The Value of a High School GPA

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Abstract

This paper provides novel evidence on the causal effect of high school Grade Point Average (GPA) on the human capital development and labor market trajectory of individuals. Causal identification is achieved by exploiting a unique feature of the Norwegian education system that produces exogenous variation in GPA among high school students. We find little effect on the number of completed years of higher education, but significant effects on the number and quality of higher education programs available to students after high school. Most importantly, we find persistent effects on students' long-run labor market outcomes, most notably market wage.

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1 Introduction

High school GPA is one of the most frequently used metrics for identifying academic achievement, and it plays a pivotal role in determining an individual's future education and labor market career. It is used in the admissions process to college, by grant offices when awarding scholarships, by career offices when allocating internships, and by employers when recruiting graduates. However, a lack of exogenous variations in GPA has prevented researchers from identifying the true value of a high school GPA.

This paper provides some of the first evidence on the impact of high school GPA on an individual's education and labor market career, exploiting a unique feature of the Norwegian education system that produces exogenous variation in GPA among high school students with identical abilities. In Norway, high school GPA is based not only on the grades obtained in high school courses, but also on a set of randomized exams taken throughout high school. These exams are conducted in subjects chosen randomly by the municipality among the courses that the student takes, and are announced just days prior to the exams. Each exam counts as much as a course grade when calculating a student's GPA. This feature induces exogenous variation to a student's GPA depending on whether the subjects drawn for the exams correspond to the student's academic strengths or weaknesses.

We use this random exam feature of the Norwegian high school system to construct an instrument, GPA luck, which measures whether the students are allocated to exams in subjects corresponding to their academic strengths or weaknesses. This enables us to identify the causal effects of high school GPA. The instrument we construct is consistent with the general principles developed by Borusyak and Hull (2020), and our paper can be viewed as an empirical application of their method for the case where exposure of individuals to random shocks varies according to some of their pre-determined characteristics. We use the instrument to identify the impact of GPA on the student's long-term education and labor market outcomes.

Exploiting rich administrative data covering the universe of Norwegian senior high school students, we first verify that our GPA luck measure has a significant first-stage effect on high school GPA. We then demonstrate that our measure of GPA luck is unrelated to a rich set of baseline characteristics that may affect students' outcomes (e.g., course grades received from teachers during the year). Finally, we show that GPA luck has significant effects on the number and selectivity of higher education programs that are available to students after high school, as well as persistent effects on students' long-run labor market outcomes. In particular, improvements in GPA luck produce significant increases in market wages eight years after the exams (age 27). While data limitations prevent us from exploring even longer-run outcomes, we show that there is a strong correlation between earnings at age 27 and earnings at age 35, an age at which income is often considered free of life-cycle bias (Böhlmark and Lindquist, 2006; Haider and Solon, 2006).

After having verified the relevance condition of the instrument with a strong first stage and demonstrated that it is unrelated to other student characteristics that may impact their GPA, we use our GPA luck variable to estimate the causal effects of high school GPA on students' labor market outcomes. We find that high school GPA has little impact on subsequent employment probability, but a large impact on labor income flows (conditional on employment). Specifically, we find that a one standard deviation increase in high school GPA generates a 33% increase in individuals' earnings eight years after the end of high school. The effect is equally strong for low and high income students. It is most pronounced for students who pursue a short university education after high school (3 years or less). This highlights that GPA is an important asset when entering the labor market shortly after high school.

The main contribution of our paper is to provide some of the first evidence in the literature on the causal effect of high school GPA on the human capital development and labor market trajectory of individuals. We contribute to the existing literature in several ways. Specifically, there exists a rich literature exploiting test score thresholds in regression discontinuity designs to examine the effect of high school diplomas, college admissions, scholarships, and the return to majors (e.g., Clark and Martorell, 2014; Cohodes and Goodman, 2014; Goodman, 2008; Hastings, Neilson and Zimmerman, 2013; Heinesen, 2018; Hoekstra, 2009; Kirkeboen, Leuven and Mogstad, 2016; Ockert, 2010; Ost, Pan and Webber, 2016; Zimmerman, 2014). In addition, there exists a set of studies which have explored the potential signaling effect of college grades among employers (e.g., Hansen, Hvidman and Sievertsen, 2021; Kessler, Low and Sullivan, 2019; Quadlin, 2018). However, no study has disentangled how high school GPA affects outcomes. We complement these papers by providing the first evidence on the effect of GPA on long-run educational and labor market outcomes. This helps shed light on the true value of a high school GPA, the mechanisms through which these effects operate, and speaks to the importance of designing a GPA metric that accurately reflects ability.

More generally, our paper advances the literature on the impact of secondary schooling on later outcomes. Several important studies have approached this question using lotteries that regulate access to charter schools in the US (e.g., Abdulkadiroğlu et al., 2011; Angrist et al., 2016; Deming et al., 2014; Dobbie and Fryer, 2015). These studies typically document significant effects on access to elite universities, without necessarily detecting improved exam scores in high school. Other important studies have based their identification strategy on the rules governing access to the most selective high schools (see e.g., Abdulkadiroğlu, Angrist and Pathak, 2014; Dobbie and Fryer Jr., 2014). Using regression discontinuity designs, they typically find little effect on college enrollment and ambiguous effects on high school exam scores. This literature highlights the potential impact of school quality on high school and college outcomes, but it is not clear whether these effects extend to labor market outcomes (see, however, Dobbie and Fryer, 2020). In addition, it is not clear whether the effect of school quality on higher education outcomes can be interpreted as reflecting an improvement in students' ability to pass high school tests (see e.g., Goldhaber and Özek, 2019; Hitt, McShane and Wolf, 2018).

In addition to the above literatures, it has long been asserted that high school GPA is a strong predictor of later-in-life outcomes,[1] and our paper is among the first to identify the extent to which this is indeed a cause-and-effect relationship. Our article also contributes to this literature by highlighting the mechanisms involved, thereby helping us understand why GPA plays such an important role. It is not because it increases years of higher education or because it gives access to the most lucrative fields of studies (as measured by the correlation between field of study and later-in-life earnings), such as computer science or business. Rather, it is because a higher GPA increases the possibility of enrolling in university programs that best corresponds to one's specific aspirations/talents (i.e., it improves the student's program match) and because it is in itself an important asset when entering the labor market shortly after high school.

