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Impressum:

CESifo Working Papers

ISSN 2364-1428 (electronic version)

Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH

The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute

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Editor: Clemens Fuest

<https://www.cesifo.org/en/wp>

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Getting Lucky: The Long-Term Consequences of Exam Luck

Abstract

This paper studies the impact of exam luck on individuals' education and labor market success. We leverage unique features of the Norwegian education system that produce random variation in the content of the exams taken by students at the end of high school. Lucky students take exams in subjects they are better at, and we show that this generates significant improvements in both their high school GPA and diploma probability. Subsequently, exam luck generates substantial and persistent wage differentials across otherwise identical individuals. These luck-induced wage effects are of a similar magnitude as those generated by well-known education inputs, such as parental education and teacher quality.

JEL-Codes: D630, H520, I210, I230, I240, I260, J240, J310.

Keywords: luck, fairness, wage differentials, returns to education, high-stakes exams.

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This project received financial support from the Research Council of Norway through its Centers of Excellence Scheme, FAIR project no. 262675, and from the NORFACE projects GUODLCCI and HuCIAW. The authors would like to thank Kjell Salvanes, Joshua Goodman, Michael Lovenheim, Richard Murphy, Martin Eckhoff Andresen, and Analisa Packham, as well as participants at the FAIR VirtualWorkshop on the Economics of Education and seminar participants at CREST, for helpful discussions.

1 Introduction

Standardized screening and assessment tests are used frequently across the globe, both in the education sector and the labor market. These tests are designed to provide an objective measure of ability, and are heavily utilized for decisions related to university admission, internships, occupational licensing, and entrance into prestigious occupations. Performance on these tests therefore has important and lasting consequences not only for individuals' professional lives, but also for economic growth and efficiency. However, performance on test day depends on several factors that are difficult to control, and test results do therefore not necessarily provide an accurate reflection of an individual's ability. Consequently, individuals with identical skills and abilities can end up with meaningfully different scores simply due to luck.

A primary source of luck in standardized screening and assessment tests is the assignment of questions or topics. Specifically, only a small subset of all possible questions are asked on an exam, and individuals with the same underlying ability may score differently depending on which questions are asked or which topics are tested. Lucky individuals will be asked questions on topics they are most comfortable with, and unlucky individuals will be asked questions on topics they know very little about. This luck component is likely particularly important in high school exit exams, as the results on these exams not only determine if students graduate from high school and become eligible for university, but also influence the high school GPA with which students apply to university (conditional on graduation).

Luck-induced variation in high school exit exams may have detrimental consequences for the individuals who end up being unlucky. In addition, it may have adverse effects on the allocation of talent across occupations, with negative effects on productivity. Understanding the extent and magnitude of the luck components in high school exit exams—and its effect on individual students—is therefore of great importance, as much from the point of view of social justice as from the point of view of economic efficiency. However, little is known about the role of luck and its two key components (i.e., the diploma component and the GPA component) on high school exit exams. Empirically, it is an extremely challenging set of questions to address, because it requires a setting in which high school students with identical underlying ability are randomly assigned to different high school exit exams (or exposed to different exam questions) that are more or less aligned with their academic strengths. In addition, it requires an institutional context in which such luck-induced variation does not affect the probability of obtaining a high school diploma and the probability of obtaining a high GPA in exactly the same way, such that the effects of the two components can be separately identified.

In this paper, we directly address these questions by exploiting features of the Norwegian education system that produce random variation in the exams taken by students at the end of high school. In the Norwegian context, the final evaluation of a student is based not only on teacher grades, but also on the grades obtained on a set of externally set and assessed written and oral exams that are randomly drawn from the courses that students take. These exams generate exogenous variation in the probability of obtaining a good GPA as well as in the probability of obtaining a high school diploma across otherwise identical individuals. From the point of view of GPA, a good draw is a draw that exposes students to exams in courses they are relatively strong in. From the point of view of graduation, a good draw is primarily one that minimizes the risk of receiving a failing grade in a subject, since graduation requires that one has no failing grade. One interesting feature of this setting is that one draw of exams may be better than another draw from the point of view of obtaining a good GPA, but not from the point of view of obtaining a high school diploma and vice versa.

We use these features of the Norwegian education system to construct and separately identify the effects of two luck components that depend exclusively on the random draw of exams—one designed to predict students' GPA and one designed to predict students' probability of earning a high school diploma at the end of the school year. Exploiting rich population-wide administrative data covering the universe of Norwegian students and much of their demographic, education, and labor market information, we examine the impact of our two luck measures on high school performance, college enrollment and performance, and long-term labor market outcomes. Our estimates rely on the assumptions that the measures of GPA luck and diploma luck are uncorrelated with other characteristics that predict student outcomes. We provide strong support for these assumptions; using extensive balance tests, we find that both luck components are unrelated to students' baseline characteristics (as measured in pre-assignment years).

Our analysis generates four key results. First, both luck components have a substantial impact on students' high school outcomes, demonstrating that exam luck can have an important effect on educational performance. Second, GPA luck has significant effects on the number and quality of higher education programs that are available to students at the end of high school. Third, we find that GPA luck has persistent impacts on students' longer run outcomes. Eight years after the exams, increases in this luck component produce increases in market wages that are similar to those induced by critical inputs into the education production function, such as parent education or teacher quality. The diploma luck component also has positive effects on students' longer run outcomes, but they tend to be weaker than those of the GPA luck components and only marginally significant. The effects of GPA luck are equally strong

for low-ability and high-ability students. This luck component enables students to enter more selective universities, meet peers of higher academic standing, and make academic choices that are more in line with their aspirations.

Finally, under the assumption that exam luck affects students' long-term outcomes only through its effects on high school diploma probability and high school GPA, it is possible to use an instrumental variable design to separately estimate the effects of high school graduation and GPA on students' outcomes. This analysis reveals that both credentials have a very large impact on earnings. In particular, we find that a one standard deviation increase in high school GPA is associated with a 36% increase in high school graduates' earnings, eight years after the end of high school. This finding is consistent with the recent literature on the decisive role played by field of study choice in college (Bleemer and Mehta, 2022; Hastings, Neilson and Zimmerman, 2013; Kirkeboen, Leuven and Mogstad, 2016).

Overall, the results from our analysis demonstrate that random variation in high school exit exam scores generates long-term differences between individuals with the same initial level of ability, consistent with the idea that using high-stakes tests as a selection device is generally sub-optimal in terms of equity and fairness. However, when we compare the impact of exam luck on lucky and unlucky students, we find no evidence that students lose more by being unlucky than they gain by being lucky. Specifically, the reallocation of students to academic programs induced by exam luck does not appear to generate more losses than gains in terms of skill accumulation and wages.

Our paper contributes to the long-standing literature that explores the role luck plays in social and economic success (e.g., Audas, Barmby and Treble, 2004; Bertrand and Mullainathan, 2001; Frank, 2016; Jenter and Kanaan, 2015). The most studied form of luck is the birth lottery that allocates genes and early social environments to individuals (e.g., Black and Devereux, 2011; Mogstad and Torsvik, 2021). This birth lottery can be seen as an example of the "brute luck" that is randomly distributed to individuals throughout their lives (Dworkin, 1981), and many social policies are designed to counteract this form of luck and level the playing field (e.g., Cappelen et al., 2013; Konow, 2000).¹ One of the contributions of our paper is to show that the "brute luck" that inevitably determines the results of high-stakes exams can have long-run effects of the same order of magnitude as those of the birth lottery: a one SD difference in our measures of GPA luck generates differences in students' labor market outcomes that are not much different from the improvements generated by about 0.7 of a SD increase in paternal education (or by 0.5 of a SD increase in maternal education). Identifying and measuring the role of luck is all the more

¹Dworkin (1981) introduced the distinction between "brute luck" and "option luck", where option luck results from deliberate gambling choices.

important because the perception of its role determines people's attitudes towards redistribution and taxation (e.g., [Alesina, Stantcheva and Teso, 2018](#); [Lefgren, Sims and Stoddard, 2016](#)).

