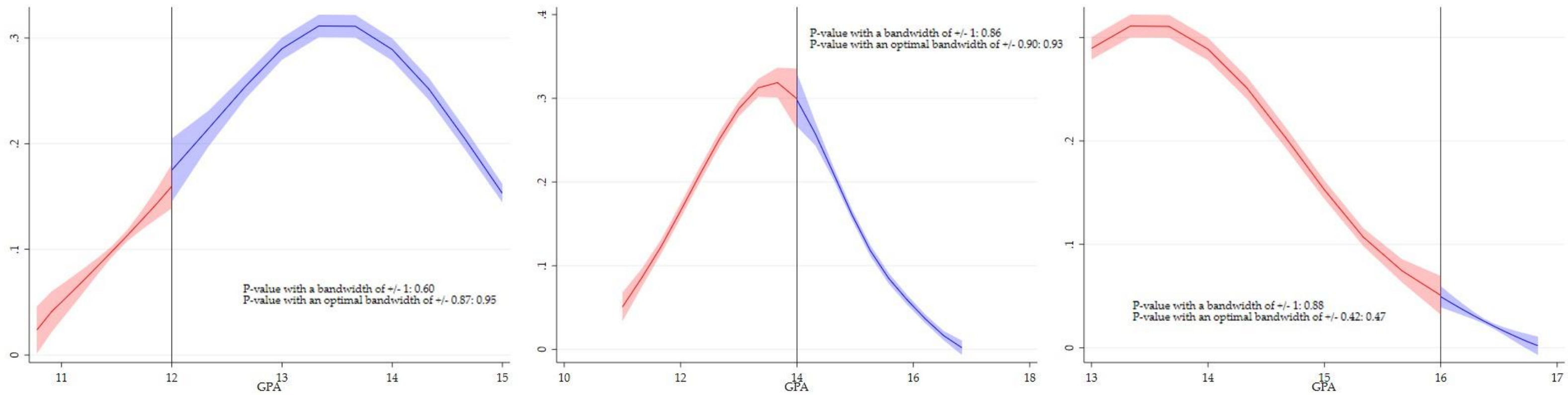


Figure A.4: GPA distribution for respondents versus non-respondents to the survey

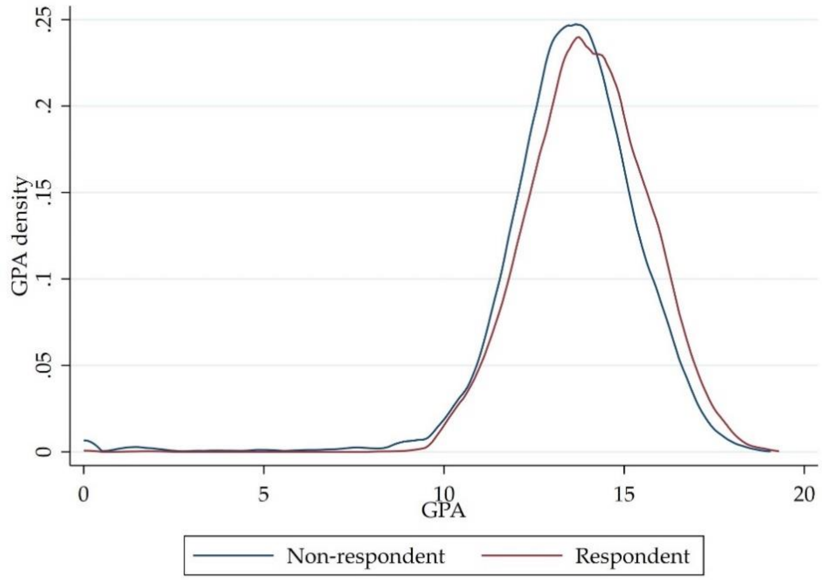
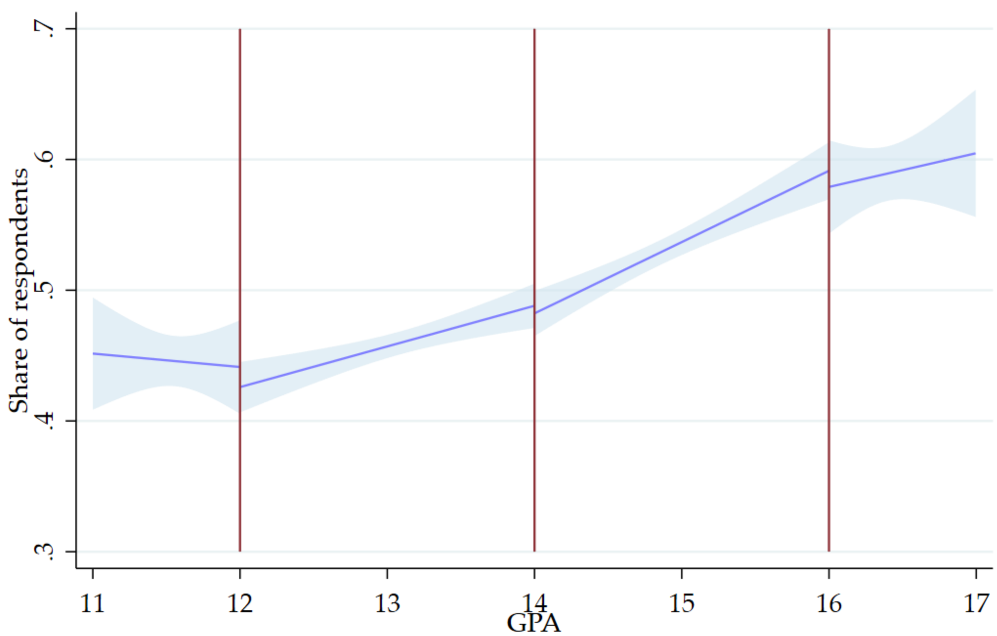