Finally, there is a well-established literature on the role of luck in determining an individual's education and labor market success (e.g., Audas, Barmby and Treble, 2004; Bertrand and Mullainathan, 2001; Frank, 2016; Jenter and Kanaan, 2015). The most studied form of luck in this literature is the birth lottery, which allocates genes and early social environments to individuals (e.g., Black and Devereux, 2011; Mogstad and Torsvik, 2021). More related to our study, however, are the papers that have looked at exam luck in terms of the external conditions prevailing on test days, whether in terms of outdoor temperature, time of the day, or the presence of pollutants or pollen in the atmosphere (e.g., Amanzadeh, Vesal and Ardestani, 2020; Bensnes, 2016; Ebenstein, Lavy and Roth, 2016; Gaggero and Tommasi, 2020; Garg, Jagnani and Taraz, 2020; Park, 2022). We contribute to this literature by demonstrating the importance of another form of luck, linked to the content of the exams themselves, which always have an element of randomness impossible to anticipate by the students.

[1] e.g., Allensworth and Clark (2020); Black, Cortes and Lincove (2016); Galla et al. (2019); Geiser and Santelices (2007).

2 Background

2.1 The Norwegian Education System

The Norwegian education system consists of 10 years of compulsory school starting at age 6. Upon successful completion of compulsory school, all children have the right to attend 3 to 4 years of high school. Approximately 95% of students choose to enroll in high school and about 80% of each cohort ends up with a high school diploma. Education is free at all levels, including post-secondary school.

High school consists of two different tracks: an academic track which provides students with direct access to higher education, and a vocational track which results in a trade or journeyman's certificate. Approximately 50% of students choose to enroll in the vocational track, and 50% choose to enroll in the academic track. In this paper, we focus on students in the academic track. The reason is that the random exams for vocational track students follow a specific structure based on the chosen vocational field of study, and there is therefore little random variation in the exams that these students face. We do not consider this a limitation of the study as few vocational track students pursue higher education.

Several universities and colleges offer higher education in Norway, and the majority of these are tuition-free public institutions. Admission is conditional on graduating from high school. The Norwegian Universities and Colleges Admission Service coordinates the admission process. Students apply to specific fields of study and universities, and if the number of applications exceeds the number of seats, students are assigned almost exclusively based on high school GPA.[2] The more demand for a specific program (that is, a field of study within a given university), the higher the GPA required to gain admission to that program.

2.2 High School GPA and Randomized Exams

In Norway, as in most countries, high school GPA is one of the most frequently used metrics for identifying academic achievement, and it plays a pivotal role in determining an individual's future education and labor market career. Specifically, a higher GPA provides access to a larger set of university programs, and to higher quality university programs. In addition, it may be used by grant offices when awarding scholarships, by career offices when allocating internships, and by employers when recruiting graduates. High school GPA is therefore a decisive feature for high school students. In this subsection, we describe how the students' GPA depends not only on course grades, but also on grades obtained from randomized external exams taken throughout high school.

[2]There are a few bonus points that students can obtain (related to age, gender, and military service experience), but the main determinant is the GPA (Kirkeboen, Leuven and Mogstad (2016)).

In Norway, high school GPA depends on a combination of course grades from teachers and exam grades. The exams take place at the end of each school year, the exam subjects are chosen randomly for each individual student, and the subjects are announced less than a week prior to the exam.[3] In terms of exam structure, students take between five and six exams throughout high school. In the first year, 20% of students are randomly selected for either a written or oral exam in a randomly chosen subject. In the second year, all students take either a written or an oral exam in a randomly chosen subject. In the third and final year, all students take three written exams and one oral exam.

Exam performance in the first and second year of high school may impact which courses students choose in the third year, what study specializations they select, and could even have an effect on dropout rates (see e.g., Andresen and Løkken, 2020; Hvidman and Sievertsen, 2021).[4] To avoid sample selection problems, we focus exclusively on the exams in the third and final year.

Before 2008, the exams in the final year of high school consisted of two written exams in Norwegian, one written exam in a randomly chosen subject and one oral exam in a randomly chosen subject. Since 2008, it consists of one written exam in Norwegian, two written exams in randomly chosen subjects and one oral exam in a randomly chosen subject. The randomization of students to subjects and types of tests is delegated to the municipality. While the written exams are designed and graded at the national level, the oral exams are designed and graded at the local level. In our analysis, we focus on the variations in GPA generated by the written exams alone. This removes any endogeneity risk driven by local exam designs.

An exam grade counts as much towards GPA as a course grade. High school GPA consists of the average grade of all of a given student's course grades and randomized exam grades in high school. Exams and courses are graded on a scale from 1 (worst) to 6 (best), where 1 constitutes a failing grade.

It should be noted that successful graduation from academic high school, and eligibility for higher education, requires that the student passes all high school courses. However, there is an exception to this rule. This exception would arise if a student has failed the course, but been randomly drawn into and passed an exam in the subject. In such an event, the "pass" status from the randomized exam trumps the "fail" status from the course grade, and the student receives a high school diploma.

The vast majority (92%) of students do not fail a course. For these students, a good exam draw

[3]Even if the delay is short, students can use these few days to prepare for exams (Bensnes, 2020). This can mitigate the impact of being lucky (or unlucky).

[4]For example, Hvidman and Sievertsen (2021) exploits a Danish grade scale recoding reform that impacted students in the first year of high school to isolate the behavioral response to a change in the incentives associated with high-stakes exam grades. They find that individuals who experienced a reduction in score due to the reform exerted more effort and performed better in subsequent years.

unambiguously corresponds to a draw that matches their academic strengths. For the small fraction (8%) of senior students who failed a course during the year, the effects of the draw are more complex.[5] We focus on the 92% of senior students who did not fail a course during the year, i.e. on students for whom the definition of a good exam draw is unambiguous.

3 Data, Variables and Samples

3.1 Data Registers

Our data come from population-wide registers covering all Norwegian residents who were enrolled in the final year of high school between 2003 and 2009. We follow these individuals over time and across registers, such that we can construct a longitudinal panel covering the universe of students and much of their demographic, education, labor, and family background information.

In terms of education data, we have information on high school GPA, diploma status, and whether the student has qualified for higher education. In addition, we have data on all courses that students take in high school, the grades they received in these courses, which courses students were randomized to take exams in, and which grades they received on those exams. Finally, we have information on enrollment in higher education, college major choice, and college degree completion.