Our paper also advances the burgeoning body of research examining the importance of exogenous shocks to the conditions under which high-stake exams are taken. So far, the literature has focused on the external conditions prevailing on the day of the test, 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, 2020](#)). In addition, three papers have used the specific structure of Norwegian exams to study the effect of exam preparation ([Bensnes, 2020](#); [Falch, Nyhus and Strøm, 2014](#)), or the effect of exam format ([Andresen and Løkken, 2020](#)). Similar to our setting, all these papers generally find that student performance is affected by exam conditions. However, our paper focuses not on the external conditions of the exam (or in the period leading up to the exam), but on another fundamental source of randomness, namely the content of the exams themselves. This source of randomness is different in nature, especially since it cannot be easily remedied by harmonizing exam preparation and exam format; it is at work in all outdoor conditions, in all climates, and can affect all students equally, whether or not they have health problems. We also complement this literature by simultaneously examining the two main channels through which test-taking may affect students' outcomes—the diploma channel and the GPA channel.

Our paper also contributes to, and complements, the literature on the effects of high school GPA and high school graduation on student's later-in-life outcomes. There is a well-established strand of education research that has identified a strong correlation between students' high school GPA and their subsequent performance, but it is still not clear whether these correlations should be interpreted as causal (e.g., [Black, Cortes and Lincove, 2016](#); [Cohn et al., 2004](#); [Cyrenne and Chan, 2012](#); [French et al., 2015](#)). Also, it is not completely clear whether what matters is the impact of the high school GPA on the probability of high school graduation or the impact of the high school GPA on the range of academic programs that students can choose from when they enter university. Using random variation in the contents of exams as a source of identification, our findings suggest that both channels matter. Specifically, for high school graduates who go to university, a higher GPA at the time of entry into university appears to be a decisive factor in later career success, most likely because it increases the possibility of specializing in one's preferred fields. For those who do not go to university, high school graduation in itself is found to be a very important factor in access to better-paid jobs.

The rest of this paper is organized as follows: In Section 2, we provide an overview of the education

system in Norway, as well as detailed information about the randomized exams that students take during high school; In Section 3, we introduce our data, discuss our sample, and outline our empirical method; In Section 4, we present the main results from our analysis, explore mechanisms, and provide a rich set of robustness tests and sensitivity analyses; In Section 5, we conclude and discuss policy recommendations.

2 Background

2.1 The Norwegian Education System

The Norwegian education system consists of 10 years of compulsory school starting the year children turn 6. Upon successful completion of compulsory school, all children have the right to attend 3 to 4 years of high school. Even though 95% of students choose to enroll in high school, only 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: a three-year academic track which provides students with direct access to higher education, and a four-year vocational track (two years in school followed by a two-year apprenticeship period) 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. As very few vocational track students pursue higher education, this paper will focus on high school students who are enrolled in the academic track.

A range of universities and colleges offer higher education in Norway, and the majority of these are tuition-free public institutions. Eligibility for admission to these institutions is conditional on graduating from high school. The Norwegian Universities and Colleges Admission Service coordinates the admission process. Students apply to specific programs 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 there is for a specific university, the higher is the minimum GPA required to gain admission to that university.

2.2 High School GPA, High School Diploma, and Randomized Exams

In the Norwegian context, a higher GPA provides access to a larger set of universities, and to higher quality universities. High school graduation and high school GPA are thus two decisive outcomes for

²There are also a few bonus points (related to factors such as age, gender, and military service experience), but the main determinant is the GPA. For more details, see [Kirkeboen, Leuven and Mogstad \(2016\)](#).

high school students. In this subsection, we describe how they both depend not only on course grades, but also on grades obtained from randomized external exams taken throughout high school.

The exam subjects are chosen randomly, take place at the end of each school year, 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. Before 2008, the composition of 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 oral exams are locally designed and graded, the written exams are centrally designed and graded.

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. The exams account for approximately 20% of the total number of elements that make up the GPA. Exams and courses are graded on a scale from 1 (worst) to 6 (best), where 1 constitutes a failing grade.

Successful graduation from academic high school, and eligibility for higher education, requires that the student passes all high school courses. This means that a student does not qualify for higher education in the event of receiving a grade of 1 in any of her courses. However, there is an exception to this rule that relates to a situation in which 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 can receive a high school diploma and become eligible to enroll in higher education.

The selection of students into randomized exams therefore impacts students in two distinct ways. First, it impacts their diploma probability. Second, it impacts their high school GPA. However, it is not the same criterion that determines high school diploma and high school GPA; diplomas are awarded based on the absence of failed courses (subject to the exception mentioned above) while GPA is a linear function of course grades and exam grades. In this context, a draw of exams may be good from the point of view of graduation, but not from the point of view of high school GPA, and vice versa.⁴ It is this unique

³Even if the delay is short, students can use these few days to prepare for exams (Bensnes, 2020). This can have the effect of mitigating the impact of being lucky (or unlucky) in the draw on subsequent exam results.

⁴For example, for students who receive a failing grade in one of the courses they are relatively weak in, being drawn to take

feature of the Norwegian education system that will enable us, for the first time, to separately identify the effect of high school GPA luck and high school diploma luck on students' subsequent outcomes.

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](#)).⁵ To avoid sample selection problems, we abstract away from randomized exams in the first two years of high school, and focus exclusively on the exams in the third and final year. As oral exams are locally set and graded, we also abstract away from the oral exams and focus only on the random draw of written exams.

3 Data and Method

3.1 Data

Our data come from national population-wide registers covering all Norwegian residents who were enrolled in the final year of high school between 2003 and 2009. A unique personal identifier enables us to follow 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. We obtain demographic characteristics from the central population register, we collect education information from the national education register, and we use income information from the tax register.

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.

With respect to labor market information, we have detailed information on both income as well as 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 leave and unemployment benefits). Employment status (employed, unemployed, and not in the labor force) is defined based on the individual's status in the employment register. In our

an exam at the end of the year in that subject is excellent from a graduation standpoint (because it gives the opportunity to erase the fail grade), but bad from a GPA standpoint (because they are relatively weak in this subject).

⁵For 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 GPA due to the reform exerted more effort and performed better in subsequent years.

analysis, we focus on employment and income eight years after high school graduation. Data limitations prevent us from exploring longer-term outcomes.

Concerning background characteristics, we have access to information on compulsory school GPA, age, sex, and municipality of residence. By exploiting unique family identifiers in the Norwegian registers, we are also able to link students to their parents and collect information on parents' age, educational attainment, and earnings.

3.2 Construction of Luck Variables

We use the unique setting in the Norwegian education system to construct two random variables that depend exclusively on the random draw of exams—one that is designed to predict students' final GPA and one that is designed to predict students' probability of completing high school. Both variables are constructed in the spirit of [Borusyak and Hull \(2020\)](#). These variables enable us to separately identify the effect of high school diploma luck and high school GPA luck on students' short- and long-term education and labor market outcomes, while taking into account that students face different exam lotteries depending on their baseline ability and course selection.

GPA Luck. To construct our GPA luck variable ($Luck_{GPA_i}$) we first generate, for each student i and course s , a measure of the score that student i can expect on an exam in subject s ($Exam_{i,s}^e$). We define $Exam_{i,s}^e$ as the average score obtained on the end-of-year exam in subject s by students (other than student i) who attended the same high school as student i , earned the same teacher assessment in the course on subject s as student i , and were randomly assigned to an exam in subject s . The underlying assumption is that teachers' assessments are good predictors for their students' exam results.

Building on this set of expected exam results, we then construct—for each student i and each possible combination (c) of exams⁶—a measure of the GPA that student i can expect if randomly assigned to that combination c of exams:

$$GPA_{i,c}^e = \frac{1}{S + K} \left(\sum_{s \in S} Course_{i,s} + \sum_{s \in c} Exam_{i,s}^e \right), \quad (1)$$

where S and K are the number of courses and exams that student i takes, and $Course_{i,s}$ is the score that student i obtained from the teacher's assessment on course s . The expected total number of grade points is in parentheses. The first sum is the number of grade points from teachers' course assessments

⁶A 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.

across all courses that the student takes. The second sum is the expected number of grade points from the randomly-assigned exams.

