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

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Abstract

As tertiary education expands, employers increasingly rely on academic distinctions to screen among similarly qualified graduates. We study the labor-market effects of honors using administrative and survey data on Sorbonne master's graduates. We exploit France's fixed GPA thresholds for honors assignment to implement a fuzzy regression discontinuity design. Returns are concentrated at the intermediate distinction ("High Honors"), indicating that credentials are most informative when they separate above- from below-average students. We find that High Honors accelerate school-to-work transitions, increasing the monthly job-finding rate by about 40%. Honors also generate an initial wage premium, which fades within two years, and lead to persistent improvements in job quality, including greater access to master's-level positions and faster transitions to permanent contracts. These results highlight the role of academic distinctions as short-run signals that shape early career allocation rather than long-term earnings.

JEL classification

J23, J24, J31, I23, I28

Keywords

signaling, honors, regression discontinuity design, fuzzy RDD

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1. Introduction

As tertiary education expands, employers must increasingly screen among graduates holding similar degrees. Academic distinctions such as honors or degree classifications may therefore serve as simple, easily interpretable signals of performance among otherwise comparable graduates (NACE, 2020). By relying on standardized GPA thresholds, these distinctions allow employers to differentiate candidates without interpreting detailed transcripts or grading scales. Yet thresholds need not be equally informative: their signaling value depends on how they partition the ability distribution. Identifying which thresholds convey meaningful information, and quantifying their labor-market effects, is therefore central to understanding how academic signals shape early career outcomes.[1]

To address this question, we combine administrative GPA records of master's graduates from *Université Paris 1 Panthéon-Sorbonne* with an original alumni survey tracking employment outcomes. The French honors system assigns distinctions at three fixed GPA thresholds: 12 ("Honors"), 14 ("High Honors"), and 16 ("Highest Honors") on a 0-20 scale. These thresholds have been stable for over fifty years, are widely used, and are comparable to Latin honors in the US, providing a clean setting for a regression discontinuity design (RDD). Because a small fraction of students just below each cutoff receive honors through discretionary grade adjustments, we implement a fuzzy RDD, instrumenting honors receipt with an indicator for crossing the pre-bonus GPA threshold.

Our results show that academic honors significantly improve early labor-market outcomes for master's graduates. A key finding is that the signaling value of academic distinctions depends on where thresholds lie in the ability distribution. Thresholds that are too common and too low to meaningfully differentiate among applicants (Honors), or too rare (Highest Honors), fail to provide useful information. By contrast, distinctions are most informative when they separate candidates around the average GPA (High Honors), where the pool of applicants is largest and employers likely face the greatest uncertainty.

We then show that crossing the High Honors threshold increases the monthly job-finding rate by about 40%, reducing time to first employment by roughly two months. The effect is particularly strong in the initial months after graduation—consistent with résumé experiments showing that

[1] The broader signaling literature has also examined other forms of differentiation among graduates holding similar qualifications. These include non-academic signals at the individual level, such as work experience (Neyt et al., 2020, 2022; Baert and Verhaest, 2021; Humburg and Van der Velden, 2015), leadership roles (Lundin et al., 2021), or international mobility experience (De Benedetto et al., 2023). Another strand of the literature focuses on signals related to educational institutions or programs, such as college quality (Black and Smith, 2004; Dale and Krueger, 2002; Long, 2008; Atay et al., 2024).

graduates with honors receive more job interview invitations (Baert and Verhaest, 2021)—and gradually fades within a year as most graduates eventually find employment. Honors recipients also earn about 8% higher wages in their first year after graduation. This wage premium disappears thereafter, consistent with employer learning models in which academic signals matter primarily at labor-market entry (Ablay and Lange, 2023; Aryal et al., 2022; Lange, 2007; Lange and Topel, 2006).

However, honors generate more persistent improvements in job quality. Graduates just above the threshold remain substantially more likely to hold permanent contracts and master's-level positions two years after graduation. We interpret this as an initial allocation mechanism: by accelerating labor-market entry and improving first job matches, honors place graduates on career tracks that continue to diverge even after the informational advantage of the signal has dissipated (on persistent effect of initial labor-market conditions, see Oreopoulos et al., 2012; Kahn, 2010).

The results are robust across a range of specifications, including alternative bandwidths, functional forms, estimators, and clustering choices. They are also reinforced by placebo cutoffs, while standard validity checks confirm the absence of manipulation in the density of the running variable (pre-bonus GPA) and show no discontinuities in covariates or survey response rates around the thresholds.

Our paper contributes to the literature in three ways. *First*, we provide new evidence on what makes a credential an effective signal. Exploiting three thresholds within the same institutional context, we show that signaling arises only at the intermediate cutoff, where the GPA distribution is dense and High Honors provides a salient signal for employers.[2] The RDD further implies that such coarse signals can generate unequal outcomes among otherwise comparable graduates.

Second, we show that the economic impact of academic signals extends beyond wage premia, the primary focus of the existing literature.[3] The acceleration of school-to-work transitions, which we document at monthly frequency, accounts for a large share of the total income gain associated with honors (25% higher income in the first year after graduation). This suggests that existing estimates of the returns to academic distinctions, which typically focus on wages conditional on employment, likely understate the economic value of these credentials.

[2] In contrast, comparable studies reviewed in **Table A1** tend to estimate returns to crossing a single threshold or pooled thresholds (e.g., Khoo & Ost, 2018). An exception is Feng & Graetz (2017), which considers multiple cutoffs in the British system and to which we provide a detailed comparison below.

[3] **Table A1** shows that earnings is the main outcome in most of the comparable studies based on RDD and focused on honors or letter grades. Studies that also examine employment effects typically do so over very short time horizons (e.g. Tan, 2023); the two-year observation window in our data improves on most existing quasi-experiments. The few studies with long-term employment outcomes examine other types of treatments, such as certifications and recommendations, all at undergraduate level (e.g. Carranza et al., 2022).

Third, we focus on the master's level, where causal evidence on the effects of honors remains scarce despite its growing importance.[4] Master's degrees are described as the "new bachelor" (Blagg, 2018; OECD, 2022) and increasingly constitute the effective entry point for high-skilled occupations.[5] Moreover, the rapid expansion of master's programs raises concerns about credential inflation and overeducation (Hartog, 2000). Our results suggest that academic distinctions can mitigate these risks by facilitating the allocation of graduates to appropriate jobs and reducing occupational downgrading.

The remainder of the paper is organized as follows. Section 2 provides institutional background. Section 3 describes the data and empirical strategy. Section 4 presents the validity checks, main results, and robustness analyses. Section 5 concludes and discusses implications for educational policy and employer behavior.

2. Institutional Background

2.1 Honors

Signaling often operates through systems of Latin honors (*cum laude*, *magna cum laude*, *summa cum laude* or close variants) or degree classifications, i.e., distinctions awarded when GPAs exceed certain thresholds. These distinctions provide a coarse but easily interpretable measure of academic achievement for employers. While interpreting continuous GPAs would require recruiters to assess grading scales and institutional contexts, broadly accepted honors schemes reduce the information and transaction costs of evaluating candidates.

As a result, honors systems are widely used across many education systems, from primary education to the master's level, creating common reference points for academic performance. They exist as Latin honors in the United States, the Netherlands, Indonesia, and Mexico, and as degree-classification systems in the United Kingdom, India, Singapore, and South Africa. In practice, institutions typically award honors to roughly the top quarter to third of students, keeping the signal informative while maintaining a sufficiently large pool of candidates for employers. For instance, many US universities award honors above a GPA of 3.0 out of 4.0 (75%), while in the UK the threshold for a First-class degree ("First") is 70% and the more common Upper second-class threshold ("2:1") is 60%.[6]

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[4] Existing quasi-experiments exploit specific institutional settings, namely a comparison between law and medicine Master's degrees in Germany, where only law awards honors (Freier et al. 2015), and a reform of grading scales in Denmark affecting grade distributions rather than honors distinctions (Hansen et al. 2021).

[5] The share of students completing a master's degree today resembles the share completing a bachelor's degree in the 1960s. In France, the proportion of bachelor graduates continuing to a master's program rose from 39% in 2000 to 54% in 2018 (OECD, 2022), an expansion reflecting the restructuring of European higher education (Bologna Process).

[6] Academic honors, as described here—i.e. distinctions awarded to students based on their academic achievements—

2.2 French System

In France, grades range from 0 to 20, with 10 as the minimum passing mark for an exam and, when averaged across courses, for obtaining a degree. Higher education institutions award academic honors (*mentions*) based on fixed thresholds of the final GPA at 12, 14, and 16. As in the US, these thresholds are absolute and do not depend on percentile rankings. The distinctions correspond to: (i) *mention assez bien* ("Honors"), awarded for a final GPA between 12 and 14; (ii) *mention bien* ("High Honors") for GPAs between 14 and 16; and (iii) *mention très bien* ("Highest Honors"), for GPAs above 16. These distinctions broadly correspond to the Latin honors system used in North America. Transcripts of French students studying in the US commonly translate *cum laude*, *magna cum laude*, and *summa cum laude* as Honors, High Honors, and Highest Honors. This classification system has long been standard in French universities.[7]

3. Data and Empirical Strategy

3.1 Data

Data and Key Variables. We combine administrative records from the Sorbonne on students' GPAs with a survey conducted by ORIVE (the Observatory of Results, Professional Integration and Student Life) two years after graduation. The administrative data contain information on students' major, master's type (research or professional), graduation year, grades, and honors. The employment survey provides information on labor-market outcomes, including monthly employment status as well as earnings and job characteristics (contract type, occupational level) one and two years after graduation. The sample includes 3,876 students who graduated between 2015 and 2018 from master's programs in Business Administration (34%), Law (33%), Economics (21%), and Political Science (11%) at the Sorbonne. These disciplines are similar to those examined in Bratti et al. (2008) and Walker and Zhu (2011), which identify them as sectors where academic signaling is likely to be particularly relevant.

Selection. Since we are interested in the effect of honors assigned around the 12, 14, and 16 thresholds, reasonable bandwidths for the RDD correspond to ±1 point around each cutoff, as justified below. Our baseline specification therefore excludes 7% of the initial sample at the tails, retaining observations between 11 and 17. We also exclude respondents from a minority of

shall not be confused with 'honor tracks', corresponding to elite programs involving specific courses, smaller classes, or other specialized structures (Bui et al., 2014; Card and Giuliano, 2016; Cohodes, 2020; Szlendak and Mansfield, 2024).

[7] In the 1960s, a letter-based honors system similar to the standardized US system at the time (or the Singaporean system today, see Tan 2023) was proposed but ultimately not adopted (Schneider and Hutt 2014). The current honors distinctions were introduced in 1971 for secondary-school diplomas and most university degrees. A few exceptions exist, mainly in some law master's programs, where alternative thresholds of 13, 15, and 16 are used; these cases are excluded from our empirical analysis.

master's programs in Law that apply alternative honors thresholds (11% of the initial sample). This leaves a baseline sample of 3,166 individuals.