From these data, we can construct a variable (denoted $Share_{i,t}$) identifying the proportion of university programs for which each student is eligible. Specifically, for each program s available in year t, we identify the minimum GPA (denoted $Min\_Gpa_{s,t}$) of the students enrolling in the program. For each student i, the variable $Share_{i,t}$ is equal to the proportion of programs whose $Min\_Gpa_{s,t}$ is below the GPA of student i. We also construct a variable measuring the selectivity (denoted $Select_{i,t}$) of the programs in which students enroll. To define $Select_{i,t}$, we ranked all higher education programs in year t based on their minimum student GPA ($Min\_Gpa_{s,t}$). If $Min\_Gpa_{s(i),t}$ denotes the minimum GPA of the first program in which student i enrolls after high school, the selectivity level of student i's first enrollment is defined as the percentile rank of $Min\_Gpa_{s(i),t}$, that is: $Selectivity\_level_{i,t} = Percent\_rank(Min\_Gpa_{s(i),t})$.

With respect to labor market information, we have detailed information on income and employment for the entire sample for each year up until 2018. Income is measured as pre-tax income (labor income and income from self-employment) including certain taxable government transfers (parental leave, sickness

[5] If they draw exams in their strong subjects, this potentially increases their GPA, but not their chance of graduating and of going to college. As it happens, to have a chance at graduating and going to university, they must necessarily draw the subject they failed during the year and do better on the exam.

leave and unemployment benefits). Employment status is defined based on the individual's status in the employment register. In our analysis, we focus on employment and income eight years after high school graduation. Data limitations prevent us from exploring even longer-run outcomes.

Concerning background characteristics, we have information on compulsory school GPA, age, sex, and municipality of residence. We can also link students to their parents and collect information on parents' age, educational attainments, and earnings.

3.2 The GPA Luck Instrument

In Norway, students' GPA at the end of high school depends not only on the course grades given by teachers, but also on the results obtained at the randomly drawn end-of-the-school-year exams. The draw produces an exogenous shock that is more or less favorable for students' GPA depending on whether the subjects drawn correspond to the students' academic strengths or weaknesses. We construct an instrument that uses the random nature of the end-of-year examinations to identify the causal effect of students' GPA on their outcomes.

We begin by defining $Exam^e_{i,s}$ as a measure of the score that student i can expect on an end-of-year exam in subject s if that subject is drawn. As discussed below, this measure can be constructed from our knowledge of the grades previously received by student i in subject s during the school year. Based on a complete set of predictions of $Exam^e_{i,s}$, we can then construct a measure of the expected contribution of exams to the final GPA of student i if the student is randomly assigned to a specific combination c[6] of end-of-year exams:

$$GPA\_luck^e_{i,c} = \frac{1}{S+K} \sum_{s \in c} Exam^e_{i,s}, \tag{1}$$

where S and K are the number of courses and exams that student i takes. The sum on the right-hand-side represents the expected number of grade points from the randomly-assigned exams.

For each i, $GPA\_luck^e_{i,c}$ is a predictor of the contribution of exams to student's final GPA; it varies randomly with the exogenous shock c, but this alone does not necessarily make it a good instrument for identifying the impact of the GPA on subsequent outcomes (see e.g., Borusyak and Hull, 2020). The problem comes from the fact that students' exposure to more or less favorable shocks (i.e., to stronger or weaker average $Exam^e_{i,s}$) is not randomly distributed, but depends on their initial academic level, as

[6] A given combination of exams c is drawn from all possible combinations of exams C. The set of possible combinations C is determined by the number of exams taken (K) and the number of courses taken (S). For example, if $S = 10$ and $K = 3$, there are $\frac{10 \times 9 \times 8}{3 \times 2} = 120$ possible combinations.

measured for example by the grades obtained during the school year. In short, randomizing exams is not exactly the same as randomizing the scores students receive on these exams.

As shown by Borusyak and Hull (2020), however, there is a simple way to neutralize the potential endogeneity bias that affects the use of an instrument constructed as $GPA\_luck^e_{i,c}$. Specifically, it is sufficient to center $GPA\_luck^e_{i,c}$, that is to consider its deviation with respect to its mean value (denoted $\overline{GPA\_luck^e_{i,c}}$) through the set of all possible exogenous shocks c,[7]

$$GPA\_luck_{i,c} = GPA\_luck^e_{i,c} - \overline{GPA\_luck^e_{i,c}}. \tag{2}$$

We base our analysis on the $GPA\_luck_{i,c}$ instrument constructed by defining $Exam^e_{i,s}$ as the average score obtained on the end-of-year exam in subject s by students (other than i) who attended the same high school as i in the same year, earned the same teacher assessment in the course on subject s as i and where randomly assigned to an exam in subject s. This variable can be interpreted as the payoffs that students can expect from the exam lottery. As discussed below, this instrument is both a strong predictor of students' GPA and is uncorrelated with students' predetermined characteristics.

As a robustness check, we examine an alternative version of the instrument obtained by defining $Exam^e_{i,s}$ as the average exam score obtained not in the same year, but in the previous year by students from the same high school as i and having obtained the same teacher assessment in subject s as i.[8] As discussed below, the first-stage effect on high-school GPA becomes slightly weaker, but remains highly statistically significant, when we use this version of the instrument.

3.3 Sample Selection and Descriptive Statistics

Our data include all full-time high school students enrolled in the final year of the academic high school for the first time between the academic year 2003-2004 and 2009-2010 (130,000 students). We exclude the small share (less than 8%) of students who received a grade of 1 during the school year and for which the definition of a favorable exam draw is not straightforward. This provides us with an analysis sample of about 119,000 individuals. Table A1 provides descriptive statistics on all individuals in our sample.

Figure A1 shows the distribution of our GPA luck instrument $GPA\_luck_{i,c}$. It follows a Gaussian-type distribution, evenly distributed around zero. In the remainder of the paper, we winsorize the top

[7]Alternatively, as shown by Borusyak and Hull (2020), one could use the uncentered version of the instrument and add the average value taken by these instruments across possible shocks (in our case, $\overline{GPA\_luck^e_{i,c}}$) as a control.

[8]For individuals from the first cohort (for whom we do not observe peers from the previous cohort), and for individuals from the 2008 cohort (who are the first to have new course codes due to nationwide changes in high school curriculum), we used peers from the following cohort.

and bottom 0.1% of our instrument to ensure that our results are not driven by a few outliers.[9] Table A2 demonstrates that there is very little correlation between the GPA luck instrument and observed student characteristics measured in pre-assignment years. When we regress our GPA luck variable on students' average high school course grade (linear and squared), average middle school GPA (linear and squared), sex, age (linear and squared), parents' age (linear and squared), parents' years of schooling (linear and squared), parents' log earnings, a conventional F-test cannot reject that the estimated coefficients are jointly equal to zero (P-value = 0.41).