After constructing $GPA_{i,c}^e$ for each student i and possible exam combination c , we subtract its average across all possible combinations c and scale the resulting difference by the standard deviation of its distribution across all possible combinations c .⁷ This allows us to define a normalized version of the variable $GPA_{i,c}^e$, which harmonizes the measure of luck in the student population. Specifically, denoting $c(i)$ the specific combination of exams that student i is randomly assigned to, we define our luck GPA variable as the value taken by the normalized version of $GPA_{i,c}^e$ when $c = c(i)$:

$$Luck_{GPA_i} = \frac{GPA_{i,c(i)}^e - \overline{GPA_i}}{SD_i(GPA)}. \quad (2)$$

Diploma Luck. In Norway, at the end of each course, students receive a grade between 1 and 6 from their teachers. To graduate from high school and become eligible for higher education, a student must earn a minimum teacher grade of 2 in each course, except in courses that are randomly selected for an end-of-year exam. In these courses, students must earn a minimum grade of 2 in the end-of-year exam, and the teacher grade does not matter for passing the course. Put differently, when a student has a “fail” status from the course grade and a “pass” status from the end-of-year exam, the “pass” status from the end-of-year exam trumps the “fail” status from the course grade. Conversely, the “fail” status from an end-of-year exam trumps the “pass” status from a course grade.⁸

To define our diploma luck variable ($Luck_{Diploma_i}$), we first construct, for each student i and course s , a measure of the probability that student i obtains a “pass” grade (i.e., a grade of 2 or more) on the final exam in subject s ($D_{i,s}^e$). Specifically, we define $D_{i,s}^e$ as the proportion of students who obtained a “pass” on the final exam in course s among students (other than student i) who take a final exam in course s and who earned the same teacher assessment as student i in course s . Building on this set of measures, we then construct—for each student i and possible combination of exams c —a measure of the high school diploma status that student i can expect if randomly assigned to that combination c of exams:

$$Diploma_{i,c}^e = \prod_{s \notin c} \mathbb{1} \{Course_{i,s} > 1\} \times \prod_{s \in c} D_{i,s}^e. \quad (3)$$

⁷For each student i , the average value and standard deviation of $GPA_{i,c}^e$ across all possible c is given by $\overline{GPA_i} = \sum_{c \in C} P_c \times GPA_{i,c}^e$ and $SD_i(GPA) = \sqrt{\sum_{c \in C} P_c (GPA_{i,c}^e)^2 - (\overline{GPA_i})^2}$. P_c is the probability of drawing a particular combination of exams as measured by the fraction of all students who draw that combination. As discussed in Section 2, not all subjects are used for the end-of-year exams, and some subjects have a higher probability of being drawn than others.

⁸As noted in Section 2, the randomization of students to exam subject is delegated to the municipality. Thus, students cannot simply choose to opt into an exam for a certain subject once they have realized they are failing a course.

The first product is equal to 1 if the student passed all courses for which they were not randomly assigned an end-of-year exam, where passing is earning a teacher assessment of 2 or more. The second product is the probability that the student earns a two or more on all exams they were randomly assigned in. A student earns a high school diploma if they pass all exams, and if they pass all courses for which they were not randomly asked to take an exam.

After having constructed $Diploma_{i,c}^e$ for each student i and possible combination c , we subtract its average across all possible combinations c and scale the resulting difference by the standard deviation of its distribution across all possible combinations c .⁹ This allows us to obtain a normalized version of $Diploma_{i,c}^e$, which enables us to compare students with different portfolios of courses and different academic abilities. Denoting the specific combination of exams that student i is randomly assigned to as $c(i)$, we define our luck diploma variable as the value taken by the normalized version of $Diploma_{i,c}^e$ when $c = c(i)$:

$$Luck_{Diploma_i} = \frac{Diploma_{i,c(i)}^e - \overline{Diploma_i}}{SD_i(Diploma)} \quad (4)$$

3.3 Sample Selection and Descriptive Statistics

Our analysis includes all regular full-time students enrolled in the academic high school track for the first time between 2003-2004 and 2009-2010 (about 135,000 individuals). We exclude students for whom the exam draw generates no variation in their GPA or probability of graduation, either because there is only one possible draw of written exams (about 30,000 individuals) or because there is no variation in our luck measures across possible draws (about 12,000 individuals). This provides us with a working sample of approximately 92,000 students.¹⁰

Table 1 provides descriptive statistics on all individuals in our analysis sample. The table shows that 88% of the sample earn a high school diploma on time, 97% eventually earn a high school diploma, and 94% start college. 83% are ever employed, and 75% are employed eight years after the end of their third year of high school. Conditional on having earnings, log earnings in the first job are 12.3 NOK (approximately 220,000 NOK) and log earnings eight years after taking 3rd year exams are 12.7 NOK (approximately 330,000 NOK).

⁹For each student i , the average value and standard deviation of $Diploma_{i,c}^e$ across all possible c are given by $\overline{Diploma_i} = \sum_{c \in C} P_c \times Diploma_{i,c}^e$ and $SD_i(Diploma) = \sqrt{\sum_{c \in C} P_c (Diploma_{i,c}^e)^2 - (\overline{Diploma_i})^2}$. P_c is the probability of drawing a particular combination of exams as measured by the fraction of all students who draw that combination.

¹⁰In Subsection 4.6 we show that our results are robust to including students with no variations in their GPA or diploma probability.

Appendix Figure A1 shows the distribution of our luck measures. Both measures follow a Gaussian-like distribution and, as expected, they appear to be evenly distributed around zero. In the remainder of the paper, we winsorize the top and bottom 0.1% of our luck measures to ensure that our results are not driven by a few outliers.¹¹ Our two luck measures are positively correlated, but this correlation is far from perfect (0.4) and $Luck_{Gpa}$ only explains about 17% of the variation in $Luck_{Diploma}$. In this context, it is possible to simultaneously investigate the role of $Luck_{Gpa}$ and $Luck_{Diploma}$ for students' subsequent outcomes.

3.4 Empirical Method

After constructing our luck variables for high school diploma and high school GPA, we leverage these variables to estimate the impact of high school diploma luck and high school GPA luck on students' short- and long-term education and labor market outcomes. Specifically, denoting Y_i the outcome of individual i , we estimate versions of the following regression model:

$$Y_i = \alpha + \beta_1 Luck_{GPA_i} + \beta_2 Luck_{Diploma_i} + \eta_l + u_t + X_i\gamma + \epsilon_i, \quad (5)$$

where $Luck_{Gpa_i}$ and $Luck_{Diploma_i}$ represent our GPA and diploma luck variables while η_l and u_t represent a full sets of high school and year fixed effects. Equation 5 also contains a rich set of demographic controls (X_i). They 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. In Section 4, we show that our results are robust to using alternative sets of demographic controls. Standard errors are clustered at the high school-by-year level (i.e., the level of random assignment).

The coefficients of interest in Equation 5 are β_1 and β_2 . They measure the impact of high school GPA luck and high school diploma luck, respectively. They are identified under the assumption that the luck variables are uncorrelated with unobserved determinants of students' outcomes (ϵ_i). In theory, the validity of this assumption follows directly from the fact that the two luck variables only depend on the combinations of exams to which students are assigned in each high school, which is random by design. In practice, it is possible to obtain suggestive evidence on the validity of this assumption by examining if the two luck variables are correlated with observed determinants of student outcomes (as measured in pre-assignment years). To this end, Table 2 shows results obtained from separately regressing the

¹¹In Subsection 4.6, we show that our results are robust to not winsorizing and to using unscaled versions of $Luck_{Gpa}$ and $Luck_{Diploma}$.

two luck variables on the grades assigned to students by teachers during the academic year (high school course grades), the grades assigned to students by teachers and their exam grades at the end of middle school (middle school GPA), and numerous sociodemographic variables (students' age and gender as well as parents' average age, education, and income). We also include the square term of each of the continuous variables.

Consistent with the random assignment assumption, the results in Table 2 demonstrate that there is very little correlation between the luck variables and observed student characteristics as measured in pre-assignment years. Specifically, none of the regression coefficients are statistically significant at the 10% level and none of them are economically meaningful. For both regressions, conventional F-tests cannot reject that the estimated coefficients are jointly equal to zero.