Descriptive Statistics. **Table A2** reports descriptive statistics for our sample. Looking first at the overall sample (column 1), students take 6.2 months on average to secure their first job, and 80% are employed one year after graduation. Most alumni were born in France (74%), with the next largest group coming from Africa (10%). The majority of students were enrolled in professional master's programs (90%), while the remaining 10% pursued research master's degrees. The subsequent columns present statistics by relevant GPA intervals (columns 2–5) and tests of mean differences across intervals (columns 6–8). Consistent with our later results, we observe faster job finding just above the 14 cutoff compared with just below. Most observable characteristics appear balanced around this cutoff, as well as around the other thresholds (formal balance tests are discussed in Section 4).

Figure A1 presents the GPA distribution together with the honors thresholds. No visible density discontinuities appear at the cutoffs (formal McCrary tests are reported in Section 4). However, the presence of jury points slightly distorts the distribution around the thresholds, which motivates a specific treatment in our RDD. The figure also shows that GPAs are concentrated between 12 and 15. Specifically, 55% of students obtain a GPA between 12 and 14, suggesting that the basic "Honors" distinction carries limited informational value. At the other extreme, only 2.2% of students obtain a GPA above 16 ("Highest Honors"), making this signal too rare to be widely used by employers. The most relevant group is therefore students with GPAs between 14 and 16, i.e., receiving "High Honors" distinction, who represent 32% of the sample.[8]

3.2 Empirical Strategy

Principle. To estimate the causal impact of honors on labor-market outcomes, we use a regression discontinuity design (RDD) exploiting the assignment of honors based on evenly spaced GPA cutoffs. For observations close to the threshold, treatment assignment can be considered as good as random (Lee and Lemieux 2010), implying that crossing the GPA cutoff affects labor-market outcomes only through the honors received, not through differences in students' underlying ability or academic effort.

[8] A minority of students attend a second examination session to re-sit exams they failed or could not attend during the regular session. This feature of the grading system does not affect our analysis. In practice, these cases mostly reflect re-sit obligations due to compensation rules across subject blocks, rather than strategic attempts by students to raise their GPA in order to obtain honors. Specifically, second sessions concern 276 students near the Honors threshold (90 near the High Honors cutoff), but only 13 (2) of them ultimately obtained the distinction—i.e., reached 12 (14) thanks to the re-sit. Excluding these small groups, or more broadly all students attending a second session, does not affect our results.

However, examination boards may grant small discretionary GPA boosts (jury points) to push some students whose pre-bonus GPA lies just below a cutoff above it. In practice, these boosts are mostly awarded to students very close to the cutoff, creating a small dip in the density just below the threshold and a corresponding increase just above it, as illustrated in **Figure A1**. Because some students below the pre-bonus threshold ultimately receive honors, treatment assignment is not perfectly sharp when using pre-bonus GPA as the running variable. We therefore adopt a fuzzy RDD, estimated using two-stage least squares (2SLS). Although the number of students receiving jury points is small, their concentration near the cutoff could introduce bias if a sharp RDD based on final GPA were used instead (Di Pietro 2017; Feng and Graetz 2017).

Formal Approach. Let S_i denote the running variable (pre-bonus GPA). Define $T_c(S_i) = 1\{S_i \geq c\}$ as an indicator for crossing cutoff $c \in \{12,14,16\}$ based on the original GPA, and $T_c(S_i + b_i) = 1\{S_i + b_i \geq c\}$ as a dummy for whether the student ultimately receives the honor after discretionary jury points b_i. Because some students below the pre-bonus threshold receive honors, we instrument $T_c(S_i + b_i)$ with $T_c(S_i)$ in a 2SLS framework. In the *first stage*, we regress the binary honors indicators $T_c(S_i + b_i)$ on the pre-bonus cutoff dummy $T_c(S_i)$, a flexible function of the running variable $\theta(S_i)$, and covariates X_i:

$$T(S_i + b_i) = \pi_0 + \pi_1\, T(S_i) + \theta(S_i) + \gamma X_i + \delta_{year} + \varepsilon_i \tag{1}$$

where π_1 captures the discontinuity in the probability of receiving honors when the pre-bonus GPA crosses the cutoff.

In the *second stage*, we regress each labor-market outcome Y_i on the fitted values $\hat{T}(S_i + b_i)$ from the first stage, including the same controls:

$$Y_i = \alpha + \beta\, \hat{T}(S_i + b_i) + \vartheta(S_i) + \psi\, X_i + \delta_{year} + \epsilon_i \tag{2}$$

The outcome variable Y_i captures alternative labor-market outcomes for graduate i. First, we analyze school-to-work transitions using three approaches: (i) a linear probability model for a binary indicator equal to one if the individual has found a job after $t = 1,2,\ldots,27$ months following graduation (separate regression for each t); (ii) a specification where Y_i is the number of months needed to obtain the first job after graduation; and (iii) duration-model specifications. We then examine additional outcomes measured one and two years after graduation, namely earnings, an indicator for holding a permanent contract, and an indicator for whether the job matches master's-level qualifications.

Specifications and Interpretation. The pre-bonus GPA is a suitable running variable since it captures students' underlying academic performance. The local continuity assumption requires that $\theta(S_i)$ be a smooth function; that is, labor-market outcomes should not change discontinuously at GPA cutoffs except through the effect of receiving honors. We verified that no institutional rule or hiring policy tied to specific GPA thresholds applies to the careers associated with the disciplines in our sample, namely law, economics, business administration, and political science (Vincens and Johnston 1995). We estimate specifications with alternative parametric forms (quadratic, cubic, linear spline) for $\vartheta(S_i)$ in equation (2) and $\theta(S_i)$ in (1), as well as local approaches with optimal bandwidth selection (Calonico et al. 2014) and nonparametric estimations.

This design isolates variation in honors status generated by crossing the pre-bonus GPA cutoff while holding constant the smooth relationship between GPA and labor-market outcomes. The 2SLS coefficient β therefore identifies the Local Average Treatment Effect (LATE) for compliers, i.e., students who receive honors when their pre-bonus GPA crosses the threshold but would not receive them otherwise. Always-takers correspond to students who obtain honors through jury points even though their pre-bonus GPA lies below the cutoff. Never-takers are absent in our setting because crossing a given threshold mechanically grants the corresponding honor. As a result, the monotonicity condition holds: moving from left to right across the pre-bonus cutoff cannot reduce the probability of receiving the treatment.

In all estimations, we pool the different graduation cohorts available in the data to maximize sample size while controlling for business-cycle conditions and cohort effects through a set of year fixed effects δ_{year}. To improve precision, we include a set of individual controls X_i (age, gender, and continent of birth). Clustering at the cohort–nationality level is used in the baseline specification to account for correlated shocks among graduates entering the labor market in the same year and sharing similar migration-background conditions. Alternative clustering schemes are examined in sensitivity checks.[9]

Bandwidths. We focus on the effect of honors assigned at the 12, 14, and 16 thresholds, with RDD bandwidths corresponding to ±1 point around each cutoff, i.e., GPAs between 11 and 13, 13 and 15, and 15 and 17, respectively. The regular spacing of the cutoffs ensures non-overlapping windows (Cattaneo et al., 2019, 2024) and facilitates comparability when considering multiple cutoffs simultaneously. In particular, we can stack observations across cutoffs after normalizing each student's GPA around the nearest threshold. This allows estimation of a single RDD on the stacked sample (with cutoffs centered at zero), summarizing the average effect across thresholds while improving statistical precision. When analyzing each cutoff separately, we will also relax the ±1 bandwidth rule and report sensitivity checks using optimal bandwidth selection.

[9] Unlike some studies that rely on a discrete running variable (e.g., Khoo and Ost 2018) and therefore cluster standard errors at the score level, our GPA variable is reported with three decimals and can be treated as continuous.

4. Results

4.1 Internal Validity

The RDD relies on the assumption that individuals are comparable around the cutoff and that their characteristics vary smoothly with the running variable, so that any observed discontinuity can be attributed to treatment assignment (Cattaneo et al., 2019, 2024). In this section, we verify that no discontinuities are observed around the cutoffs other than in the outcomes of interest.

Manipulation Tests: Density, Covariate Balance and Placebo Outcome. We address the concern that students might "target" the honors cutoff by manipulating their GPA to land just above 14. Although thresholds are widely known, a master's GPA aggregates roughly 15–20 course grades and reflects heterogeneous grading practices and exam difficulty, making ex ante precision at 14.00 implausible. Moreover, the running variable (pre-bonus GPA) is not affected by jury points: they alter only the *final* GPA. Nonetheless, we conduct specific checks regarding the density of the pre-bonus GPA around the cutoffs. **Figure A1** already illustrated the absence of visible discontinuity around thresholds. **Figure A2** focuses on each cutoff separately (12, 14 and 16), reporting confidence bounds and the results of formal density discontinuity tests, namely the McCrary (2008) test and the refinements with optimal bandwidth selection (Cattaneo et al., 2020). We cannot reject equality of densities at any cutoff (at 14, in particular, p-values are 0.86 and 0.93, respectively). We also examine local covariate balance. **Table A3** reports standard balance tests, showing that observable characteristics evolve smoothly at the cutoffs. Finally, **Table A4** presents a placebo RDD on outcomes predicted solely from covariates (X_i, δ_{year}). The estimates reveal no discontinuous jumps at the cutoff, suggesting that any minor covariate imbalances around the threshold do not mechanically generate the observed treatment effect. Overall, these results provide no evidence of manipulation of the running variable and support the local continuity assumption underlying the RDD.

Non-response and Selection. We also examine whether survey nonresponse could bias our analysis. Although 13.2% of alumni from the 2015–2018 cohorts responded to the survey, administrative records are available for the full cohorts, allowing us to compare respondents and nonrespondents. **Figure A3** shows nearly identical distributions of pre-bonus GPA across the two groups, with very similar means (13.37 among respondents versus 13.15 among nonrespondents). More importantly, lack of representativeness would be problematic only if it generated selection precisely at the honors cutoffs. To assess this, **Figure A4** plots response rates by GPA with piecewise linear trends between thresholds. While response rates are positively correlated with GPA—stronger students are somewhat more likely to respond—the relationship remains smooth around the cutoffs. Consistent with this visual evidence, RDD estimates of response rates reported in **Table A5** show no statistically significant discontinuities at 12, 14, or 16, supporting the smooth-selection condition required for our RDD.

Fuzzy Design. Because jury points generate imperfect compliance with the *mention* rule, we estimate a fuzzy RDD using an indicator for crossing the pre-bonus GPA cutoff as instrument for honors receipt. To assess the strength of the first stage, **Figure A5** plots the relationship between the probability of receiving honors and the running variable. Each dot depicts the average probability (share of treated) within bins of the centered pre-bonus GPA. Solid lines represent local polynomial fits on each side of the cutoff. The figure shows that although some students below the threshold receive honors due to jury points, a sharp discontinuity in the probability of receiving honors remains at the cutoff. This provides clear visual evidence of a strong first-stage relationship, consistent with the large Cragg–Donald F-statistic.

4.2 Baseline Results: Honors and Labor Market Outcomes

Employment: Baseline Pooled Estimates. We first visualize the impact of honors on the probability of obtaining the first job after $t = 1, \dots, 27$ months following graduation. For each t, we repeat the fuzzy RDD estimations using the ±1 bandwidth. To begin, we use the pooled specification across cutoffs, which increases statistical power and provides a summary estimate of the average signaling effect across thresholds. We will then examine each cutoff separately, as heterogeneity across thresholds is central to our analysis.