4 Results

We first present the first-stage and reduced-form effects of GPA luck on students' outcomes. We then present results from an IV analysis in which we use GPA luck as a source of identification for the causal effect of students' high school GPA on their labor market outcomes.

4.1 GPA luck and Students' Outcomes

Table 1 shows the results of regressing students' education and labor market outcomes on our measure of GPA luck. Our regression model includes a full set of high school and year fixed effects as well as a rich set of demographic controls. These controls include students' average high school course grade (linear and squared), average middle school GPA (linear and squared), sex, age (linear and squared), parents' age (linear and squared), parents' years of schooling (linear and squared), and parents' log earnings. Standard errors are clustered at the high school-by-year level (i.e., the level of random assignment). In Table A3 of the Online Appendix, we show that our main results are robust to the use of a double lasso procedure for selecting control variables, and that the precision of our main estimates remains unchanged when we compute standard errors using a wild bootstrap procedure. We also provide results of permutation tests for the main first-stage and reduced form regression models.

In Panel A of Table 1, we study the effect of GPA luck on students' high school outcomes.[10] The results confirm that our GPA luck variable has a statistically significant effect on students' exam grades (first column), on their high school GPA (second column), as well as on their probability of on-time graduation (third column), and of ever receiving a high school diploma (fourth column). Specifically, a one SD improvement in GPA luck leads to 10% of a standard deviation increase in exam grades, to 2% of

[9] Our results are robust to not winsorizing; results are available upon request.

[10] For legibility, we divided GPA_luck by its standard deviation over the sample, so that a one unit increase in the instrument corresponds to a 1 SD improvement in GPA luck.

a SD increase in GPA, to a 1 percentage points increase in the probability of on-time graduation, and to a 0.3 percentage point increase in the probability of ever receiving a high school diploma.[11] The smaller effect on the probability of ever receiving a diploma suggests that many students who fail to secure an on-time diploma due to bad luck return to school to take supplemental classes and receive a diploma at a later time.

In Panel B of Table 1, we study the effect of GPA luck on students' higher education outcomes, both on the extensive margin (first column) as well as on the intensive margin (second to fourth columns). In terms of the extensive margin, the GPA luck variable has no effect on the probability of ever going to university. This finding is consistent with the small effect on the probability of ever graduating from high school documented in the fourth column of Panel A.

Based on the lack of an extensive margin effect, the remainder of the analysis focuses on the subsample of students who went to university. First, we explore the effect of GPA luck on the share of higher education programs that the students qualify for (second column) and on the selectivity of the first higher education program in which they enroll (third column). These two outcomes provide measures of the set of choices available to students, and of the education quality that students are exposed to in college (conditional on attending college).

Consistent with the fact that GPA luck raises a student's high school GPA, the results in the second and third columns of Panel B show that GPA luck has a sizable impact on both outcomes. The second column shows that a one SD change in GPA luck shifts the share of higher education programs available to the students by 0.1 percentage points. This indicates that GPA luck broadens the choice set of higher education programs. The third column shows that a one unit change in GPA luck increases the selectivity of the higher education program in which students enroll by about 0.15 percentile ranks. This reveals that students take advantage of the broader choice set of higher education programs and "upgrade" their college quality through enrollment into more selective programs and universities.[12]

The result in the fourth column of Panel B demonstrates that there is no impact of GPA luck on the number of years completed in higher education. In the Online Appendix, we also show that the probability of completing more than 3 years of higher education (the Bachelor level) is not affected by

[11] Auxiliary analysis confirm that the effect of GPA luck on GPA is a combination of a strong positive effect on the average score in written exams and a smaller negative effect on the average score in oral exams. This reflects the fact that when one draws one of one's strong subjects for the written exam, one is less likely to have subsequently an oral exam in one of one's strong subjects (since one cannot have two exams in the same subject).

[12] We have also explored the impact of GPA luck on the likelihood of enrolling in each of the main fields of study (medicine, law, business, engineering...). The estimated impacts are small and generally not statistically significant (see Table A4 in the online Appendix). A favorable exam draw therefore appears to enable students to choose the programs best suited to their specific aspirations, but it does not lead to a preference for a particular field of study.

GPA luck (see Table A5). GPA luck allows students to study in more selective programs, but this does not translate into shorter or longer studies. In particular, the quality upgrading that GPA luck contributes to is not offset by a potential reduction in educational attainment due to admission into more difficult education programs.

In Panel C of Table 1, we study the effect of GPA luck on students' labor market outcomes. We begin by examining the impact of GPA luck on the probability of ever having been employed. The result from this analysis is shown in the first column. The result shows that GPA luck has no significant effect on student's probability of ever having been employed.

In light of the lack of an overall employment effect, in the second column of Panel C we constrain our sample to the group of students who went to university and held at least one job in their lifetime, exploring the impact of GPA luck on the annual labor income at the first job the students secure. The result shows that GPA luck has a sizable impact on the annual labor income at the first job the students secure.

Our data enables us to follow students up to eight years after they have taken their third-year high school exams. Using this information, the third column of Panel C shows that GPA luck has no significant effect on the probability of being employed eight years after the exams. The fourth column of Panel C therefore zooms in on the students who went to university and were employed 8 years after the exams, and it shows a significant effect on annual labor income. The magnitude of the effect on earnings is about the same eight years after the exams as it was at labor market entry.[13]. We note that there is a strong correlation between earnings at age 27 and earnings at age 35, an age at which income is often considered free of life-cycle bias (Böhlmark and Lindquist, 2006; Haider and Solon, 2006). Specifically, using all individuals who are 27 years old between 1993 and 2010, the correlation in inflation-adjusted gross earnings is 0.51.

4.2 Heterogeneity

In the Online Appendix, we explore effect heterogeneity by student gender, initial academic level, and parental income (Tables A6 to A9). The first-stage effects of $GPA\_luck_{i,c}$ on GPA do not vary much across subgroups. The wage effects observed eight years after the exams also does not vary much by initial academic level or parental income. However, wage effects tend to be higher for female than for

[13]In Table A3 in the online Appendix, we show that the reduced-form effect on annual labor income is slightly smaller, but remains statistically significant, when we use the version of the instrument constructed using non-contemporary exam scores. Auxiliary analyses available upon request also shows that GPA luck enables students to upgrade their position in the wage distribution

male students (although the gap is not statistically significant), perhaps because women are more likely to work in the public sector, where educational attainment plays a particularly important role in gaining access to higher paid positions.