4 Results

In this section, we present and discuss results on how exam luck affects students' short- and long-term education and labor market outcomes. In Section 4.1 we explore high school outcomes; in Section 4.2 we examine higher education outcomes to disentangle the channels through which exam luck may impact career trajectories; and in Section 4.3 we look at labor market outcomes. Following students from high school into the labor market enables us to trace the full effect of exam luck on students—from the immediate impact on exam grades to the long-run impact on labor market earnings—and provides us with a rich understanding of how exam luck impacts the human capital accumulation and labor market trajectory of students. In Section 4.4, we present results from an IV analysis where we use exam luck as a source of identification for the causal effect of students' high school GPA and graduation outcomes on their subsequent labor market outcomes. In Section 4.5, we explore effect heterogeneity across student gender and ability. In Section 4.6, we document the robustness of our results to a range of falsification tests and sensitivity analyses. Lastly, in Section 4.7 we explore the asymmetry of exam luck effects to assess whether luck in exam content induces inefficiencies in the allocations of students across universities.

4.1 High School Outcomes

The effect of exam luck on high school outcomes are shown in Table 3. The primary high school outcomes we examine are the students' exam grades (column (1)), the students' GPA for the third year of high school (column (2)), a dummy variable indicating if the students receive on-time high school

diplomas (column (3)), and a dummy variable indicating if the students ever receive high school diplomas (column (4)). Given the way our luck variables are constructed, we expect the first two outcomes to be impacted first and foremost by our GPA luck variable and the last two outcomes by our diploma luck variable.

The results in Table 3 are very much in line with our expectation. The first two columns reveal that both measures of luck have a statistically significant and economically meaningful effect on students' exam grades and high school GPA, but that the effect of GPA luck is larger than the effect of diploma luck. For example, the result in column (1) reveals that a one SD increase in GPA luck leads to a 10% of a standard deviation increase in students' exam grades while a one SD increase in diploma luck only generates a 4% of a standard deviation increase in exam grades. The impact of GPA luck on students' high school GPA is also considerably larger than the impact of diploma luck. This last result means that GPA luck directly impacts the metric with which students apply to university and college, and that it may have important implications on individuals' careers not only in the short-run, but also in the long-run.¹² We explore this in greater detail below.

In terms of on-time diploma receipt, the results in column (3) show that both GPA luck and diploma luck causally impact students' probability of obtaining an on-time high school diploma. However, as expected, the impact of the diploma luck component is now larger than that of the GPA luck component, with a coefficient that is about two times larger. Again, this is expected, as the diploma luck variable is designed to predict students' probability of earning a high school diploma at the end of the school year, while the GPA luck variable is designed to predict students' GPA. In terms of magnitudes, a one SD improvement in diploma luck leads to a 1.1-percentage point increase in the probability of receiving an on-time high school diploma, while a one SD increase in GPA luck leads to a 0.5-percentage point increase in the probability of on-time diploma receipt.

Finally, the results in column (4) show that the effect on on-time diploma receipt extend to ever receiving a high school diploma as well. However, the magnitude of the effect is smaller, which 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.

¹²The high school GPA which is used to apply to universities and colleges includes teacher and exam grades during the three years of high school. As we only have GPA data available from year 2003, we are unable to calculate the entire high school GPA for the oldest cohorts of our sample. Using the cohorts 2005-2009, we nevertheless checked that $Luck_{GPA}$ impacts the overall high school GPA (+1% of a SD, significant at the 1%), and the overall high school GPA taking into account course retaking (+1% of a SD, significant at the 1%).

4.2 Higher Education Outcomes

The effects of high school exam luck on higher education outcomes are shown in Table 4. The primary outcomes we explore in this section are a dummy indicating if the students receive any college education (column (1)), the share of higher education programs that their GPA make available to them (column (2)), the selectivity level of the first higher education program in which students can enroll (column (3)), and the number of completed years in higher education (column (4)). While the results in column (1) provide us with information on the extensive margin effect of high school exam luck on higher education outcomes, the results in columns (2) and (3) provide measures for the set of choices available to students, and for the education quality that students are exposed to in college (conditional on going to college).

The results displayed in column (1) suggest that diploma luck has a small (marginally significant) impact on the college enrollment decisions of individuals. Specifically, a one SD increase in the diploma luck variable yields a 0.2-percentage point increase in the probability of receiving some college education. The GPA luck variable, on the other hand, has no effect on the decision of attending college. This result is consistent with our priors, as the diploma luck variable has a much greater effect on the probability that students obtain a high school diploma (which improves students' chances of qualifying for college), while the GPA luck variable has a bigger impact on the GPA with which students apply to college (which improves students' chances of qualifying for better programs and colleges). As such, we would expect a larger extensive margin effect of diploma luck, and a potentially larger intensive margin effect of GPA luck.

In terms of education quality, the results in columns (2) and (3) demonstrate that the GPA luck variable has a sizable impact on both the share of higher education programs available to the students, and on the selectivity of the higher education program in which the students enroll. To construct these two outcome variables, for each program s in year t we consider the minimum GPA of the students enrolled in this program in year t : $Min_Gpa_{s,t}$.¹³ For each student i enrolling for the first time in higher education in t , the share of higher education programs available to him/her corresponds to the proportion of programs for which $Min_Gpa_{s,t}$ is below student i 's GPA: $Share_available_{i,t} = \frac{\sum_1^{S_t} \mathbb{1}\{GPA_{i,t} \geq Min_Gpa_{s,t}\}}{S_t}$, with S_t the number of higher education programs in year t . To define the selectivity levels, we ranked all higher education programs in year t based on their minimum student GPA ($Min_Gpa_{s,t}$). The selectivity level of student i 's first enrollment in higher education is then defined as the percentile ranking of the first higher education program in which he/she enrolls: $Selectivity_level_{i,t} = Percentile_ranking_{s(i),t}$. Column (2) shows that a one SD change in GPA luck shifts the share of higher education programs

¹³A program is defined as a field of study within a university.

available to the students by 0.15-percentage points. This indicates that GPA luck broadens the choice set of higher education programs. Column (3) further shows that a one SD change in GPA luck increases the selectivity of the higher education program in which students enroll by about 0.23 percentile ranks, meaning that students take advantage of the broader choice set of higher education programs offered to them and “upgrade” their college quality through admission into more selective fields of study and universities. By design, a better high school GPA also enables students to attend preferred programs and universities, i.e., programs and universities that students ranked higher when submitting their college applications. In this context, GPA luck may also enable students to attend programs and universities in which they have a comparative advantage (Kirkeboen, Leuven and Mogstad, 2016).

In terms of diploma luck, we do not detect any impact on the college quality dimension. However, it is important to note that the extensive margin effect of diploma luck identified in column (1) means that there are compositional changes in terms of who enters college as a function of this variable, and we must therefore be careful when interpreting the intensive margin quality effects of diploma luck in columns (2) and (3).

Finally, the results in column (4) demonstrate that there is no impact of GPA luck or diploma luck on the number of years completed in higher education. This has two important implications. First, it suggests that the quality upgrading that GPA luck contributes to is not offset by a potential reduction in educational attainment due to admission into more difficult schools and programs. Second, it implies that the enrollment effect generated by diploma luck is not permanent, in the sense that those who are induced to enroll because of diploma luck do not pursue higher education until they complete their degree. Taken together, this implies that GPA luck is more likely to impact students’ labor market outcomes once they have finished their education, as GPA luck has persistent effects on students’ trajectories in higher education. By contrast, the education effects of diploma luck on students’ high school diploma are partly offset by endogenous responses: students who fail to graduate on time due to bad luck at the exams take supplemental classes and manage to graduate later in time; and students who manage to enroll in higher education due to diploma luck drop out before obtaining additional degrees.

4.3 Labor Market Outcomes

Understanding the impact of exam luck on the short- and long-run educational attainments of students is of great independent value. However, we are ultimately interested in understanding to what extent these effects translate into meaningful changes in the labor market opportunities of students once they have completed their human capital investments. To this end, we follow the affected students into the

labor market and examine both their employment status as well as their earnings. These results are shown in Table 5. The data we have access to enable us to follow students up to eight years after they have taken their third year high school exams, and we use these data to study a range of outcomes: the probability of ever having been employed (column (1)), log annual labor income at the first job (column (2)), the probability of being employed eight years after taking the tests (column (3)), log annual labor income measured eight years after graduating from high school (column (4)), and individuals' percentile ranking in the distribution of wages eight years after the exams (column (5), the percentile rankings are cohort-specific).