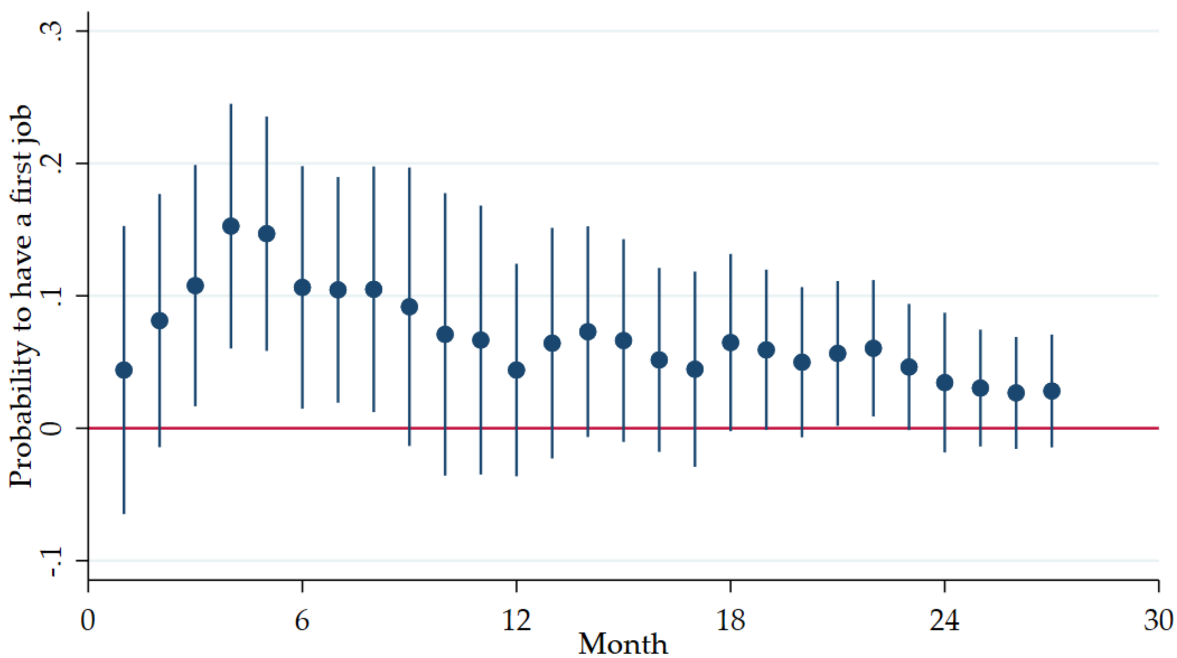
Figure 1 plots the estimated coefficients together with 95% confidence intervals. The estimates indicate a clear positive effect of honors in the first months after graduation. The advantage peaks around months 4–5, when graduates just above the honors threshold are about 15 percentage points more likely to have secured a first job than those just below. The effect then gradually declines and becomes statistically insignificant within 9-10 months after graduation, as employment rates rise and most graduates eventually enter the labor market.

Interpretations. This pattern suggests that academic honors primarily accelerate school-to-work transitions, with the signal playing its largest role at the initial screening stage of recruitment, when employers have limited information about candidates. Examining time to first job is important because even small timing advantages may have meaningful practical consequences. Starting a job one or two months earlier allows graduates to accumulate experience sooner, shorten probation periods, and progress more quickly toward tenure or stable positions, which can translate into higher cumulative earnings and improved career prospects, as shown below.

Before exploring the sensitivity of these results to alternative specifications, we focus on the effect of honors four months after graduation. As before, GPAs are centered on the nearest cutoff and normalized to zero. In the standard RDD graph of **Figure 2**, the dots represent average employment probabilities within GPA bins. A visible discontinuity appears at the threshold: receiving honors increases the probability of employment by a significant margin.

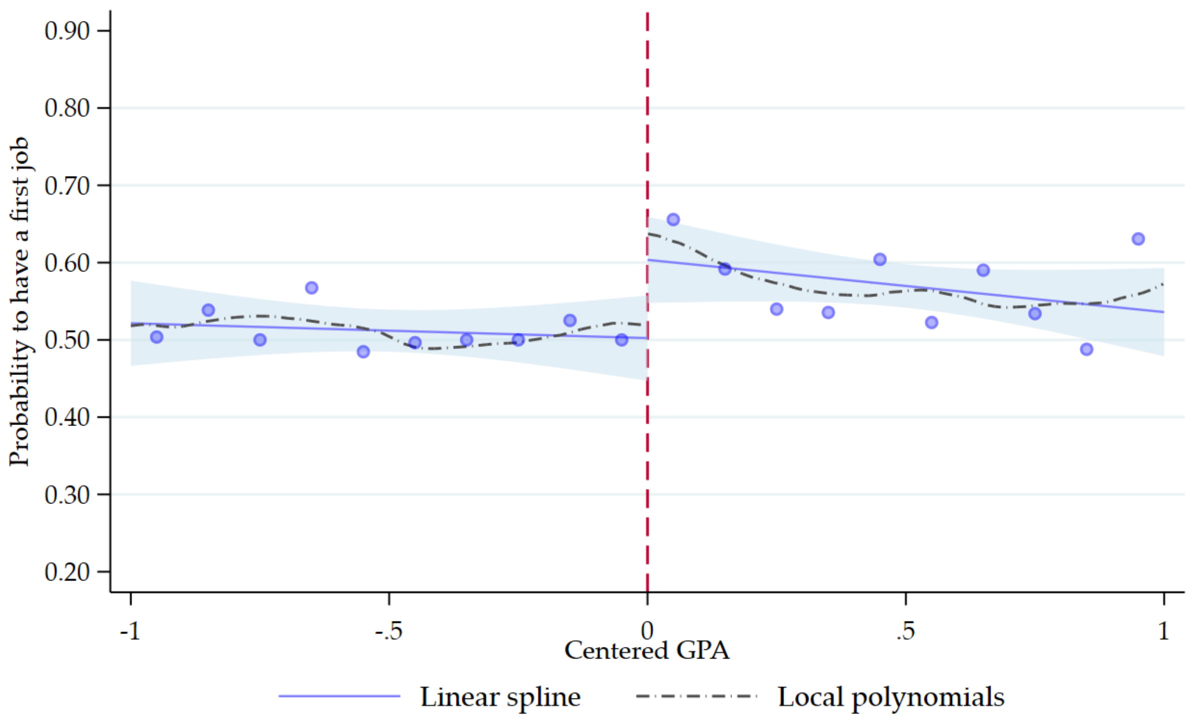
The magnitude of the discontinuity varies somewhat depending on how the relationship around the cutoff is approximated. Using linear trends on both sides of the threshold (solid lines) yields an estimated effect of about 10 percentage points. A local polynomial fit that follows the binned averages more closely (dashed lines) suggests a larger jump, closer to 15 percentage points and consistent with the estimate reported at 4 months in **Figure 1**.

Figure 1: Fuzzy RDD Estimates of the Effect of Honors on Monthly Employment Probability (Pooled Cutoffs)



Notes: This graph summarizes the results of 27 independent fuzzy RDD estimates of the impact of honors on the probability of employment at different months after graduation. 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

Figure 2: Employment Probability Four Months After Graduation Around the Honors Cutoffs (Pooled Cutoffs with Centered GPA)



Notes: The figure plots the probability of having a first job four months after graduation against the centered GPA. GPA is normalized around the closest honors cutoff and centered at zero. Dots represent mean outcomes within GPA bins of width 0.1. The solid line shows a linear spline fit, with the shaded area indicating the 95% confidence interval. The dashed line shows local polynomial estimates using bandwidth 0.1. The vertical line indicates the honors threshold. The sample includes 1613 observations below the cutoff and 1553 above.

Erreur ! Source du renvoi introuvable. reports the estimated treatment effects of receiving honors at the master's level on the probability of securing a first job 4, 6, 8, 10, and 12 months after graduation. We present estimates using different parametric specifications for the smooth function of GPA, alongside local polynomial regressions. Consistent with the graphical evidence above, we find robust effects on employment at the four-month horizon, although the magnitude varies across specifications: 6–7 percentage points with cubic or quartic controls for GPA, 11 points with linear splines, and up to 15 points with local polynomial regression. These effects correspond to a 12–29% increase relative to alumni below the cutoff, whose employment rate after four months is 51%.

All specifications continue to show statistically significant effects at 6 and 8 months, but the magnitude of the effect decreases steadily over time. Estimates become insignificant across all specifications within 10 months, as most alumni have entered employment by that time. Overall, these results consistently indicate that academic honors significantly accelerate early labor market entry, with the largest effects occurring in the first months following graduation.

Table 1: Fuzzy RDD Estimates of the Employment Probability at Different Months after Graduation (Pooled, Centered Cutoffs)

	4 months (1)	6 months (2)	8 months (3)	10 months (4)	12 months (5)
Linear Spline	0.11***	0.071*	0.075**	0.073*	0.045
	(0.030)	(0.036)	(0.032)	(0.038)	(0.031)
Cubic	0.061***	0.040**	0.027**	0.029	0.010
	(0.016)	(0.017)	(0.012)	(0.019)	(0.015)
Quartic	0.071***	0.048***	0.034***	0.033*	0.014
	(0.016)	(0.018)	(0.013)	(0.018)	(0.014)
Local polynomial	0.15***	0.11**	0.10**	0.071	0.044
	(0.047)	(0.047)	(0.047)	(0.054)	(0.041)
Control group mean	0.51	0.62	0.69	0.73	0.79
Obs.	2,519	2,519	2,519	2,519	2,519

Notes: This table presents the fuzzy RDD estimates of the impact of honors on the probability of employment at different months after graduation.Reported coefficients are based on Equations (1) and (2).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. Standard errors, clustered by cohort x continent of birth, are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Estimates at Multiple Cutoffs. We now turn to cutoff-specific estimates: as motivated before, exploiting multiple cutoffs within the same institutional setting allows us to assess how the signaling value of academic distinctions varies across thresholds. Results are reported in **Table 2** for different functional forms and multiple horizons (4, 6, 8, 10, and 12 months after graduation).

We find that the effect of academic honors is concentrated at the 14 cutoff ("High Honors"), while little impact appears at the 12 ("Honors") or 16 ("Highest Honors") thresholds. This pattern likely reflects employer screening practices shaped by the distribution of grades and labor-market equilibrium. The intermediate distinction tends to be relevant because it helps screening within a sufficiently large pool of candidates, possibly sorting above- from below-average applicants.

By contrast, the highest distinction is too rare to function as a practical hiring threshold—only 2.2% of students obtain a GPA above 16—and the corresponding estimates are therefore highly imprecise.[10] At the lower extreme, roughly 90% of graduates score above 12, so this threshold is effectively perceived as a baseline pass standard rather than a meaningful sorting device. This is confirmed by precisely estimated near-zero coefficients at the 12 cutoff.

[10] A similar mechanism operates in the UK, where employers commonly use the Upper second-class threshold rather than the rarer First-class degree as a screening rule (Walker and Zhu 2011).