Figure A.5: Checking for potential discontinuity in respondent rate around honors cutoffs



Notes: This illustrates the RD estimates of potential discontinuities around the different cutoffs. The horizontal axis corresponds to the GPA obtained. This graph uses a piecewise linear spline smooth function of the running variables with three different treatments variables corresponding to the three cutoffs. The shaded area represents the 90% confidence interval of the fitted values with the linear estimations.

Table A.1: Descriptive statistics

	Mean statistics (overall and by GPA intervals)					Testing differences		
	Full Sample	11-12	12-14	14-16	16-17	11-12 vs 12-13	13-14 vs 14-15	15-16 vs 16-17
Running Variable								
GPA	13.53	11.54	13.04	14.64	16.25	0.98***	0.93***	0.88***
	(1.18)	(0.28)	(0.54)	(0.52)	(0.25)	(0.02)	(0.01)	(0.02)
Outcomes								
Time to find a job	6.24	6.91	6.62	5.48	5.49	-0.23	-1.34***	-0.66
	(6.64)	(6.59)	(6.82)	(6.26)	(7.01)	(0.28)	(0.37)	(1.01)
Employment 1 year	0.80	0.77	0.79	0.83	0.80	0.00	0.04*	-0.02
	(0.40)	(0.42)	(0.41)	(0.37)	(0.41)	(0.02)	(0.02)	(0.04)
Employment 2 years	0.94	0.93	0.94	0.95	0.88	0.01	0.01	-0.09**
	(0.24)	(0.26)	(0.24)	(0.21)	(0.33)	(0.02)	(0.01)	(0.03)
Wages 1 year	2265	2218	2243	2313	2131	37	13	-382
	(985)	(527)	(605)	(1403)	(685)	(48)	(64)	(249)
Wages 2 years	2501	2436	2502	2523	2429	77	18	-127
	(855)	(789)	(808)	(936)	(887)	(72)	(27)	(123)
Permanent contrat 1 year	0.71	0.73	0.73	0.70	0.54	0.02	0.02	-0.10
	(0.45)	(0.45)	(0.45)	(0.46)	(0.50)	(0.04)	(0.04)	(0.07)
Permanent contrat 2 years	0.81	0.81	0.83	0.79	0.66	0.05*	0.00	-0.05
	(0.39)	(0.40)	(0.37)	(0.41)	(0.48)	(0.03)	(0.02)	(0.06)
Controls								
Age	26.50	26.67	26.44	26.56	26.33	-0.03	0.17	-0.56**
	(3.38)	(2.62)	(3.16)	(3.88)	(3.27)	(0.17)	(0.16)	(0.21)
Women	0.58	0.48	0.56	0.64	0.61	0.06	0.05**	-0.06
	(0.49)	(0.50)	(0.50)	(0.48)	(0.49)	(0.05)	(0.02)	(0.06)
France	0.74	0.62	0.72	0.80	0.73	0.05	0.04	-0.11*
	(0.44)	(0.49)	(0.45)	(0.40)	(0.45)	(0.03)	(0.03)	(0.06)
America	0.04	0.06	0.04	0.03	0.05	-0.01	-0.02	-0.00
	(0.19)	(0.23)	(0.20)	(0.17)	(0.21)	(0.01)	(0.01)	(0.01)
Asia	0.04	0.08	0.05	0.03	0.02	-0.03	-0.02	0.00
	(0.20)	(0.27)	(0.21)	(0.16)	(0.15)	(0.03)	(0.01)	(0.01)
Africa	0.10	0.17	0.12	0.06	0.06	-0.01	-0.02	0.04
	(0.30)	(0.37)	(0.33)	(0.24)	(0.24)	(0.02)	(0.02)	(0.03)
Oceania	0.01	0.01	0.01	0.01	0.00	-0.01	-0.00	-0.01
	(0.09)	(0.11)	(0.09)	(0.10)	(0.00)	(0.01)	(0.00)	(0.01)
Professional master	0.90	0.82	0.91	0.93	0.89	0.08***	0.02	-0.02
	(0.29)	(0.38)	(0.29)	(0.26)	(0.31)	(0.02)	(0.01)	(0.04)
Obs.	3,166	311	1,689	1,081	85	1,069	1,733	364