In terms of extensive margin employment effects (columns (1) and (3)), the results show that neither diploma luck nor GPA luck has a significant effect on employment. With respect to earnings, the table shows that GPA luck has a sizable impact both on the annual labor income at the first job the students secure (+0.8%, column (2)), as well as on their annual labor income eight years after having taken their high school exit exams (+0.6%, column (4)). In the previous section, we found that GPA luck enables students to upgrade the selectivity of their enrollment in higher education by about 0.23 percentiles. In this context, we may wonder whether GPA luck also enables students to upgrade their position in the distribution of wages. Column (5) shows that this is the case: GPA luck shifts individuals' position in the distribution of wages by about 0.21 percentiles. Put it differently, we find that the gain in individuals' relative earnings is similar to their gain in the relative selectivity of their higher education enrollment.

With respect to diploma luck, we find that it too has a positive effect on the level of wages and on the rank in the wage distribution. However, these effects are weaker than those of GPA luck and only marginally statistically significant (the p-value of the effect on rank is 0.2). This suggests that GPA luck — through its impact on both graduation probability and higher education quality — is the main driver of the long-term effects of exam luck on earnings.¹⁴

To compare the wage differentials generated by exam luck to those generated by the birth lottery, we estimated the relationship between parental education and child's earnings. In our Norwegian sample, we find that a 1 SD increase in fathers' (mothers') years of education is associated with a 0.9% (1.2%) increase in children's annual labor income eight years after the exams. This suggests that GPA luck generates wage differences that are similar to those generated by a 66% (50%) SD increase in paternal

¹⁴The lack of an extensive margin employment effect suggests that the identified earnings effects of high school exam luck may be operating through a change in the type of job individuals hold or in the type of firm they work at. To examine this in more detail, we have studied the impact of exam luck on a number of key firm characteristics: the size of the firm, a dummy variable indicating if the firm is in the public or private sector, and the share of coworkers who have at least some college education (which can be thought of as a proxy for occupational quality). We find no evidence of differential sorting into the public sector or the size of the firm, but we find suggestive evidence that GPA luck has a positive impact on the quality of the coworkers individuals are exposed to (the effects are positive but only marginally significant).

(maternal) education.

To further put these effects in perspective, it is also possible to compare them with the labor market impacts of well-known education inputs analyzed in prior studies, such as teacher quality. [Chetty, Friedman and Rockoff \(2014\)](#) find that a one standard deviation increase in teacher value-added during one grade is associated with 1.3% higher annual earnings. Thus, luck at high-stakes high school exams has almost the same impact on students career trajectories as half of a standard deviation increase in teacher quality.¹⁵

4.4 The Causal Effects of High-School Credentials: IV Estimations

Assuming that our measures of luck influence students' subsequent outcomes only through their impact on diploma probability and high-school GPA, it is possible to use an instrumental variable approach to estimate the effects of high school graduation and high school GPA on students' long-term outcomes.

We begin this exercise by noting that GPA luck has no impact on the probability of entering university, but a very strong impact on high school GPA. It is therefore possible to identify the causal effect of high school GPA on the outcomes of individuals who enter university using only GPA luck as an instrument.

The results from this exercise is shown in column (1) of Table 6. The results show that high school GPA has a very large impact on the earnings of high school graduates. Specifically, a one standard deviation increase in high school GPA appears to generate a 36% increase in students' earnings eight years after the end of high school. This finding is consistent with the recent literature on the decisive role played by field of study choice in college ([Bleemer and Mehta, 2022](#); [Hastings, Neilson and Zimmerman, 2013](#); [Kirkeboen, Leuven and Mogstad, 2016](#)). For comparison, column (2) reports the result from an OLS estimation of the same parameter. The OLS impact of a one SD increase in GPA on earnings appears to be only +12%. The difference between these IV and OLS estimates suggests a negative correlation between the unobserved determinants of high school graduates' performance on the labor market and the unobserved determinants of their high school GPA.

To push this analysis one step further, column (3) of Table 6 uses the full sample and provides the results when using both of our luck measures (and their interaction) as instruments to simultaneously identify the causal effects of high school graduation and high school GPA (conditional on high school graduation) on earnings eight years after the exams. The results confirm that high school GPA has an

¹⁵In addition to education and labor market outcomes, we have also examined the potential impact of exam luck on other fundamental societal outcomes that have been shown to be affected by education interventions in prior literature: teenage pregnancies and marital behavior. However, we find little evidence to suggest that these outcomes are impacted by exam luck. Results are available upon request.

economically meaningful and statistically significant effect on the earnings of high school graduates, and further suggest that high school graduation in itself has a very significant effect on earnings. Again, the IV estimates appear to be larger than the corresponding OLS estimates (column (4)), in line with the idea that unobserved determinants of performance in high school are negatively correlated with those of performance on the labor market.

Taken together, the results from this subsection point to sizable effects of high school credentials on students' long-run labor market outcomes, something that has important policy implications. In interpreting the results from our IV estimations, we reiterate, however, that they rely on an exclusion restriction which we are unable to examine directly. Specifically, we cannot rule out that luck on exams, in itself, has a direct effect on students' subsequent motivation and effort, with the consequence that our IV estimates may be biased (and perhaps overstate the effect of GPA and diploma status on later-in-life earnings).

4.5 Heterogeneity

In this section, we further probe the data and analyze potential heterogeneous effects of exam luck on the education and labor market outcomes of students by ability and gender.

The role of ability. Appendix Tables [A1](#) and [A2](#) show the main education and labor market effects stratified by students who are above or below median ability (as measured by the students' course grades). In terms of education outcomes (Table [A1](#)), we find suggestive evidence that the effects on diploma receipt load on students at the lower-end of the ability distribution, while the effects on exam grades and high school GPA are more equally distributed across high- and low-ability students. That individuals at the bottom of the ability distribution are more impacted by diploma luck than high ability students are consistent with the notion that high-ability students are generally not at risk of failing to obtain a diploma.

With respect to labor market outcomes (Table [A2](#)), we find an impact of GPA luck on individual labor earnings both among those who have above median ability as well as those who have below median ability. The size of the coefficients are relatively similar across the two groups, and we are unable to rule out equality of coefficients through conventional t-tests. Table [A2](#) further confirms that diploma luck does not translate into long-term wage gains, even when we focus on low-ability students (students who are the most likely to fail high school).

Gender differences. Appendix Tables [A3](#) and [A4](#) show the main education and labor market results separately for boys and girls. The main take-away from this table is that exam luck—whether in terms

of GPA luck or diploma luck—impacts boys and girls similarly. The one exception concerns diploma luck and on-time diploma receipt, where the effect is significantly larger for boys. Taken together, we interpret the results from these tables as indicating that there are minimal gender differences in the effect of high school exam luck on educational attainment and later-in-life labor market outcomes.

4.6 Robustness and Sensitivity

Parameters β_1 and β_2 in Equation 5 are identified under the assumption that the luck variables are uncorrelated with unobserved determinants (ϵ_i) of students' outcomes. The results in Table 2 provide strong suggestive evidence in favor of this assumption. In this section, we probe the data further and explore the robustness of our results to a number of sensitivity checks and falsification tests. All of these results are provided in Appendix Table A5.

In Panel A, we explore the sensitivity of our results to using control variables selected with the double lasso procedure of Belloni, Chernozhukov and Hansen (2014). The idea behind this exercise is to obtain a more objective set of control variables that are outside the researchers' control. The results in Panel A demonstrate that using the control variables recommended by the double lasso approach does not generate coefficients that are statistically different from our main findings. This suggests that the findings we present in the paper are not driven by the particular set of control variables we use.

In Panel B, we show the p-values obtained from two sets of (1000) permutation tests in which we have randomly assigned GPA or diploma luck values to students, holding the distribution of values of these luck variables constant. The first row shows p-values that measure the probability that randomly assigning GPA luck values to students will generate point estimates at least as large as our baseline estimates. The second row report p-values that measure the probability that randomly assigning luck diploma values to students will generate point estimates at least as large as our baseline estimates. If our results were picking up spurious correlation between the treatment variables and outcomes, we would expect these p-values to be large, but our permutation results provide clear evidence against this concern. In particular, only about 1% of the permutations for GPA luck generate wage coefficients of the same size as our main findings.

In Panel C, we relax the winsorization restrictions on our luck measures to ensure that our findings are not driven by the way in which we restrict the range of luck values. This panel demonstrates that our results are unaffected by this adjustment.