Table 2: Fuzzy RDD Estimates of the Employment Probability at Different Months after Graduation (Multiple Cutoffs)

	4 months	6 months	8 months	10 months	12 months
	(1)	(2)	(3)	(4)	(5)
Panel A: Around 12					
Linear Spline	0.034	-0.043	-0.0094	-0.032	-0.043
	(0.071)	(0.080)	(0.076)	(0.061)	(0.056)
Cubic	0.12	0.025	0.039	0.0039	0.023
	(0.13)	(0.15)	(0.14)	(0.11)	(0.11)
Quartic	0.12	0.025	0.039	0.0039	0.023
	(0.13)	(0.15)	(0.14)	(0.11)	(0.11)
Local polynomial	0.051	-0.043	-0.0019	-0.032	-0.029
	(0.11)	(0.11)	(0.10)	(0.085)	(0.083)
Control group mean	0.47	0.56	0.64	0.70	0.77
Obs.	887	887	887	887	887
Panel B: Around 14					
Linear Spline	0.20***	0.16***	0.12***	0.14***	0.086**
	(0.046)	(0.046)	(0.040)	(0.046)	(0.040)
Cubic	0.30***	0.26**	0.16*	0.074	0.022
	(0.099)	(0.12)	(0.082)	(0.11)	(0.085)
Quartic	0.30***	0.26**	0.16*	0.074	0.022
	(0.099)	(0.12)	(0.083)	(0.11)	(0.084)
Local polynomial	0.25***	0.21***	0.15**	0.12*	0.062
	(0.059)	(0.066)	(0.057)	(0.066)	(0.049)
Control group mean	0.52	0.63	0.70	0.73	0.80
Obs.	1,359	1,359	1,359	1,359	1,359
Panel C: Around 16					
Linear Spline	-0.043	-0.045	0.19	0.12	0.16
	(0.21)	(0.21)	(0.15)	(0.14)	(0.13)
Cubic	-0.11	-0.098	0.17	0.096	0.14
	(0.22)	(0.22)	(0.17)	(0.16)	(0.14)
Quartic	-0.11	-0.098	0.17	0.096	0.14
	(0.22)	(0.22)	(0.17)	(0.16)	(0.14)
Local polynomial	-0.12	-0.13	0.21	0.11	0.17
	(0.22)	(0.20)	(0.14)	(0.14)	(0.13)
Control group mean	0.56	0.66	0.71	0.78	0.82
Obs.	273	273	273	273	273

Notes: This table presents the fuzzy RD estimates of the impact of honors on the probability of employment at different months after graduation. Reported coefficients are based on Equations (1) and (2). Each coefficient corresponds to a unique estimation, with a different smooth function of the running variable per row and a different outcome per column. Panel A, B and C respectively focus on the 12, 14 and 16/20 cutoffs with a bandwidth of ± 1. Controls include age, gender, continent of birth and a cohort fixed-effect. Standard errors, clustered by cohort x continent of birth, are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

From this point onward, we focus on the 14 cutoff (High Honors), which appears to be the most salient signal for employers. In

Table 2, the estimates reveal large and precisely measured short-run effects across specifications. At the four-month horizon, magnitudes range from 20 to 30 percentage points, corresponding to a 39–58% increase relative to the employment rate below the cutoff. **Figure A6** reports estimates at finer time intervals and confirms stronger short-run effects than in the pooled multi-cutoff analysis of **Figure 1**, while showing a similar timing pattern, with the effect disappearing within a year.

Robustness Checks. We next conduct a series of sensitivity checks to assess the stability of our results around the 14 cutoff. We first re-estimate fuzzy RDD models using *alternative bandwidths*. **Table A6** shows results very similar to the baseline estimates: across bandwidth choices, receiving honors increases the probability of securing a first job by about 20–30 percentage points four months after graduation, with the effect gradually declining thereafter. Wider bandwidths use more observations, yielding more precise estimates, but may introduce bias if observations far from the cutoff violate the local continuity assumption. Consistent with this trade-off, narrowing the bandwidth increases the estimated coefficients but also their standard errors.

We also report results using *MSE-optimal bandwidth* selection (Calonico et al., 2014; Cattaneo et al., 2019, 2020). This procedure selects the bandwidth that balances the bias-variance trade-off. Using optimal bandwidths, the estimated effect is slightly larger than with the ±1 window, reaching about +28 percentage points at four months. Because optimal bandwidths vary across outcomes, comparisons across months rely on slightly different samples and thus differ in precision. Nevertheless, the employment effect remains positive and statistically significant up to eight months, as in the baseline specification. Overall, our conclusions are robust to bandwidth choice.

Next, **Figure A7** reports *placebo cutoff tests* using local polynomial fuzzy RDD estimates within the GPA interval [13,15]. The estimation is repeated at a sequence of artificial thresholds around the true cutoff of 14. Estimates remain close to zero and statistically insignificant at placebo cutoffs, while a large and significant discontinuity appears only at the true threshold, supporting the interpretation that the employment effect identified in the baseline analysis is driven by honors assignment rather than by a spurious relationship between GPA and employment outcomes.[11]

[11] We also verify that our results are robust to alternative clustering schemes. While our baseline specification clusters standard errors at the cohort x continent-of-origin level to account for correlated shocks among graduates entering the labor market under similar aggregate conditions, clustering at the cohort level or at the cohort x field-of-study level yields similar standard errors.

4.2 Alternative Employment Outcomes and Discussion

We examine alternative outcomes to estimate the effect of High Honors on employment. Rather than the discrete-time employment probability, we can estimate a fuzzy RDD using directly the *number of months needed to obtain the first job after graduation* as the outcome. Results in **Table 3** (column 1) indicate that receiving High Honors reduces job-search duration by 1.7 to 2 months. Compared with the average time of 6.6 months needed to find a first job, these estimates correspond to a 26-31% shorter transition into employment, implying that High Honors accelerate job matching by 35-45%.[12]

Table 3: Fuzzy RDD Estimates of Alternative Employment Outcomes (14 Cutoff)

	Time to find a first job	Accelerated Failure-Time model	Discrete-time hazard model
	(1)	(2)	(3)
Linear Spline	-2.05***	-0.40***	1.47***
	(0.70)	(0.14)	(0.19)
Cubic	-1.70*	-0.40***	1.47***
	(0.91)	(0.15)	(0.21)
Quartic	-1.70*	-0.37**	1.46***
	(0.91)	(0.18)	(0.23)
Local Polynomial	-1.94***	.	.
	(0.73)	.	.
Control group mean	6.57	.	.
Obs.	1,310	1,141	1,141

Notes: This table presents the fuzzy RDD estimates of the honors' impact using different two-stage models (and alternative smooth function of the running variable in rows). In Column (1), we treat the number of months required to obtain the first job after graduation as outcome. In Column (2), we take the log of it, which boils down to an Accelerated Failure-Time model. Column (3) reports estimates of a discrete-time hazard model, reporting the corresponding hazard ratios. These estimations focuses on the 14 cutoff with a bandwith of ±1. On top of the first-stage prediction and the smooth function of GPA, controls include age, gender, continent of birth and a cohort fixed-effect (plus month fixed effects in the last model). Standard errors, clustered by cohort and continent of birth, are reported in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$. Note that the number of observations varies across models due to differences in the estimation process. In particular, the first model includes graduates who obtained their first job the month of their graduation, i.e. at time 0 (218 observations around the 14 cutoff).

We next estimate duration models, which provide a more natural framework for analyzing school-to-work transition because they exploit the timing information in the data. First, we estimate an *accelerated failure time* (AFT) model, where the dependent variable is the logarithm of the number of months required to obtain the first job after graduation, regressed on the same

[12] Decreasing the time required to find a job by 26% on average is equivalent to finding it in 74% of the original time or 1/74% ≈ 1.35 ≈ 35% faster.

right-hand-side variables as in equation (2). The AFT specification accommodates the typically skewed distribution of job-search durations. Second, we estimate a *discrete-time hazard model*, where the dependent variable is a logit of the probability of obtaining the first job in month t conditional on not having found one earlier; it includes month fixed effects to capture the baseline hazard and the same fuzzy RDD controls as in equation (2).

Results from the AFT model in column 2 imply that High Honors reduce job-search duration by about 37–40% across specifications of the smooth function of GPA. We report the hazard ratio of the discrete-time hazard model in column 3; it indicates that High Honors increase the monthly job-finding rate by about 46–47%. Overall, these duration models lead to consistent estimates and confirm that academic honors primarily accelerate the school-to-work transition.

Mechanisms and Comparison with Past Studies. These employment results are consistent with a signaling interpretation. At labor-market entry, graduates typically apply to similar jobs with comparable educational backgrounds. Employers therefore rely on the limited differentiating information available in résumés, and academic honors provide a salient and easily interpretable signal of performance. The fading of the employment effect over time appears largely mechanical, as most graduates eventually enter employment.

As shown in **Table A1**, the quasi-experimental literature offers limited points of comparison regarding faster early-career recruitment, particularly at the master's level. Two studies exploit RDD around degree-class thresholds in the UK (Di Pietro 2017; Feng and Graetz 2017) and report small, often statistically insignificant effects on employment probability when crossing the Upper-Second-class threshold. In contrast, our interpretation aligns with employer-side experiments. They show that recruiters value academic performance signals when screening graduates (Humburg and van der Velden 2015; Pinto and Ramalheira 2017). Résumé experiments provide direct evidence that stronger academic distinctions increase the probability of receiving job interview invitations: Baert and Verhaest (2021) finds that top distinctions at the master's level raise this probability by about 3.6 points (≈14%).

4.3 Earnings and Job Quality

The signaling value of academic performance is most often studied through its effects on wages and the types of jobs obtained. We therefore examine whether High Honors also affect wages and other dimensions of job quality in the French labor market. Information on these outcomes is available one and two years after graduation, and we estimate the fuzzy RDD model separately for each horizon. **Table 4** indicates that crossing the High Honors threshold improves the quality of early job matches in terms of wages, contract stability, and job–education match.

Earnings. We first see that graduates just above the cutoff earn 5–10% higher wages in their first year after graduation (column 1). This effect disappears two years after graduation (column 2). These findings are consistent with the literature documenting wage effects shortly after graduation (e.g., Freier et al., 2015; Hansen et al., 2024) and the rapid decline in this signaling value of academic distinctions, as employers observe young workers and learn about their productivity (Khoo and Ost, 2018; Ablay and Lange, 2023; Graetz, 2021; Lange, 2007; Lange and Topel, 2006).[13]

Table 4: Fuzzy RDD Estimates of Earnings and Job Quality (14 Cutoff)

	Log Earnings		Permanent contract		Master level job
	+1 year	+2 years	+1 year	+2 years	+2 years
	(1)	(2)	(3)	(4)	(5)
Linear Spline	0.050**	0.040	0.19***	0.11***	0.084***
	(0.023)	(0.044)	(0.067)	(0.041)	(0.026)
Cubic	0.097*	-0.016	0.22***	0.14**	0.098**
	(0.054)	(0.081)	(0.078)	(0.067)	(0.044)
Quartic	0.097*	-0.016	0.22***	0.14**	0.098**
	(0.054)	(0.081)	(0.080)	(0.067)	(0.044)
Local polynomial	0.075**	0.020	0.21***	0.13***	0.090**
	(0.036)	(0.051)	(0.064)	(0.047)	(0.039)
Control group mean	7.76	7.88	0.70	0.82	0.93
Obs.	654	620	786	1,133	959

Notes: This table presents the fuzzy RDD estimates of the impact of honors on different labor market outcomes. Reported coefficients are based on Equations (1) and (2). 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 focus on the 14/20 cutoff with a bandwith of ±1. Controls include age, gender, continent of birth and a cohort fixed-effect. Standard errors, clustered by cohort x continent of birth, are presented in parentheses. Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1.