Notes: This table presents the variables' mean and standard deviation in parentheses in Columns 1 to 5 for different samples. Column 1 corresponds to the full sample and Column 2 to 5 correspond to subsample averages depending on GPA ranges. Column 6 to 8 present the estimated differences in means of subsamples around the cutoffs. Standard errors in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table A.2: RDD estimates of the employment probability at various months after graduation (14 cutoff)

	4 months	6 months	8 months	10 months	12 months
Linear Spline	0.13***	0.090**	0.083**	0.12***	0.078**
	(0.034)	(0.040)	(0.039)	(0.040)	(0.038)
Quadratic spline	0.16***	0.12*	0.089	0.058	0.019
	(0.054)	(0.066)	(0.052)	(0.085)	(0.084)
Cubic	0.15***	0.12**	0.089**	0.069	0.041
	(0.046)	(0.051)	(0.041)	(0.063)	(0.071)
Quartic	0.15***	0.12**	0.089**	0.069	0.043
	(0.046)	(0.050)	(0.041)	(0.063)	(0.072)
Local polynomial	0.14***	0.11***	0.088***	0.097**	0.058
	(0.033)	(0.035)	(0.031)	(0.039)	(0.040)
Obs.	1,285	1,285	1,285	1,285	1,285

Notes: This table presents the RD estimates of the honors' impact on the probability to have already found a first job at various months after graduation. Reported coefficients are based on Equation 1. Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and a different outcome per column. These estimations focuses on the 14/20 cutoff with a bandwidth of ± 1. Controls include age, gender, continent of birth and a cohort fixed-effect. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1

Table A.3: RDD estimates of control variables around the different cutoffs

	Centered	Around 12	Around 14	Around 16
Age	0.093	0.40	0.094	-0.76
	(0.37)	(0.53)	(0.54)	(0.95)
Woman	0.0027	-0.12	0.019	0.061
	(0.061)	(0.099)	(0.084)	(0.22)
France	0.0089	0.018	-0.019	-0.010
	(0.054)	(0.11)	(0.067)	(0.16)
America	0.024	0.045	0.011	0.065
	(0.018)	(0.042)	(0.017)	(0.072)
Asia	-0.041	-0.10*	-0.014	0.018
	(0.029)	(0.059)	(0.034)	(0.028)
Africa	-0.044	-0.0099	-0.045	-0.050
	(0.037)	(0.077)	(0.044)	(0.060)
Oceania	0.0047	0.016	0.0054	-0.058
	(0.011)	(0.025)	(0.011)	(0.055)
Professional master	0.014	0.072	-0.013	-0.090
	(0.041)	(0.079)	(0.046)	(0.13)
# obs. left	1491	309	917	265
# obs. right	1526	730	726	70