In Panel D, we use unscaled luck measures. To ensure the comparability of the point estimates to our main specification, we standardize the luck measures by the average standard deviations in the sample:

$\frac{\sum_1^N SD_i(GPA)}{N}$ and $\frac{\sum_1^N SD_i(Diploma)}{N}$. This panel shows that our results are robust to the choice of rescaling specification.

In our main specification, we exclude students whose GPA or diploma probability are unaffected by the random draw of exams. To show that our results are robust to this sample selection, Panel E shows our main results when we include these students. This panel demonstrates that our results are largely insensitive to including or excluding the students who are unaffected by the random draw of exams.

Individuals with a failing course grade (i.e., a teacher grade of 1) may be systematically different from students without a failing course grade. In particular, the luck measures we have constructed may impact these students differently. To ensure that our results are robust to eliminating this subset of students, we re-estimate our main results using only those students who do not have a failing course grade. Panel F presents these results, and shows that our findings are robust to this restriction.

Taken together, we interpret the evidence in Appendix Table A5 as providing strong additional support for our identifying assumption, thereby reinforcing the credibility of a causal interpretation of our findings.

4.7 Good Luck versus Bad Luck

The luckiest students have better GPAs and the opportunity to apply to a wider range of university programs. They crowd out students who performed better than them on the continuous in-class assessment during the school year, but were unlucky on end-of-year high-stake exams. The substitution of lucky students for unlucky ones can be socially inefficient if luck leads the lucky ones to choose programs that are too difficult for them while unlucky students are forced to major in fields that are not their preferred ones, that motivate them less, and where they perform less well.

In the end, an important question is whether individuals gain as much from being lucky as they lose from being unlucky. If, for example, moving from $Luck_{GPA} = 0$ to $Luck_{GPA} = +L$ ends up having no effect on skills accumulation and wages while moving from $Luck_{GPA} = 0$ to $Luck_{GPA} = -L$ has a significant negative effect, it will clearly suggest that the random noise component of rankings induced by exam luck is a source of economic inefficiency.

If $Luck_{GPA}^+ = \max(0, Luck_{GPA})$ denotes the positive component of $Luck_{GPA}$ and $Luck_{GPA}^- = \min(0, Luck_{GPA})$ its negative component, the question boils down to whether increases in $Luck_{GPA}^+$ have the same effects on outcomes as increases in $Luck_{GPA}^-$. In other words, do we gain as much from being more lucky as from being less unlucky? The most direct way to test this type of hypothesis is to regress the different dependent variables of interest simultaneously on the sum and the difference of

$Luck_{GPA}^+$ and $Luck_{GPA}^-$: the regression coefficient of the sum identifies the average effect of the two variables while the regression coefficient of the difference identifies the half difference of their effects.¹⁶ In this set up, testing for the absence in differential effects between the two variables amounts to testing that the regression coefficient associated with their difference is negligible.

Table 7 shows the result from this exercise using students' GPA, their high school completion probability, the range of their university choices, and their wages as dependent variables. Taken together, the results provide little support for the idea that there may be asymmetric effects of good and bad exam luck. Specifically, we do not detect any significant asymmetry between what one gains from being lucky and what one loses from being unlucky.

The fact that the lucky students gain as much as the unlucky ones lose is consistent with the idea that what matters is not so much the difficulty of the programs students can access to, but the degree to which these programs match their aspirations. In this regard, the lucky students seem to gain about as much as the unlucky ones lose.

5 Conclusion

There is a long-standing debate in the social sciences about the root causes of economic and social inequalities between individuals. The fundamental question is whether such inequalities reflect the fact that individuals make different choices, or that they are not all equally lucky; especially in terms of the family into which they were born and raised. In this paper, we contribute to this debate by showing that exam luck at key points in students' educational careers can have long lasting effects on individuals' outcomes, of the same order of magnitude as the effects of the "brute" luck that assigns them better or worse families.

To reach these conclusions, we rely on unique features of the Norwegian educational system that produces random variation in the content of the high school exit exams taken by students. These exams generate exogenous variation in the probability of obtaining a good GPA, as well as in the probability of obtaining a high school diploma across otherwise identical individuals. From the point of view of GPA, a good draw is a draw that exposes students to exams in courses they are relatively strong in. From the point of view of graduation, a good draw is primarily one that minimizes the risk of receiving a failing grade in a subject, since graduation requires that one has no failing grade.

¹⁶Because $Luck_{GPA} = Luck_{GPA}^+ + Luck_{GPA}^-$ and $|Luck_{GPA}| = Luck_{GPA}^+ - Luck_{GPA}^-$, it amounts to regressing the outcomes of interest simultaneously on $Luck_{GPA}$ and $|Luck_{GPA}|$. Also, for any regression coefficients α and β , it is not difficult to check that $(\alpha Luck_{GPA}^+ + \beta Luck_{GPA}^-)$ can be rewritten $\frac{\alpha+\beta}{2} Luck_{GPA} + \frac{\alpha-\beta}{2} |Luck_{GPA}|$.

We use these features of the Norwegian education system coupled with rich population-wide register data to construct and separately identify the effects of two luck components that depend exclusively on the random draw of exams—one that is designed to primarily affect students' GPA and one that is designed to primarily affect students' probability of earning a high school diploma at the end of the school year.

We find that both luck components have a highly significant impact on students' high school performance. In addition, the luck diploma component has a positive effect on the probability of entering college, while the GPA luck component has significant effects on the number and quality of higher education programs to which students are allowed to apply after high school.

The effects persist over time, especially those of the GPA luck component. Eight years after the exams, a one standard deviation increase in the GPA luck component yields increases in annual market wages that are similar to the effects of critical inputs in the education production function, such as teacher quality or parental education. In terms of mechanisms, we show that our results are consistent with the assumption that high school diploma and high school GPA are, as such, very important determinants of students' long-term outcomes, primarily through their effects on the quality of the higher education to which students have access.

Taken together, our findings suggest that luck can have an important impact on high-stakes test scores with very significant long-term consequences for all types of test-takers. These findings are of independent interest, but they also have important implications for the design of education systems. They show that by relying too heavily on high-stakes exams at a few key stages in students' educational careers, we run the risk of misclassifying a large number of students, resulting in an unfair allocation of students to different types of higher education programs and of young workers to different jobs and occupations. Our findings emphasize the importance of utilizing measures of student quality that are less random and subject to more frequent revision over time than those currently used in many countries.

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Table 1 – Summary Statistics

Variables	Mean	SD	Observations
Outcomes			
Exam grades in 3 rd year	0.092	0.925	92201
High school GPA in 3 rd year	0.128	0.846	92201
On time HS diploma	0.879	0.326	92201
Ever HS diploma	0.965	0.184	92201
Any college	0.944	0.230	92201
Share of available HE programs	0.894	0.128	87054
Selectivity of HE enrollment	34.585	29.870	87054
Number of completed years in HE	2.879	1.835	92201
Ever employed	0.827	0.378	92201
First job labor income (log)	12.302	0.847	76246
Position in the dist. of first job labor income	52.578	28.440	76246
Employed 8 years after the exams	0.751	0.432	92201
Labor income 8 years after the exams (log)	12.669	0.617	69267
Position in the dist. of labor income 8 years after the exams	51.621	28.644	69267
Demographics			
High school course grades	0.126	0.840	92201
Middle school GPA	0.115	0.917	92201
Female	0.555	0.497	92201
Age	19.035	0.355	92201
Parents' average age	48.275	4.733	92201
Parents' average years of education	13.992	2.466	92201
Parents' average log labor income	12.633	1.163	92201

NOTE: The table refers to the sample of students who enrolled for the first time in the final year of academic high school between 2003 and 2009, who took at least one course in a subject where they could be assigned to a written exam, and whose GPA and diploma probability are impacted by the random draw of exams. The table shows the means and standard deviations of the main outcome and baseline variables. Statistics on the share of available higher education programs and on the selectivity of students' higher education programs 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 2 – Balance Tests, Association between Luck and Baseline Characteristics