Job Match Quality. High Honors also increases the probability of holding a permanent contract by 19–22 percentage points one year after graduation (column 3), a 27–31% increase relative to a control-group mean of 70%. The effect remains sizeable two years after graduation, at 11–14 percentage points (column 4). We interpret this primarily as a timing mechanism: while workers typically queue for permanent positions through successive temporary contracts, High Honors accelerates job finding and hence leads to earlier transitions into permanent contracts.

We have also discussed the risk of overqualification associated with the rapid expansion of master's programs (see Hartog, 2000, and Giret et al., 2006, for contextual evidence regarding the French labor market). Graduating with High Honors appears to mitigate this risk. Graduates just

[13] Rapid employer learning is also studied theoretically in Altonji and Pierret (2001), Farber and Gibbons (1996) and Habermalz (2006).

above the 14 threshold are 8–10 percentage points more likely (i.e., a 9–11% advantage) to hold a master's-level job two years after graduation (column 5), suggesting that academic signaling reduces the incidence of occupational downgrading.

Robustness Checks. We confirm the stability of these results using alternative bandwidths in **Figure A7**. Our baseline standard errors are slightly smaller than the ones estimated using optimal bandwidths, but conclusions are broadly preserved. The first-year wage effect is slightly larger with optimal bandwidths, namely +12% with local polynomial estimations. Placebo cutoff tests are presented in **Figure A8** using local polynomial fuzzy RDD estimates of the effect of honors on earnings and contract type at a sequence of placebo GPA cutoffs within the interval [13,15]. Estimates fluctuate around zero across most placebo cutoffs, while the estimates at the true threshold of 14 stands out as the largest and most precisely estimated effects. The volatility observed at higher GPAs is driven by sampling noise due to fewer observations. These results tend to support the interpretation that the baseline effects are driven by honors assignment.

Mechanisms and Comparison with Past Studies. Our results are consistent with an employer screening and learning mechanism. At labor-market entry, honors signal higher productivity, generating a wage premium and facilitating access to better initial job offers.[14] As firms observe workers' performance, this informational advantage fades and the wage premium disappears. By contrast, qualitative advantages persist: graduates with honors remain more likely to hold permanent contracts and master-level jobs. This persistence likely reflects differences in initial job allocation, which place graduates on distinct career tracks (master-level vs. downgraded jobs, stable vs. temporary positions), combined with the fact that faster job finding gives them more time to transition into permanent contracts.

Estimated effects at the master's level, both here and in the few studies cited in **Table A1**, appear somewhat larger than those typically found for undergraduate distinctions. Our estimates of 5–12% are comparable to those reported for master's degrees in other settings, such as 14% for German law graduates in Freier et al. (2015) and 8–12% for Danish graduates in Hansen et al. (2024). By contrast, studies focusing on undergraduate honors generally find more moderate wage effects, i.e. about 3% in the US (Khoo and Ost, 2018), 3–5% for Turkish men (Atay et al., 2024), 3–7% in the United Kingdom (Feng and Graetz, 2017), and roughly 1–1.5% for higher letter grades in Singapore (Tan, 2023). Plausible explanations relate to signal strength and selection at the master's level. Master's cohorts are more selected, so within a more compressed ability distribution a distinction may carry stronger informational content about productivity than at the

[14] Another explanation for the wage premium is possible. The faster labor-market entry documented above might generate slightly more early-career experience, mechanically increasing first-year earnings in a Mincerian framework. This interpretation is not fully compatible with the fact that wage premia disappear after one year.

undergraduate level. Master's graduates also typically enter more skill-intensive occupations, where academic performance is more relevant and therefore plays a larger role in employer screening. In contrast, undergraduate honors may matter less when the degree itself is already a weaker signal in the presence of additional credentials.

Finally, we highlight the fact that the wage premium captures only part of the economic gains associated with High Honors in the first year after graduation. Faster school-to-work transitions generate an additional 14–17% increase in income over that year. Combined, these effects imply roughly 19–27% higher income in the first year after graduation.

5. Conclusion

This paper studies the labor-market consequences of academic honors among master's graduates using administrative and survey data from Université Paris 1 Panthéon-Sorbonne. Exploiting fixed GPA thresholds that determine the assignment of honors, we implement a fuzzy regression discontinuity design to identify the causal impact of these distinctions on early-career outcomes.

Our results show that academic honors act as a powerful signal at labor-market entry. Graduates receiving High Honors secure their first job significantly faster, with the monthly job-finding rate increasing by about 40% and time to first employment reduced by roughly two months. Honors recipients also earn about 8% higher wages in their first year after graduation. Although this wage premium disappears after two years, consistent with employer learning models, honors have lasting effects on job quality: graduates just above the threshold are more likely to hold permanent contracts and jobs requiring a master's degree.

The results carry implications for education policy and institutional design. In an environment where tertiary education is expanding and master's degrees increasingly represent the baseline qualification for high-skilled occupations, within-degree distinctions tend to play a role in helping employers screen among otherwise similar candidates. Our findings suggest that well-designed academic distinctions may improve the functioning of the school-to-work transition by facilitating the allocation of graduates to appropriate jobs. At the same time, the results highlight that such signals mainly affect early-career opportunities rather than long-term wage inequality. In labor markets characterized by informational frictions at entry, such distinctions can therefore play a meaningful role in shaping early career trajectories.

Several avenues for future research remain open. *First*, our analysis focuses on a single institution and a limited set of disciplines. Extending the analysis to other universities and fields would help assess the external validity of these findings and determine whether the value of academic signals varies across labor-market contexts. *Second*, longer-term data would allow researchers to examine whether early advantages in job matching translate into differences in career trajectories later in life, including promotions or occupational mobility. *Finally*, further research could explore how employers interpret academic signals *relative* to other information, such as internships and extracurricular activities (e.g. Lundin, 2021), when evaluating early-career candidates. Such research could also assess how these signals interact in hiring decisions, for instance by acting as substitutes or complements in employer screening when recruiters face limited information about applicants' productivity.

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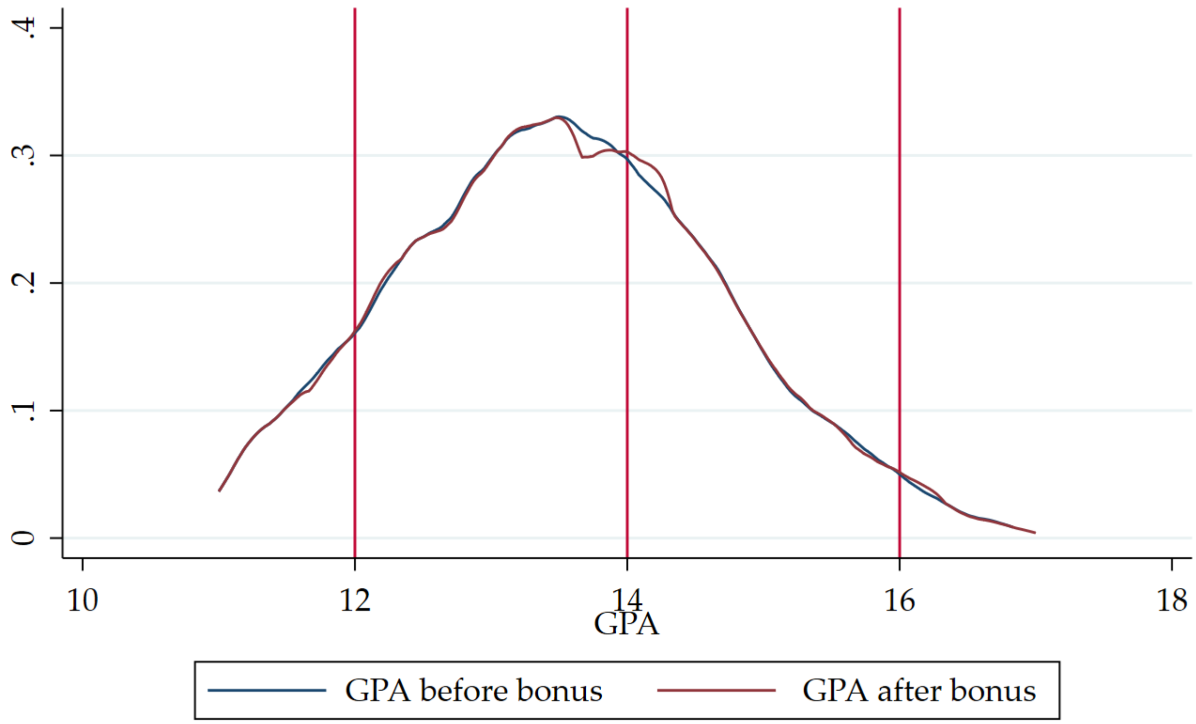
Appendix

Figure A1 : Distribution of GPA



Notes: This graph presents the distribution of respondants' GPA before and after bonus. Our sample is composed of 3166 respondants, with GPAs between 11/20 and 17/20. Within these students, 310 passed without receiving the honors, 1689 received the Honors, 1081 received the High Honors and 85 received the Highest Honors. 142 received bonus points from the jury. This allowed 112 of them to obtain better honors distributed as : 27 for the Honors, 70 for the High Honors and 15 for the Highest Honors.