Notes: For a balance test of each control variable, this table presents the RDD estimates of potential discontinuities in control variables around the different honors thresholds. Reported coefficients are based on the baseline model (equation 1) with a local polynomial smooth function of the running variable. Each coefficient corresponds to a single estimation, with one outcome per row and a different cutoff per column. These estimations use a bandwidth of ± 1. Standard errors in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table A.4: RDD estimates of predicted outcomes around different cutoffs

Alternative outcomes		Centered	Around 12	Around 14	Around 16
Time to find a first job		-0.0023	-0.29	0.14	-0.18
		(0.11)	(0.29)	(0.12)	(0.23)
First job after	4 months	-0.0023	0.024	-0.013	-0.021
		(0.0093)	(0.018)	(0.011)	(0.031)
	6 months	0.0020	0.027	-0.0077	0.0026
		(0.0074)	(0.018)	(0.0083)	(0.016)
	8 months	0.00062	0.021	-0.0083	0.0059
		(0.0066)	(0.016)	(0.0075)	(0.016)
	10 months	-0.00091	0.019	-0.0093	0.021
		(0.0064)	(0.015)	(0.0079)	(0.013)
	12 months	0.00017	0.018	-0.0086	0.018
		(0.0058)	(0.013)	(0.0070)	(0.018)
Wages after 1 year		0.00013	0.0053	-0.0045	0.014
		(0.0076)	(0.011)	(0.011)	(0.045)
2 years		0.0032	0.017	0.0023	-0.026
		(0.0074)	(0.013)	(0.010)	(0.036)
Permanent contract after 1 year		-0.011	-0.0066	-0.017	0.033
		(0.012)	(0.033)	(0.015)	(0.040)
2 years		-0.0050	0.012	-0.0078	0.011
		(0.0062)	(0.018)	(0.0066)	(0.020)
# obs. left		1491	309	917	265
# obs. right		1526	730	726	70

Notes: For a grouped balance test of all control variable, this table presents the RDD estimates of the potential discontinuities in predicted outcomes around the different honors thresholds. For each outcome, we first predict its values based on the controls used in our estimations. We then run RDD estimations (based on equation 1), using a local polynomial smooth function of the running variable and a bandwidth of ± 1. Each coefficient corresponds to a singe estimation, with one predicted outcome per row and a different cutoff per column. It should indicate if the set of controls generates itself some discontinuity at thre thresholds. Standard errors in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table A.5: RDD estimates of the employment probability at 4 months after graduation around placebo cutoffs

	Baseline sample		Complete sample	
Placebo thresholds:	13.5	14.5	13.5	14.5
Linear Spline	0.017	-0.045	0.0049	-0.027
	(0.037)	(0.050)	(0.039)	(0.052)
Quadratic spline	0.044	-0.038	0.047	-0.040
	(0.056)	(0.072)	(0.056)	(0.071)
Cubic	0.025	-0.062	0.025	-0.065
	(0.050)	(0.064)	(0.050)	(0.064)
Quartic	0.023	-0.061	0.024	-0.063
	(0.050)	(0.065)	(0.050)	(0.065)
Local Polynomial	0.027	-0.050	0.021	-0.040
	(0.039)	(0.042)	(0.041)	(0.043)
Obs.	1,397	1,020	1,472	1,094

Notes: This table presents the RD estimates of the honors' impact on the probability to have already found a first job 4 months after graduation with placebo cutoffs. Reported coefficients are based on Equation 1. Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and different cuotffs and sample per column with a bandwidth of ± 1. Columns (1) and (2) are excluding the respondents who received a jury bonus or went tot second session, while columns (3) and (4) are estimated including the full sample. Controls include age, gender, continent of birth and a cohort fixed-effect. Estimations clustered by cohort and continent of birth. Standard errors in parentheses. Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1