	Measures of Luck	
	GPA luck	Diploma luck
High school course grades	-0.0035 (0.0053)	0.0029 (0.0052)
High school course grades, squared	-0.0036 (0.0039)	-0.0036 (0.0038)
Middle school GPA	-0.0040 (0.0049)	-0.0060 (0.0050)
Middle school GPA, squared	-0.0008 (0.0025)	-0.0005 (0.0023)
Female	-0.0074 (0.0062)	-0.0098 (0.0061)
Age	-0.0035 (0.0390)	0.0078 (0.0394)
Age, squared	-0.0000 (0.0008)	-0.0002 (0.0008)
Parents' average age	0.0048 (0.0097)	0.0075 (0.0093)
Parents' average age, squared	-0.0000 (0.0001)	-0.0001 (0.0001)
Parents' average years of education	0.0060 (0.0120)	0.0013 (0.0114)
Parents' average years of education, squared	-0.0002 (0.0004)	-0.0001 (0.0004)
Parents' average log earnings	-0.0016 (0.0027)	0.0002 (0.0028)
F-statistic	0.917	0.905
Joint p-value	0.553	0.568
Mean	0.019	0.018
N	92201	92201

NOTE: The table refers to the same sample as Table 1. The first column shows the results of regressing our standardized measure of GPA luck on a set of baseline demographic characteristics. The second column shows the results of regressing our standardized measure of diploma luck on the same 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-tests of joint orthogonality control 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 3 – Effect of Luck on High School Outcomes

	Outcomes			
	Exam grades in 3 rd year	High School GPA in 3 rd year	On time HS diploma	Ever HS diploma
GPA luck	0.0978*** (0.0026)	0.0189*** (0.0007)	0.0054*** (0.0012)	0.0019*** (0.0007)
Diploma luck	0.0379*** (0.0024)	0.0052*** (0.0007)	0.0114*** (0.0012)	0.0032*** (0.0007)
Mean	0.092	0.128	0.879	0.965
N	92201	92201	92201	92201

NOTE: The table refers to the same sample as Table 1. Each column corresponds to a specific regression, and reports the estimated impacts of our two standardized measures of luck—GPA luck and diploma 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 4 – Effect of Luck on Higher Education Outcomes

	Outcomes			
	Any college	Share of available HE programs	Selectivity of HE enrollment	Number of completed years in HE
GPA luck	-0.0004 (0.0009)	0.0015*** (0.0002)	0.2331** (0.1149)	0.0012 (0.0064)
Diploma luck	0.0017* (0.0009)	-0.0002 (0.0002)	-0.0610 (0.1184)	0.0040 (0.0063)
Mean	0.944	0.894	34.585	2.879
N	92201	87054	87054	92201

NOTE: The table refers to the same sample as Table 1. Each column corresponds to a specific regression, and reports the estimated impacts of our two standardized measures of luck—GPA luck and diploma luck—on the dependent variable mentioned above. The estimated effects of GPA luck and diploma luck on the share of available higher education programs and on the selectivity of students' higher education programs are conditional on enrolling in college. 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 5 – Effect of Luck on Labor Market Outcomes

	Outcomes				
	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)	Annual labor income 8 years after the exams (rank)
GPA luck	0.0010 (0.0016)	0.0078** (0.0036)	0.0010 (0.0018)	0.0061** (0.0028)	0.2246* (0.1246)
Diploma luck	0.0000 (0.0015)	0.0027 (0.0036)	-0.0003 (0.0018)	0.0030 (0.0028)	0.1611 (0.1242)
Mean	0.827	12.302	0.751	12.669	51.621
N	92201	76246	92201	69267	69267

NOTE: The table refers to the same sample as Table 1. Each column corresponds to a specific regression, and reports the estimated impacts of our two standardized measures of luck—GPA luck and diploma luck—on the dependent variable mentioned above. The estimated effects of GPA luck and diploma luck on individuals' labor incomes are conditional to being employed. 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 6 – The Causal Effects of High School GPA and Diploma on Annual Earnings: An Instrumental Variable Approach

	Outcomes			
	Log annual labor income 8 years after the exams (2SLS)	Log annual labor income 8 years after the exams (OLS)	Log annual job annual 8 years after the exams (2SLS)	Log annual labor income 8 years after the exams (OLS)
High school GPA	0.361*** (0.132)	0.115*** (0.003)		
High school GPA × HS diploma			0.367* (0.202)	0.102*** (0.003)
HS diploma			0.401** (0.159)	0.125*** (0.009)
N	65059	65059	69267	69267

NOTE: For the first two columns, the table refers to the same sample as Table 1, restricted to students who enrolled in higher education. The third and fourth column use the same sample as Table 1. The first column reports the 2SLS estimate of the impact of students' GPA in 3rd grade on the log of students' annual labor earnings eight years after the exams, using our standardized measure of GPA luck as an instrument. The value of the F-statistics for the first stage regression is 1024. The second column reports the OLS estimate of the same parameter. The third column reports the 2SLS estimates of the impact of a dummy indicating on-time high school graduation as well as the impact of GPA in 3rd year interacted with a dummy indicating on time graduation on the same dependent variable, using our standardized measures of GPA luck, diploma luck (and their interaction) as instruments. The value of the F-statistics for the first first-stage regression is 89 and it is 43 for the second one. The fourth column reports 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%.

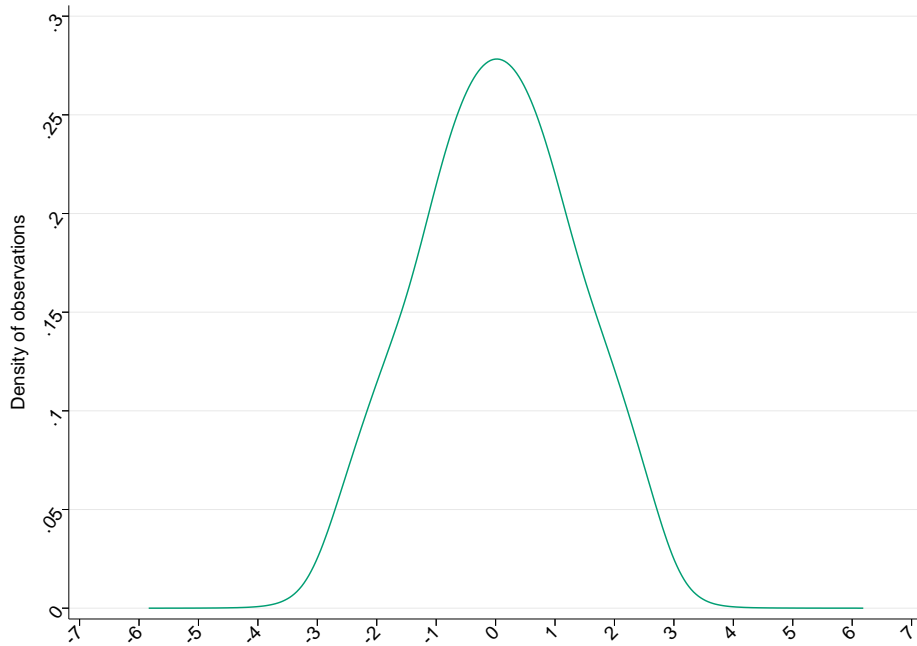
Table 7 – Bad Luck vs. Good Luck: Asymmetry in Luck Effects

	Outcomes			
	High school GPA in 3 rd year	On time HS diploma	Share of available HE programs	Labor income 8 years after the exams (log)
$Luck_{GPA}^+ + Luck_{GPA}^-$	0.0189*** (0.0007)	0.0054*** (0.0012)	0.0015*** (0.0002)	0.0061** (0.0028)
$Luck_{GPA}^+ - Luck_{GPA}^-$	-0.0019 (0.0016)	-0.0021 (0.0029)	-0.0006 (0.0005)	0.0009 (0.0068)
$Luck_{diploma}^+ + Luck_{diploma}^-$	0.0050*** (0.0007)	0.0113*** (0.0012)	-0.0002 (0.0002)	0.0033 (0.0029)
$Luck_{diploma}^+ - Luck_{diploma}^-$	-0.0039** (0.0018)	-0.0008 (0.0029)	0.0002 (0.0005)	0.0050 (0.0070)
Mean	0.128	0.879	0.894	12.669
N	92201	92201	87054	69267

NOTE: The table refers to the same sample as Table 1. Each column corresponds to a specific regression, and reports the estimated impacts of the sum and difference of the positive and negative components of both $Luck_{GPA}$ and $Luck_{diploma}$. Students' high school GPA in third year is standardized to mean zero and unit variance in the universe of full time high school students. 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