Figure A2 : Density Checks around the Different Cutoffs (pre-bonus GPA)

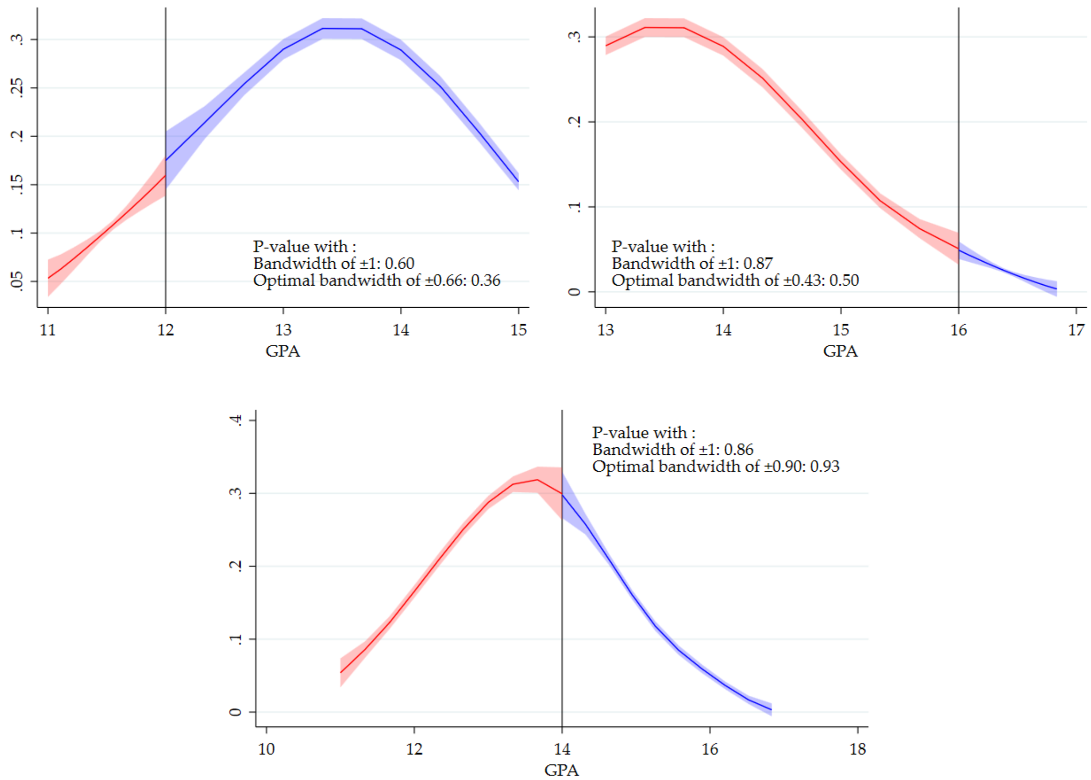


Figure A3: GPA Distribution for Survey Respondents vs. Non-respondents

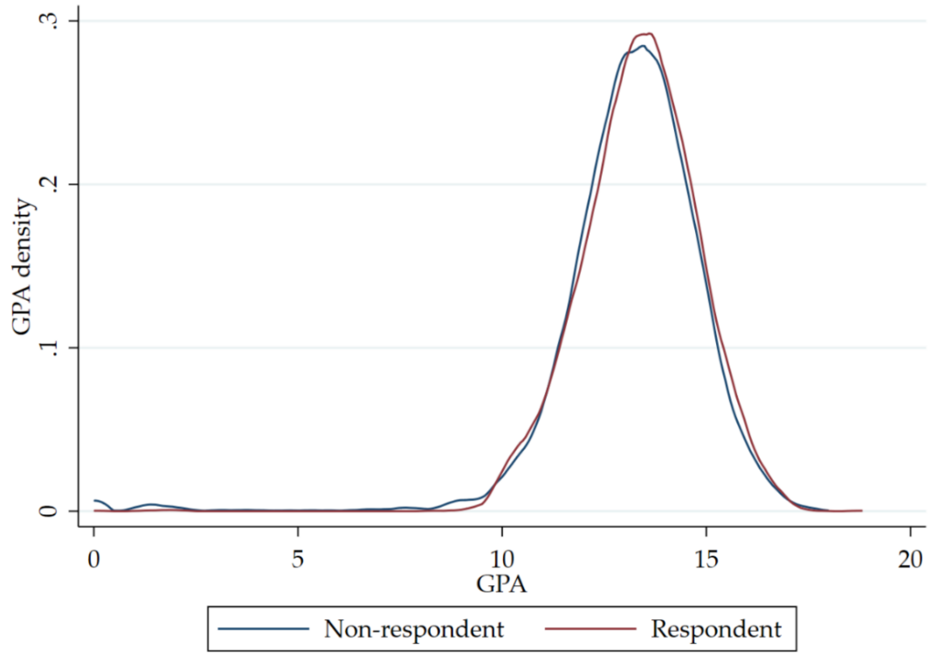
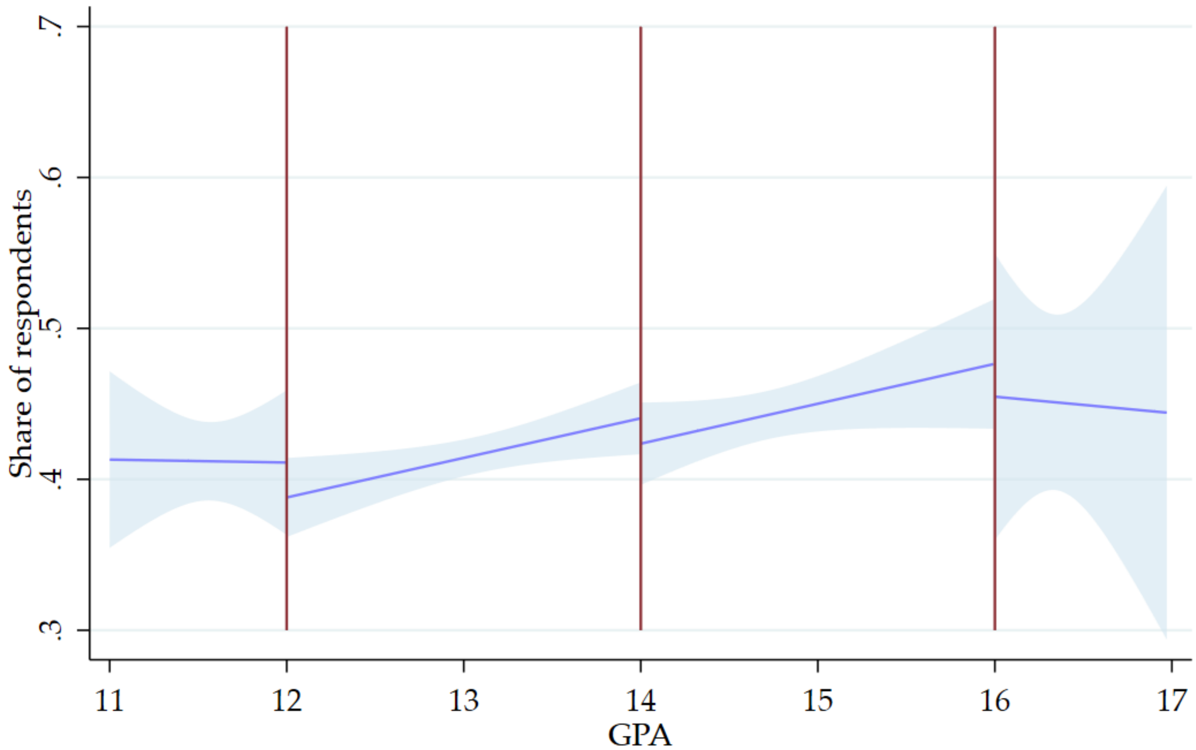
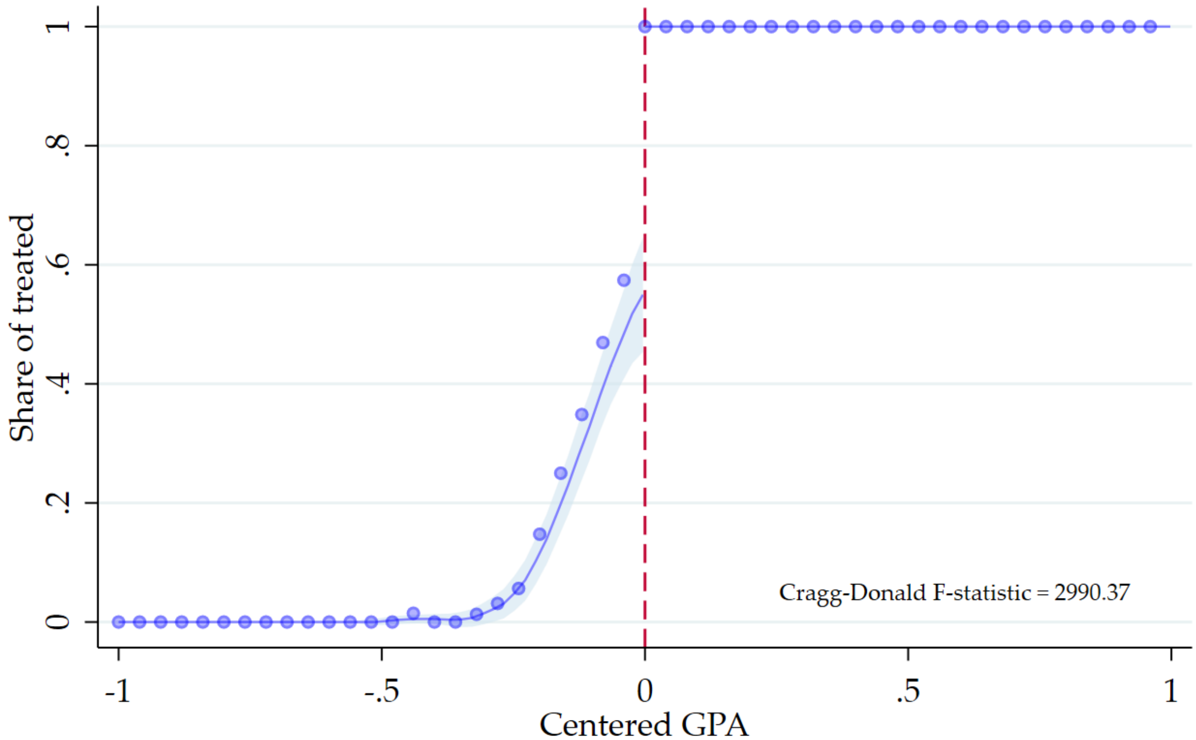


Figure A4: Checking for Potential Discontinuity in Response Rate around Honors Cutoffs



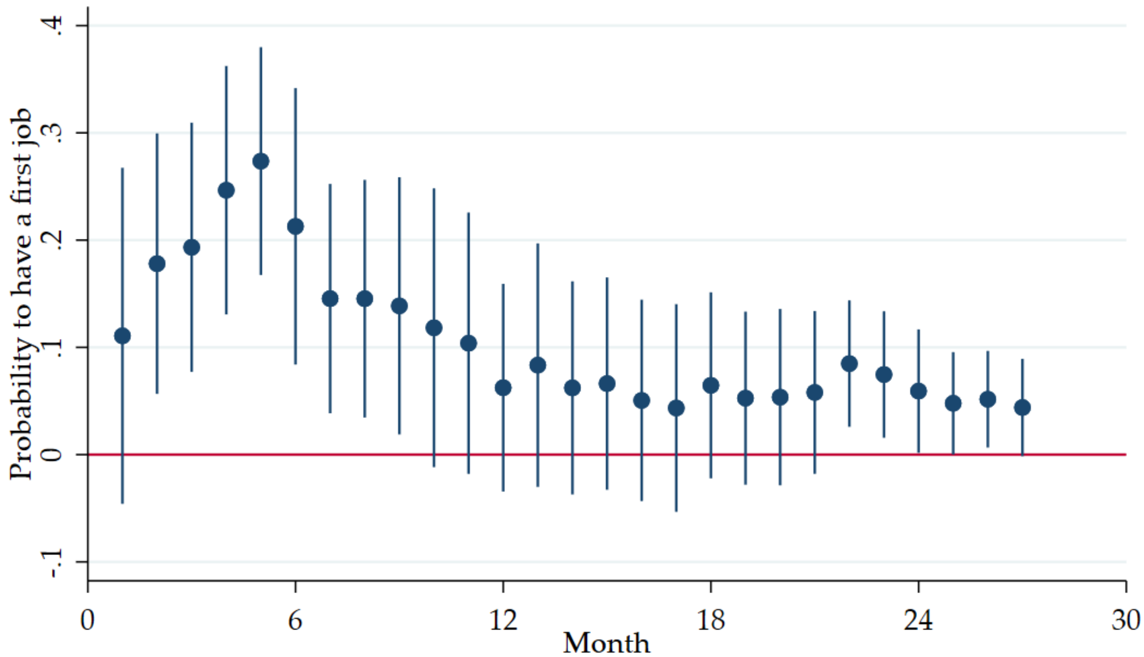
Notes: This figure illustrates the RD estimates of potential discontinuities around the different cutoffs. The horizontal axis corresponds to the GPA obtained. This graph uses a piecewise linear spline smooth function of the running variables with three different treatments variables corresponding to the three cutoffs. The shaded area represents the 95% confidence interval of the fitted values with the linear estimations.