Since $GPA\_luck_{i,c}$ has no effect on the number of years completed in higher education, we also examine if the effect of $GPA\_luck_{i,c}$ on wages is different for those with 3 years or less in higher education and for those with more than 3 years (see Table 2). Interestingly, the effects are mainly driven by students with 3 years or less of higher education. This result is consistent with the fact that a good high school GPA is, in itself, important for those who enter the labor market soon after finishing high school.

4.3 The Causal Effects of High-School GPA: IV Estimations

We showed above that GPA luck has a significant impact on the GPA of high school students, but no impact on their probability of entering university nor on their probability of holding a job after having completed their education, or eight years after the exams. Based on these results, we focus on the samples of former high school students who enrolled in university and are employed after university or eight years after the exams (i.e., the same samples as Panel C of Table 1). Using these samples, we analyze the impact of high school GPA on wages using GPA luck as an instrument in a standard 2SLS approach. The identifying assumptions are that GPA luck has a direct effect on students' high school GPA (relevance criterion) and that it influences students' subsequent labor market outcomes only through its impact on their high school GPA (exclusion restriction).

The validity of the relevance criterion has already been established above. In terms of the exclusion restriction, this assumption would be violated if, for example, GPA luck in itself had a direct effect on subsequent labor market outcomes (e.g., through affecting high school students' motivation and efforts). The fact that GPA luck has no short-term effects on the probability of ever graduating or entering college (nor on time spent in college) suggests that this is unlikely to be the case.

The results from our IV analysis are shown in Table 3. We look separately at the impact on wages received at labor market entry and wages received eight years after finishing high school. The table shows that high school GPA has a very large impact on labor market earnings. Specifically, a one standard deviation increase in high school GPA generates a 34% increase in students' earnings at entry into the labor market and a 33% increase in earnings eight years after finishing high school. These effects are economically large, but consistent with evidence on how exogenous shifts in other human capital investment inputs, such as matriculation exam scores (e.g., Ebenstein, Lavy and Roth, 2016) and access to specific majors (e.g., Kirkeboen, Leuven and Mogstad, 2016), improve earnings. To the extent that high school GPA affects wages through its impact on higher education choices (rather than by increasing the number of years in higher education or providing students with increased internship opportunities and scholarship options), the magnitude is therefore consistent with related literature.

To facilitate the interpretation of the 2SLS results, Table 3 also reports the result from an OLS estimation of the same parameters. The OLS impact of a one SD increase in GPA on earnings is 16% for entry wages and 11% for wages earned eight years after high school. The difference between the IV and OLS estimates suggests a negative correlation between unobserved determinants of high school graduates' performance on the labor market and the unobserved determinants of their high school GPA. Such negative correlation could arise if, for example, it is easier to obtain a good GPA at a bad school (where teachers more easily give out good grades).[14]

In the preceding analysis we have assumed that heterogeneity in the effects of high school GPA can be neglected. Relaxing this assumption, the estimated effects can still be interpreted as an average of heterogenous causal effects as long as it remains possible to assume that the probability of obtaining a good GPA is an increasing function of the GPA_luck instrument, for all types of students defined by baseline teacher assessments (see Borusyak and Hull, 2020). Under this monotonicity assumption, the estimated effects are averages that give more weight to those students for whom the distribution of the instrument has the highest variance across all possible exam draws, i.e. those with particularly uneven academic levels across subjects and for whom the exam draw is a particularly important issue. It is possible to obtain more conventional treatment effects by focusing on students for whom the variance of the instrument is not negligible and by rescaling the instrument by its variance across all possible exam draws. With respect to first-stage and reduced-form regression, we checked that rescaled estimators of average treatment effects remain statistically highly significant. The rescaled local average treatment effect (LATE) of high school GPA on (ln) wage remains statistically significant too and its amplitude is even larger than that of the non-rescaled estimators (about 50%, see Appendix Table A10).

5 Conclusion

This paper provides some of the first evidence on the causal effect of high school GPA on human capital development and labor market outcomes.

[14]When we measure the quality of a high school by the middle-school GPA of the pupils who enter this school, we can see in our data that students with the same middle-school GPA subsequently obtain higher high-school GPAs if they attend a school of low quality.

Our analysis shows that high school GPA has little impact on subsequent employment probability, but a large impact on labor income flows (conditional on employment). The effect is most pronounced for students who pursue a short university education after high school (3 years or less), in line with the fact that a good GPA is also in itself an important asset when entering the labor market shortly after high school.

Our paper not only helps advance the long-standing literature on the causal impact of secondary schooling on later in life outcomes, but it also offers some of the very first evidence that the correlation between high school GPA and later-in-life success is indeed a cause-and-effect relationship. Our findings also contribute to the literature by highlighting the mechanisms involved, thereby helping us to understand why high school GPA plays such an important role. It is not because it increases years of higher education or because it gives access to the most lucrative fields of studies. Rather, it is because it increases the possibility of enrolling in the programs that best corresponds to one's specific aspirations/talents and because it is in itself an important asset when entering the labor market shortly after high school.

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Table 1: Effects of GPA Luck on Later-in-life Outcomes

Panel A: High School Outcomes	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma
GPA_luck	0.1032***	0.0193***	0.0109***	0.0033***
	(0.0018)	(0.0005)	(0.0009)	(0.0005)
Mean dep. var.	0.103	0.164	0.875	0.964
N	119385	119385	119385	119385
Panel B: Higher Education Outcomes	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE
GPA_luck	0.0005	0.0012***	0.1540*	0.0016
	(0.0006)	(0.0001)	(0.0855)	(0.0047)
Mean dep. var.	0.943	0.895	34.330	3.033
N	119385	112599	112599	112599
Panel C: Labor Market Outcomes	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)
GPA_luck	0.0003	0.0064**	0.0008	0.0062***
	(0.0012)	(0.0027)	(0.0013)	(0.0022)
Mean dep. var.	0.818	12.348	0.739	12.682
N	112599	92123	112599	83217

NOTE: The table refers to the sample of regular full-time high school students who enrolled for the first time in the final year of academic high school between 2003 and 2009, and who received no failing grade (course grade = 1) in the courses they took during the school year. Higher education and labor market outcomes are restricted to the students who enrolled in college, and earnings are additionally restricted to the students who obtained a first job (Panel C, second column) and who are employed 8 years after the exams (Panel C, fourth column). Each column corresponds to a specific regression, and reports the estimated impacts of our instrument—GPA_luck—on the dependent variable mentioned above. Measures of exam grades and high school GPA in third year are standardized to mean zero and unit variance in the universe of full time high school students. Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table 2: Effects of GPA Luck on Labor Market Outcomes, by Length of University Education