Figure A5: First Stage: Probability of Receiving Honors Around the Cutoffs



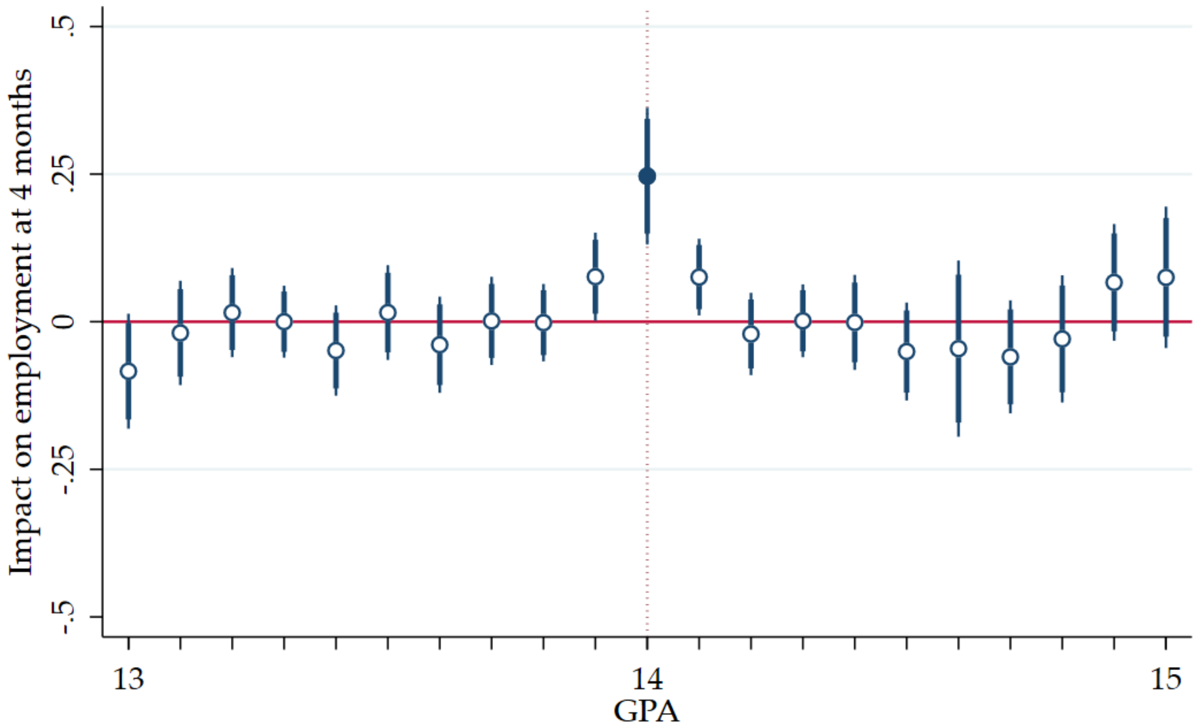
Notes: The figure plots the probability of receiving honors against GPA centered at the nearest honors cutoff. Dots represent mean outcomes within 50 GPA bins of width 0.04. The solid lines show local polynomial fits on each side of the cutoff with 95% confidence intervals. The vertical dashed line marks the honors threshold. The Cragg-Donald F-statistic is estimated with our baseline specification and a linear spline smooth function. The sample includes 1613 observations below the cutoff and 1553 above.

Figure A6: Fuzzy RDD Estimates of the Effect of Honors on Monthly Employment Probability (Local Polynomial Estimations, 14 cutoff)



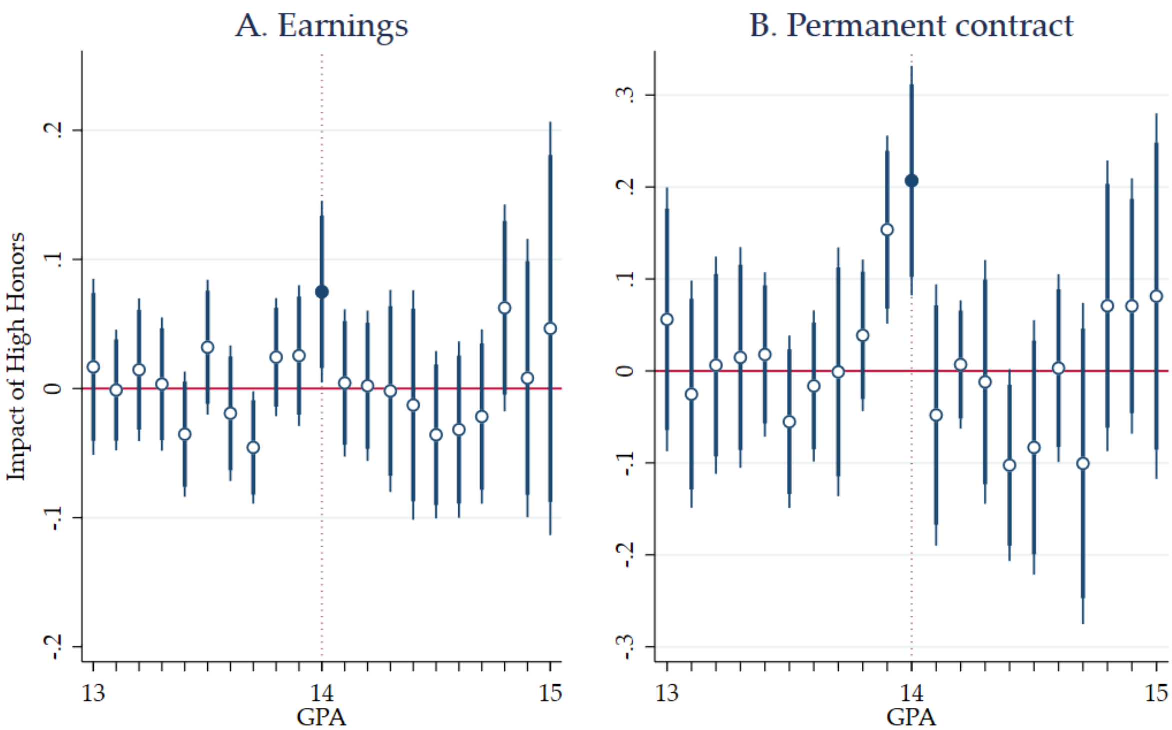
Notes: This graph summarizes the results of 27 independent fuzzy RDD estimates of the impact of honors on the probability of employment at different months after graduation. The dots present the estimated coefficient for each month. The vertical bars show the 95% confidence intervals. These estimations focus 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 A7: Fuzzy RDD Estimates of Employment Probability Four Months after Graduation (Local Polynomial Estim., Actual and Placebo Cutoffs)



The figure reports fuzzy RDD estimates of the effect of honors on employment four months after graduation at a sequence of placebo GPA cutoffs within the interval [13,15]. The dashed vertical line indicates the true cutoff at GPA = 14. Circles show point estimates and vertical bars show 90% and 95% confidence intervals. Estimates are obtained using local polynomial regressions with a bandwidth of ±1. Controls include age, gender, continent of birth, and cohort fixed effects.

Figure A8: Fuzzy RDD Estimates of Labor Market outcomes 1 year after graduation (Local Polynomial Estim., Actual and Placebo Cutoffs)



The figure reports fuzzy RDD estimates of the effect of honors on labor market outcomes one year after graduation at a sequence of placebo GPA cutoffs within the interval [13,15]. The dashed vertical line indicates the true cutoff at GPA = 14. Circles show point estimates and vertical bars show 90% and 95% confidence intervals. Estimates are obtained using loca polynomial regressions with a bandwidth of ±1. Controls include age, gender, continent of birth, and cohort fixed effects.

Table A1: Literature Review

Reference	Academic level	Treatment (academic achievement)	Method	Outcomes	Time horizon	Country	Journal / WP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Randomized and natural experiments							
Astruc-Le Souder, Bargain & Locks	Master's degree	Honors	RDD	Employment and earnings	Monthly + 1&2 years	France	WP
Freier, Schumann & Siedler (2015)	Master's degree	Honors	DiD	Earnings	5 to 6 years	Germany	Lab. Econ.
Hansen, Hvidman & Sievertsen (2024)	Master's degree	Grades (number)	IV	Earnings	5 years	Denmark	J. Labor Econ.
Khoo & Ost (2018)	Undegraduate	Honors	RDD	Earnings	1, 2 and 3 years	US	Lab. Econ.
Atay et al. (2024)	Undegraduate	Honors	RDD	Earnings	First job	Turkey	Oxf. Bulletin Eco Stat
Di Pietro (2017)	Undegraduate	Honors (degree class)	RDD	Employment	6 months	UK	J. Educ. and Work
Feng & Graetz (2017)	Undegraduate	Honors (degree class)	RDD	Earnings & employment	6 months	UK	Econ. Educ. Review
Tan (2023)	Undegraduate	Grades (letter)	RDD	Earnings & employment	6 months	Singapore	J. Labor Econ.
Busso, Montaño & Muñoz-Morales (2025)	Undegraduate	Top performers award	RDD	Earnings	1, 2, 3, 4 and 5 years	Colombia	RESTAT
Landaud et al. (2024)	Undegraduate	Grades (number)	Random exams	Earnings & employment	8 years	Norway	RESTAT
Heller & Kessler (2024)	Undegraduate	Recommandation	RCT	Earnings & employment	1, 2, 3 and 4 years	US	AEJ: Econ. Policy
Carranza et al. (2022)	Undegraduate	Certification (cognitive)	RCT	Earnings & employment	3 to 4 months	South Africa	AER
Abebe et al. (2021)	Undegraduate	Certification (cognitive)	RCT	Employment	1 and 4 years	Ethiopia	RESTUD
Correlational studies							
Bratti, Naylor & Smith (2025)	Undegraduate	Honors (degree class)	PS matching	Earnings	at 30 years old	UK	WP
Naylor, Smith & Telhaj (2016)	Undegraduate	Honors (degree class)	OLS	Earnings	at 30 years old	UK	Oxford Econ. Papers
Walker & Zhu (2011)	Undegraduate	Honors (degree class)	OLS	Earnings & experience	n.a. (experience)	UK	Econ. Educ. Review
Ireland et al. (2009)	Undegraduate	Honors (degree class)	OLS	Earnings	6 months	UK	WP
Arcidiacono, Bayer & Hizmo (2010)	HS & Undegrad.	Grades (number)	Panel	Earnings	12 years (experience)	US	AEJ: Applied Econ.
Experiments							
Baert & Verhaest (2021)	Heterog. (incl. Master's)	Honors	Audit study	Interview invitation	n.a. (experiment)	Belgium	Oxf. Bulletin Eco Stat
Van Belle (2020)	Pooled (incl. Master's)	Honors	Choice experiment	Employability	n.a. (experiment)	Belgium	Econ. Educ. Review
Humburg & van der Velden (2015)	Pooled (incl. Master's)	Grades (number)	Choice experiment	Employability	n.a. (experiment)	Europe	Econ. Educ. Review
Pinto & Ramalheira (2017)	Undegraduate	Grades (number)	Fictitious résumés	Employability	n.a. (experiment)	Portugal	J. Vocational Behavior