	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)
Subsample with 3 years of higher education or less				
GPA_luck	0.0002	0.0093***	0.0009	0.0104***
	(0.0014)	(0.0035)	(0.0017)	(0.0030)
Mean dep. var.	0.841	12.143	0.732	12.559
N	73035	61449	73035	53477
Subsample with more than 3 years of higher education				
GPA_luck	0.0002	-0.0003	0.0004	-0.0021
	(0.0021)	(0.0027)	(0.0022)	(0.0023)
Mean dep. var.	0.775	12.759	0.752	12.901
N	39564	30674	39564	29740

NOTE: The table reports similar results as Table 1 Panel C, separately on the sub-sample of students who completed 3 years of higher education or less (top panel), and on the sub-sample of students who completed more than 3 years of higher education (bottom panel). Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table 3: Effects of High School GPA on Annual Earnings: An Instrumental Variable Approach

	Outcomes			
	First job log annual labor income (2SLS)	First job log annual labor income (OLS)	Log annual labor income 8 years after the exams (2SLS)	Log annual labor income 8 years after the exams (OLS)
High school GPA in 3rd year	0.337**	0.159***	0.333***	0.092***
	(0.142)	(0.004)	(0.115)	(0.003)
N	92123	92123	83217	83217

NOTE: The table refers to the same sample as Table 1 Panel C. The first and third columns report the 2SLS estimates of the impact of students' GPA on the log of students' annual labor earnings at their first job or eight years after the exams, using GPA_luck as instrument. The value of the F-statistics for the first stage regressions are 983 and 924, respectively. The second and fourth columns report the OLS estimates of the same parameters. Each regression includes baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Appendix A

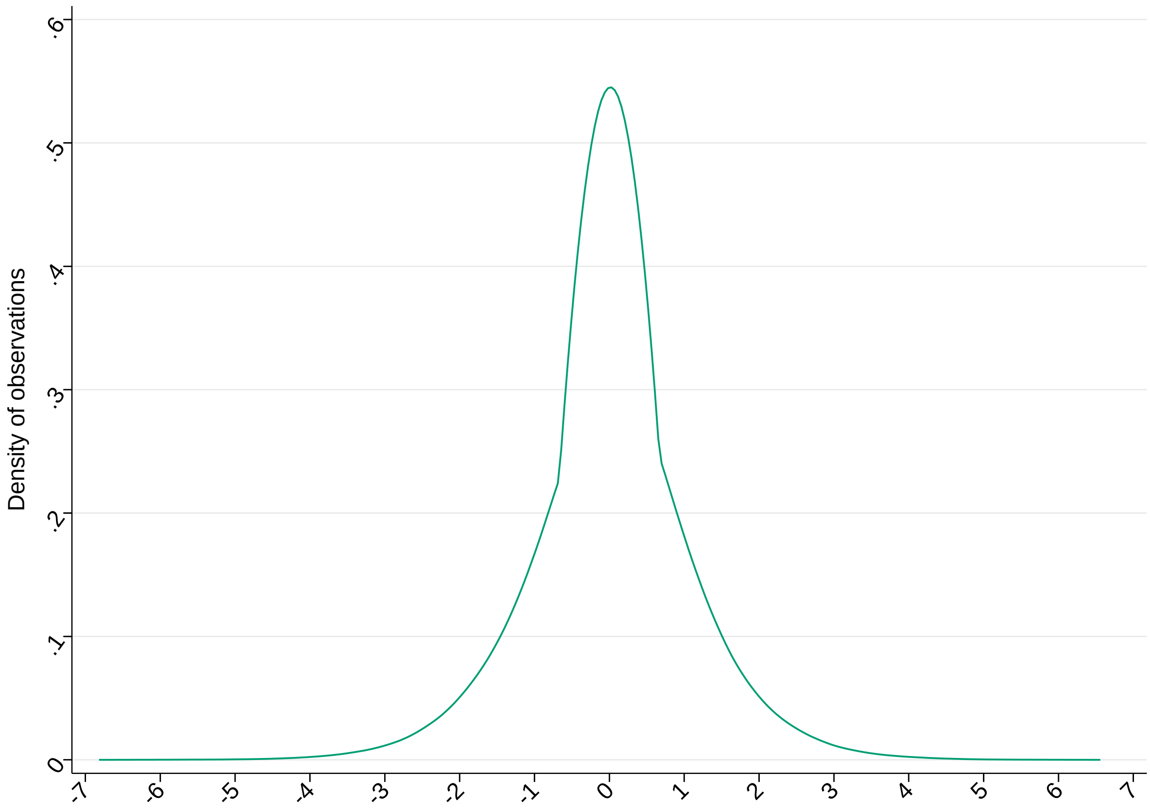

Figure A1: Distribution of the Instrument

NOTE: The figure refers to the same sample as Table 1 Panel A, and plots the distribution of our instrument, GPA_luck.

Table A1: Summary Statistics

Variables	Mean	SD	Observations
Outcomes			
Exam grades in 3^{rd} year	0.103	0.947	119385
High school GPA in 3^{rd} year	0.164	0.851	119385
On time HS diploma	0.875	0.331	119385
Ever HS diploma	0.964	0.187	119385
Ever higher education	0.943	0.232	119385
Share of available HE programs	0.895	0.127	112599
Selectivity of HE enrollment	34.330	29.840	112599
Number of completed years in HE	3.033	1.760	112599
Ever employed	0.824	0.381	119385
First job labor income (log)	12.310	0.828	98384
Employed 8 years after the exams	0.742	0.438	119385
Labor income 8 years after the exams (log)	12.678	0.600	88548
Demographics			
High school course grades	0.168	0.841	119385
Middle school GPA	0.109	0.939	119385
Female	0.563	0.496	119385
Age	19.085	0.885	119385
Parents' average age	48.268	4.788	119385
Parents' average years of education	13.913	2.519	119385
Parents' average log labor income	12.571	1.321	119385

NOTE: The table refers to the same sample as Table 1. The table shows the means and standard deviations of the main outcome and baseline variables. Statistics on the share of available higher education programs, on the selectivity of students' higher education programs, and on the number of years completed in higher education are conditional on enrolling in college. Statistics on individuals' labor incomes are conditional to being employed. Measures of exam grades, high school GPA, high school course grades in third year, and middle school GPA are standardized to mean zero and unit variance in the universe of full time high school students.

Table A2: Balance Tests, Association between the Instrument and Baseline Characteristics

	GPA_luck
High school course grades	-0.0015
	(0.0049)
High school course grades, squared	-0.0068**
	(0.0035)
Middle school GPA	-0.0011
	(0.0047)
Middle school GPA, squared	-0.0001
	(0.0019)
Female	-0.0131**
	(0.0060)
Age	-0.0113
	(0.0164)
Age, squared	0.0002
	(0.0003)
Parents' average age	0.0022
	(0.0081)
Parents' average age, squared	-0.0000
	(0.0001)
Parents' average years of education	0.0050
	(0.0101)
Parents' average years of education, squared	-0.0002
	(0.0004)
Parents' average log earnings	-0.0016
	(0.0022)
F-statistic	1.044
Joint p-value	0.405
Mean	0.018
N	119385

NOTE: The table refers to the same sample as Table 1. The table shows the results of regressing our instrument—GPA_luck—on a set of baseline demographic characteristics. Measures of high school course grades and middle school GPA are standardized to mean zero and unit variance in the universe of full time high school students. Both regressions include high school and year fixed effects, and the F-test of joint orthogonality controls for these fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A3: Effect of the Instrument on High School GPA and Annual Earnings, Robustness Tests

	Outcomes		
	High school GPA in 3rd year	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)
Panel A: Controls for Students' Baseline Characteristics Selected by Double Lasso			
GPA_luck	0.0193***	0.0009	0.0064***
	(0.0005)	(0.0013)	(0.0022)
Panel B: Controls for Students' Courses in 3rd year			
GPA_luck	0.0191***	0.0008	0.0059***
	(0.0005)	(0.0013)	(0.0021)
Panel C: P-values for GPA_luck Computed Using Permutation Tests			
P-values for GPA_luck	0.000	0.526	0.004
Panel D: P-values for GPA_luck Computed Using a Wild Bootstrap			
P-values for GPA_luck	0.000	0.515	0.002
Panel E: Expected Exam Grades Computed Using Non-contemporaneous Peers			
GPA_luck – alternative definition of $Exam^e$	0.0125***	0.0013	0.0051**
	(0.0005)	(0.0013)	(0.0021)

NOTE: The table reports similar results as Table 1, Panel A second column, and Panel C third and fourth columns. The first panel replicates the main analyses with a restricted set of baseline demographic controls selected by double lasso. Panel B replicates the main analyses controlling for indicators of students' courses in the last year of high school. Panel C reports p-values computed using permutation tests. Panel D reports p-values computed using a wild bootstrap. Panel E replicates the main analyses using an alternative instrument where students' expected exam grades are computed using peers from previous or following cohorts. Each regression—expect for Panel A—includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A4: Effect of the Instrument on Students' Fields of Study

	Humanities	Social Science	Teaching	Health	Science	Engineering	Technology	Business	Law	Medicine
GPA_luck	-0.0024**	-0.0000	-0.0003	0.0014	0.0002	-0.0005	0.0008	0.0012	0.0002	-0.0001
	(0.0009)	(0.0010)	(0.0008)	(0.0010)	(0.0009)	(0.0007)	(0.0007)	(0.0011)	(0.0004)	(0.0005)
Mean dep. var.	0.120	0.138	0.090	0.149	0.090	0.056	0.064	0.193	0.021	0.033
N	112599	112599	112599	112599	112599	112599	112599	112599	112599	112599

NOTE: The table refers to the same sample as Table 1, Panel B. Each column corresponds to a specific regression, and reports the estimated impacts of our instrument—GPA_luck—on the dependent variable mentioned above. Each dependent variable corresponds to a field of study, and indicates whether students specialized in this field when they first enrolled in higher education. Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A5: Effect of the Instrument on the Number of Years Completed in Higher Education

	0 years	1 year	2 years	3 years	4 years	5 years	6 years or more
GPA_luck	0.0001	-0.0018*	-0.0000	0.0020	0.0011	-0.0014	0.0000
	(0.0009)	(0.0010)	(0.0003)	(0.0014)	(0.0006)	(0.0013)	(0.0006)
Mean dep. var.	0.117	0.147	0.010	0.374	0.052	0.262	0.037
N	112599	112599	112599	112599	112599	112599	112599

NOTE: The table refers to the same sample as Table 1, Panel B. Each column corresponds to a specific regression, and reports the estimated impacts of our instrument—GPA_luck—on the dependent variable mentioned above. Each dependent variable corresponds to a number of completed years of higher education, and indicates whether students have reached each possible level of completion. Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A6: Effect of the Instrument on Educational and Labor Market Outcomes — Heterogeneity by Baseline Ability

	Low Ability, Below Median Course Grades				*High Ability, Above Median Course Grades*			
Panel A	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma
GPA_luck	0.1079***	0.0196***	0.0212***	0.0072***	0.0985***	0.0189***	0.0010	-0.0005*
	(0.0025)	(0.0008)	(0.0015)	(0.0009)	(0.0025)	(0.0007)	(0.0009)	(0.0003)
Mean dep. var.	-0.473	-0.516	0.808	0.936	0.682	0.848	0.943	0.991
N	59877	59877	59877	59877	59508	59508	59508	59508
Panel B	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE
GPA_luck	0.0010	0.0017***	0.1068	-0.0016	-0.0001	0.0005***	0.2021	0.0046
	(0.0011)	(0.0003)	(0.1078)	(0.0069)	(0.0004)	(0.0001)	(0.1326)	(0.0066)
Mean dep. var.	0.898	0.810	27.018	2.439	0.988	0.972	41.019	3.576
N	59877	53791	53791	53791	59508	58808	58808	58808
Panel C	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)
GPA_luck	0.0013	0.0072*	0.0031	0.0062**	-0.0005	0.0053	-0.0013	0.0064**
	(0.0016)	(0.0039)	(0.0019)	(0.0029)	(0.0016)	(0.0036)	(0.0018)	(0.0030)
Mean dep. var.	0.824	12.244	0.739	12.624	0.813	12.445	0.739	12.734
N	53791	44326	53791	39733	58808	47797	58808	43484