Note: This table summarizes the empirical literature on the labor market benefits of education at the intensive margin (i.e. academic results within a particular program). Column (1) indicates if the article focuses on Master graduates, pool them with other academic levels (undergraduates) to look at average effects, or pool them but extract heterogenous effects of honors for different degrees. Column (2) details the type of treatment, i.e. achievements based on academic performance, including **honor degrees** (GPAs above specific thresholds), also named **degree classes** in the UK; **outstanding grades** (overall or by subject); **certifications/recommendations** regarding the student's cognitive skills. We do not consider "honor *degrees* or *tracks*", understood as high-level tracks: this rather belong to the "extensive margin" definition above, i.e. engaging in additional study years or specific programs. Column (3) summarizes the main empirical method used. Column (4) indicates the main labor market outcomes. Column (5) display the time between the treatment and the labor market outcome measures. The articles are sorted in lexicographic order of key criteria for the comparison with our own article (in the first row) : first, studies focusing on Master's degrees (in purple), then using honor degrees as treatment (in blue), and finally with a longrer time horizon (in green). Our main comparators are in the first panel, i.e. studies based on randomized and natural experiments (rather than correlational studies or lab experiments).

Table A2: 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	13.52	11.58	13.09	14.70	16.31	0.98***	0.93***	0.85***
	(1.18)	(0.28)	(0.55)	(0.52)	(0.25)	(0.02)	(0.01)	(0.03)
Outcomes								
Time to find a job	6.24	6.92	6.60	5.43	5.34	-0.24	-1.33***	-0.68
	(6.64)	(6.60)	(6.80)	(6.30)	(6.57)	(0.29)	(0.34)	(1.07)
Employment 1 year	0.80	0.77	0.79	0.83	0.81	0.00	0.04*	-0.02
	(0.40)	(0.42)	(0.41)	(0.38)	(0.39)	(0.02)	(0.02)	(0.04)
Controls								
Age	26.50	26.68	26.42	26.58	26.46	-0.04	0.18	-0.34*
	(3.39)	(2.57)	(3.15)	(3.94)	(3.67)	(0.17)	(0.16)	(0.17)
Women	0.58	0.48	0.56	0.64	0.62	0.06	0.05**	-0.07
	(0.49)	(0.50)	(0.50)	(0.48)	(0.49)	(0.05)	(0.02)	(0.05)
France	0.74	0.62	0.72	0.80	0.76	0.06*	0.04	-0.10
	(0.44)	(0.49)	(0.45)	(0.40)	(0.43)	(0.03)	(0.03)	(0.06)
America	0.04	0.06	0.04	0.03	0.03	-0.01	-0.02	-0.01
	(0.19)	(0.23)	(0.20)	(0.18)	(0.17)	(0.01)	(0.01)	(0.01)
Asia	0.04	0.08	0.05	0.02	0.03	-0.04	-0.02	0.00
	(0.20)	(0.27)	(0.22)	(0.15)	(0.17)	(0.03)	(0.02)	(0.01)
Africa	0.10	0.18	0.12	0.06	0.06	-0.01	-0.02	0.04
	(0.30)	(0.38)	(0.32)	(0.24)	(0.23)	(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)	(0.32)	(0.02)	(0.01)	(0.04)
Obs.	3,166	337	1,732	1,026	71	1,078	1,732	356

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 are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table A3: Fuzzy RDD Estimates of Control Variables around the Different Cutoffs

	Centered (1)	Around 12 (2)	Around 14 (3)	Around 16 (4)
Age	0.080	0.41	0.26	-3.14
	(0.70)	(0.89)	(1.03)	(2.98)
Woman	0.0032	-0.15	0.011	0.31
	(0.12)	(0.18)	(0.17)	(0.56)
France	0.066	0.066	0.0077	0.36
	(0.10)	(0.17)	(0.13)	(0.51)
America	0.044	0.087	0.016	0.11
	(0.036)	(0.069)	(0.037)	(0.22)
Asia	-0.10*	-0.12	-0.11	0.038
	(0.053)	(0.083)	(0.074)	(0.055)
Africa	-0.084	-0.13	-0.027	-0.18
	(0.068)	(0.14)	(0.070)	(0.21)
Oceania	0.023	0.039	0.020	-0.076
	(0.020)	(0.043)	(0.021)	(0.089)
Professional master	0.027	0.11	-0.027	-0.098
	(0.069)	(0.12)	(0.084)	(0.35)
# obs. left	1606	336	989	281
# obs. right	1553	741	741	71

Notes: For a balance test of each control variable, this table presents the fuzzy RDD estimates of potential discontinuities in control variables around the different honors thresholds. Reported coefficients are based on Equations (1) and (2), 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 are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table A4: Fuzzy RDD Estimates of Predicted Outcomes around Different Cutoffs

Alternative outcomes		Centered (1)	Around 12 (2)	Around 14 (3)	Around 16 (4)
Time to find a first job		-0.077	-0.24	0.074	-0.23
		(0.20)	(0.32)	(0.26)	(1.01)
First job after	4 months	0.0024	0.015	-0.0098	0.010
		(0.016)	(0.026)	(0.021)	(0.088)
	6 months	0.011	0.024	0.0028	-0.0037
		(0.013)	(0.020)	(0.017)	(0.059)
	8 months	0.0057	0.015	-0.0012	-0.00021
		(0.012)	(0.019)	(0.015)	(0.054)
	10 months	0.0039	0.012	-0.0034	0.014
		(0.012)	(0.019)	(0.016)	(0.055)
	12 months	0.0056	0.017	-0.0032	0.020
		(0.011)	(0.017)	(0.015)	(0.052)
Wages after 1 year		-0.0060	0.0064	-0.0085	-0.034
		(0.0099)	(0.016)	(0.013)	(0.048)
2 years		-0.0065	0.0030	-0.0065	-0.034
		(0.0077)	(0.012)	(0.010)	(0.033)
Permanent contract after 1 year		-0.029	-0.011	-0.031	-0.075
		(0.022)	(0.041)	(0.028)	(0.095)
2 years		-0.0096	0.0013	-0.010	-0.050
		(0.012)	(0.022)	(0.014)	(0.056)
# obs. left		1606	336	989	281
# obs. right		1553	741	741	71

Notes: For a grouped balance test of all control variable, this table presents the fuzzy 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 fuzzy RD estimations (based on Equations (1) and (2)), 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 are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table A5: Fuzzy RDD Estimates of Response Rates around the Different Cutoffs

	Around 12	Around 14	Around 16
	(1)	(2)	(3)
Linear Spline	-0.048	-0.0027	-0.063
	(0.038)	(0.032)	(0.081)
Cubic	-0.030	-0.0021	-0.055
	(0.053)	(0.053)	(0.086)
Quartic	-0.030	-0.0021	-0.055
	(0.053)	(0.053)	(0.086)
Local polynomial	-0.042	-0.00066	-0.082
	(0.044)	(0.040)	(0.097)
Control group mean	0.40	0.42	0.46
Obs.	4,250	6,169	1,347

Notes: This table presents the fuzzy RDD estimates of the impact the honors on the probability to responde based on Equations (1) and (2). Each column corresponds to a different smooth function of the running variable and each column corresponds to a different cutoff. These estimations focus on each honor with a bandwidth of ± 1. Standard errors are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table A6: Fuzzy RDD Estimates of the Employment Probability at Different Months after Graduation (14 Cutoff, Alternative Bandwidths)

	4 months	6 months	8 months	10 months	12 months
	(1)	(2)	(3)	(4)	(5)
Bandwidths					
1.5	0.20***	0.16***	0.11***	0.12***	0.063*
	(0.042)	(0.043)	(0.035)	(0.042)	(0.035)
1.25	0.22***	0.19***	0.13***	0.13***	0.073*
	(0.048)	(0.050)	(0.041)	(0.049)	(0.039)
1	0.25***	0.21***	0.15**	0.12*	0.062
	(0.059)	(0.066)	(0.057)	(0.066)	(0.049)
0.75	0.29***	0.25***	0.16*	0.11	0.048
	(0.074)	(0.092)	(0.084)	(0.10)	(0.072)
0.5	0.36***	0.39***	0.26*	0.16	0.049
	(0.13)	(0.14)	(0.14)	(0.15)	(0.13)
Optimal Bandwidth	*0.79*	*0.59*	*0.79*	*0.55*	*0.54*
	0.28***	0.33***	0.16**	0.15	0.049
	(0.072)	(0.12)	(0.079)	(0.14)	(0.11)
Control group mean	0.51	0.62	0.69	0.73	0.79

Notes: This table presents the fuzzy RDD estimates of the impact of honors on the probability of employment at different months after graduation. Each coefficient corresponds to a unique estimation, with a bandwidth per row and a different outcome per column. These local polynomial regressions focus 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. Standard errors, clustered by cohort x continent of birth, are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table A7: Fuzzy RDD Estimates of Earnings and Job Quality
(Local Polynomial Estimations, 14 Cutoff, Alternative Bandwidths)

	Log Earnings		Permanent contract		Master level job
	+1 year	+2 years	+1 year	+2 years	+2 years
	(1)	(2)	(3)	(4)	(5)
Bandwidths					
1.5	0.046*	0.022	0.16***	0.11***	0.065**
	(0.027)	(0.034)	(0.043)	(0.036)	(0.028)
1.25	0.054*	0.025	0.18***	0.12***	0.078**
	(0.031)	(0.040)	(0.054)	(0.040)	(0.032)
1	0.075**	0.020	0.21***	0.13***	0.090**
	(0.036)	(0.051)	(0.064)	(0.047)	(0.039)
0.75	0.098**	0.013	0.24***	0.15**	0.10*
	(0.040)	(0.069)	(0.073)	(0.060)	(0.055)
0.5	0.16***	0.048	0.30***	0.21**	0.065
	(0.059)	(0.094)	(0.089)	(0.092)	(0.084)
Optimal Bandwidth	*0.61*	*0.61*	*0.82*	*0.74*	*0.84*
	0.12**	0.035	0.23***	0.15**	0.098**
	(0.048)	(0.080)	(0.067)	(0.060)	(0.048)
Control group mean	7.75	7.87	0.69	0.80	0.93

Notes: This table presents the fuzzy RDD estimates of the impact of honors on different labor market outcomes. Each coefficient corresponds to a unique estimation, with a bandwidth per row and a different outcome per column. These local polynomial regressions focus 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. Standard errors, clustered by cohort x continent of birth, are presented in parentheses. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.