NOTE: The table reports similar results as Table 1 separately on the sub-sample of students whose average course grade is below the sample median (left panel), and on the sub-sample of students whose average course grade is above the sample median (right panel). Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A7: Effect of the Instrument on Educational and Labor Market Outcomes — Heterogeneity by Gender

	Boys				*Girls*			
Panel A	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma
GPA_luck	0.1071***	0.0203***	0.0125***	0.0037***	0.0999***	0.0184***	0.0097***	0.0029***
	(0.0026)	(0.0008)	(0.0014)	(0.0007)	(0.0023)	(0.0007)	(0.0011)	(0.0006)
Mean dep. var.	-0.006	0.042	0.850	0.956	0.188	0.258	0.894	0.970
N	52184	52184	52184	52184	67201	67201	67201	67201
Panel B	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE
GPA_luck	0.0005	0.0014***	0.1380	-0.0034	0.0006	0.0010***	0.1601	0.0060
	(0.0009)	(0.0002)	(0.1239)	(0.0071)	(0.0007)	(0.0002)	(0.1175)	(0.0063)
Mean dep. var.	0.930	0.881	35.078	2.898	0.954	0.905	33.765	3.135
N	52184	48520	48520	48520	67201	64079	64079	64079
Panel C	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)
GPA_luck	-0.0019	0.0021	-0.0004	0.0037	0.0023	0.0098***	0.0019	0.0082***
	(0.0018)	(0.0044)	(0.0020)	(0.0034)	(0.0015)	(0.0032)	(0.0017)	(0.0026)
Mean dep. var.	0.803	12.299	0.724	12.722	0.830	12.384	0.750	12.652
N	48520	38961	48520	35152	64079	53162	64079	48065

NOTE: The table reports similar results as Table 1 separately on the sub-sample of boys (left panel), and on the sub-sample of girls (right panel). Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A8: Effect of the Instrument on Educational and Labor Market Outcomes — Heterogeneity by Parental Income

	Below Median Parental Income				*Above Median Parental Income*			
Panel A	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma
GPA_luck	0.1019***	0.0185***	0.0120***	0.0039***	0.1048***	0.0200***	0.0098***	0.0029***
	(0.0025)	(0.0007)	(0.0012)	(0.0007)	(0.0025)	(0.0007)	(0.0012)	(0.0005)
Mean dep. var.	-0.018	0.042	0.863	0.953	0.224	0.285	0.887	0.974
N	59693	59693	59693	59693	59692	59692	59692	59692
Panel B	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE
GPA_luck	0.0005	0.0011***	0.1171	-0.0041	0.0006	0.0013***	0.1895	0.0070
	(0.0009)	(0.0002)	(0.1259)	(0.0068)	(0.0007)	(0.0002)	(0.1172)	(0.0065)
Mean dep. var.	0.924	0.875	32.418	2.880	0.963	0.913	36.165	3.179
N	59693	55129	55129	55129	59692	57470	57470	57470
Panel C	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)
GPA_luck	0.0005	0.0073*	0.0014	0.0053*	0.0003	0.0052	0.0004	0.0068**
	(0.0016)	(0.0038)	(0.0019)	(0.0030)	(0.0016)	(0.0037)	(0.0018)	(0.0030)
Mean dep. var.	0.827	12.316	0.746	12.656	0.809	12.379	0.733	12.707
N	55129	45607	55129	41106	57470	46516	57470	42111

NOTE: The table reports similar results as Table 1 separately on the sub-sample of students whose parental income is below the sample median (left panel), and on the sub-sample of students whose parental income is above the sample median (right panel). Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A9: Effect of the Instrument on Educational and Labor Market Outcomes — Heterogeneity by Parental Education

	Below Median Parental Education				*Above Median Parental Education*			
Panel A	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma	Exam grades in 3rd year	High School GPA in 3rd year	On time HS diploma	Ever HS diploma
GPA_luck	0.1060***	0.0195***	0.0130***	0.0043***	0.1006***	0.0190***	0.0091***	0.0023***
	(0.0026)	(0.0007)	(0.0013)	(0.0008)	(0.0025)	(0.0007)	(0.0012)	(0.0005)
Mean dep. var.	-0.107	-0.043	0.851	0.949	0.317	0.375	0.899	0.979
N	60280	60280	60280	60280	59105	59105	59105	59105
Panel B	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE	Ever higher education	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE
GPA_luck	0.0013	0.0012***	0.2855**	-0.0008	-0.0002	0.0012***	0.0284	0.0039
	(0.0010)	(0.0002)	(0.1199)	(0.0068)	(0.0006)	(0.0002)	(0.1210)	(0.0065)
Mean dep. var.	0.916	0.868	30.766	2.800	0.971	0.920	37.759	3.257
N	60280	55203	55203	55203	59105	57396	57396	57396
Panel C	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)
GPA_luck	-0.0008	0.0085**	0.0008	0.0062**	0.0015	0.0046	0.0010	0.0063*
	(0.0015)	(0.0037)	(0.0018)	(0.0027)	(0.0017)	(0.0038)	(0.0019)	(0.0032)
Mean dep. var.	0.843	12.338	0.765	12.680	0.794	12.358	0.715	12.684
N	55203	46525	55203	42207	57396	45598	57396	41010

NOTE: The table reports similar results as Table 1 separately on the sub-sample of students whose parents have a below sample median level of education (left panel), and on the sub-sample of students whose parents have an above sample median level of education (right panel). We define parents' level of education as the average completed grade level between the father and the mother. Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A10: A Re-estimation of the Effect of High School GPA on Annual Earnings using a Rescaled Instrument

	First stage: high school GPA in 3rd year	Reduced form: Annual labor income 8 years after the exams (log)	2SLS: Annual labor income 8 years after the exams (log)
Rescaled GPA_luck	0.0037***	0.0018**	–
	(0.0002)	(0.0007)	
High school GPA in 3rd year	–	–	0.4967**
			(0.1968)
Mean dep. var.	0.214	12.692	12.692
N	86554	61263	61263

NOTE: The Table shows the results of using a rescaled version of the $GPA\_Luck_{i,c}$ instrument, i.e., $GPA\_Luck_{i,c}$ divided by the the variance of $GPA\_Luck_{i,c}$ across all possible draws c. We remove individuals for which the variance is below 0.01 from the working sample. The first column refers to the first stage impact of the rescaled instrument on high school GPA, the second column refers to the reduced-form impact on annual earning eight years after the exams and the last column refers to the corresponding 2SLS. Each regression includes a set of baseline demographic controls, as well as high school and year fixed effects. Standard errors clustered at the high school-by-year level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.