(a) GPA luck



(b) Diploma luck

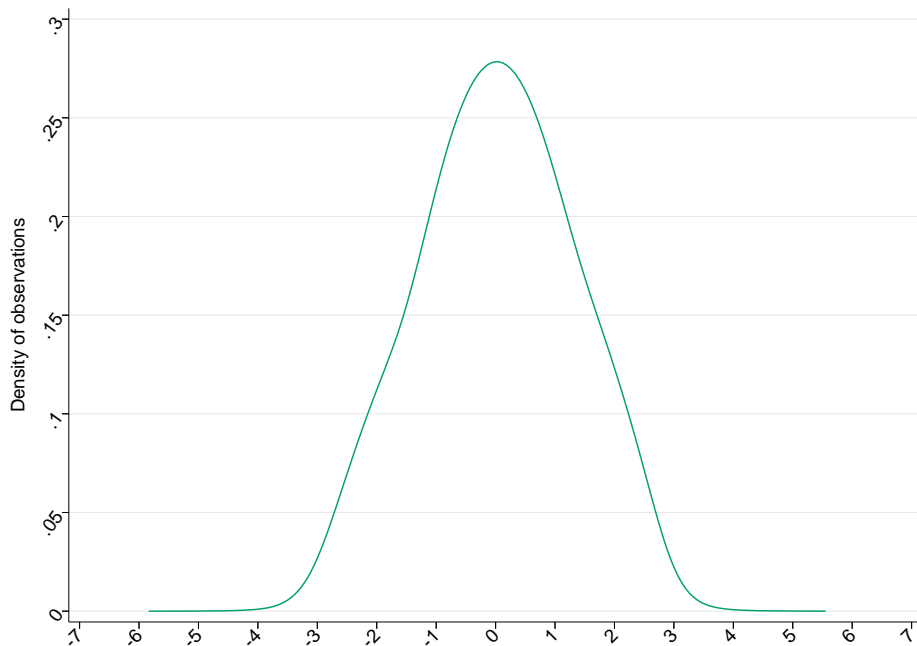


Figure A1 – Distribution of Students' GPA Luck and Diploma Luck

NOTE: The table refers to the same sample as Table 1. Figure A1a plots the distribution of our standardized measure of GPA luck. Figure A1b plots the distribution of our standardized measure of diploma luck.

Table A1 – Effect of Luck on High School Outcomes, Heterogeneity by Ability Based on Course

	Outcomes			
	Exam grades in 3 rd year	High School GPA in 3 rd year	On time HS diploma	Ever HS diploma
Panel A: High Ability, Above Median Course Grades				
GPA luck	0.0911*** (0.0035)	0.0183*** (0.0010)	-0.0009 (0.0011)	-0.0004 (0.0004)
Diploma luck	0.0370*** (0.0033)	0.0056*** (0.0009)	0.0021* (0.0011)	-0.0006 (0.0004)
Mean	0.659	0.807	0.953	0.994
N	46042	46042	46042	46042
Panel B: Low Ability, Below Median Course Grades				
GPA luck	0.1047*** (0.0035)	0.0195*** (0.0011)	0.0118*** (0.0021)	0.0043*** (0.0015)
Diploma luck	0.0379*** (0.0033)	0.0046*** (0.0010)	0.0205*** (0.0021)	0.0067*** (0.0014)
Mean	-0.473	-0.548	0.806	0.936
N	46159	46159	46159	46159

NOTE: The table report similar results as Table 3 separately on the sub-sample of students whose average course grade is above the sample median (Panel A), and on the sub-sample of students whose average course grade is below the sample median (Panel B). 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 A2 – Effect of Luck on Labor Market Outcomes, Heterogeneity by Ability Based on Course

	Outcomes				
	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)	Annual labor income 8 years after the exams (rank)
Panel A: High Ability, Above Median Course Grades					
GPA luck	-0.0010 (0.0022)	0.0057 (0.0049)	-0.0020 (0.0025)	0.0079* (0.0040)	0.1095 (0.1835)
Diploma luck	-0.0002 (0.0022)	0.0037 (0.0047)	-0.0003 (0.0025)	0.0031 (0.0040)	0.1981 (0.1863)
Mean	0.816	12.438	0.747	12.730	56.532
N	46042	37586	46042	34395	34395
Panel B: Low Ability, Below Median Course Grades					
GPA luck	0.0031 (0.0022)	0.0098* (0.0052)	0.0040 (0.0025)	0.0045 (0.0039)	0.3585** (0.1743)
Diploma luck	0.0003 (0.0021)	0.0019 (0.0055)	-0.0002 (0.0025)	0.0033 (0.0040)	0.1269 (0.1764)
Mean	0.838	12.170	0.755	12.608	46.778
N	46159	38660	46159	34872	34872

NOTE: The table report similar results as Table 5 separately on the sub-sample of students whose average course grade is above the sample median (Panel A), and on the sub-sample of students whose average course grade is below the sample median (Panel B). 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 A3 – Effect of Luck on High School Outcomes, Heterogeneity by Gender

	Outcomes			
	Exam grades in 3 rd year	High School GPA in 3 rd year	On time HS diploma	Ever HS diploma
Panel A: Girls				
GPA luck	0.0939*** (0.0032)	0.0182*** (0.0009)	0.0072*** (0.0014)	0.0020** (0.0009)
Diploma luck	0.0358*** (0.0031)	0.0048*** (0.0009)	0.0074*** (0.0014)	0.0018** (0.0008)
Mean	0.176	0.227	0.901	0.972
N	51149	51149	51149	51149
Panel B: Boys				
GPA luck	0.1029*** (0.0037)	0.0199*** (0.0011)	0.0034* (0.0020)	0.0017 (0.0012)
Diploma luck	0.0402*** (0.0035)	0.0058*** (0.0010)	0.0161*** (0.0019)	0.0049*** (0.0013)
Mean	-0.013	0.006	0.852	0.956
N	41052	41052	41052	41052

NOTE: The table report similar results as Table 3 separately on the sub-sample of girls (Panel A), and boys (Panel B). 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 A4 – Effect of Luck on Labor Market Outcomes, Heterogeneity by Gender

	Outcomes				
	Ever employed	First job annual labor income (log)	Employed 8 years after the exams	Annual labor income 8 years after the exams (log)	Annual labor income 8 years after the exams (rank)
Panel A: Girls					
GPA luck	0.0020 (0.0020)	0.0071* (0.0042)	0.0008 (0.0023)	0.0071** (0.0034)	0.1545 (0.1513)
Diploma luck	0.0028 (0.0020)	0.0033 (0.0042)	0.0019 (0.0022)	0.0023 (0.0035)	0.2012 (0.1553)
Mean	0.839	12.350	0.763	12.638	48.180
N	51149	42903	51149	39002	39002
Panel B: Boys					
GPA luck	-0.0004 (0.0024)	0.0090 (0.0063)	0.0009 (0.0027)	0.0046 (0.0046)	0.3073 (0.2137)
Diploma luck	-0.0034 (0.0023)	0.0003 (0.0063)	-0.0031 (0.0027)	0.0033 (0.0046)	0.0741 (0.2070)
Mean	0.812	12.240	0.737	12.708	56.056
N	41052	33343	41052	30265	30265

NOTE: The table report similar results as Table 5 separately on the sub-sample of girls (Panel A), and on the sub-sample of boys (Panel B). 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 Luck on Education and Labor Market Outcomes, Robustness Tests

	Outcomes			
	High school GPA in 3 rd year	On time HS diploma	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	0.0189*** (0.0007)	0.0054*** (0.0012)	0.0009 (0.0018)	0.0061** (0.0028)
Diploma luck	0.0052*** (0.0007)	0.0114*** (0.0012)	-0.0002 (0.0018)	0.0030 (0.0028)
Panel B: P-values for GPA or Diploma Luck Computed with Permutation Tests				
P-values for GPA luck	0.000	0.000	0.523	0.012
P-values for diploma luck	0.000	0.000	0.855	0.222
Panel C: Non-winsorized Measures of Luck				
GPA luck (non-winsorised)	0.0185*** (0.0007)	0.0052*** (0.0012)	0.0009 (0.0018)	0.0057** (0.0028)
Diploma luck (non-winsorised)	0.0050*** (0.0007)	0.0112*** (0.0012)	-0.0004 (0.0017)	0.0030 (0.0028)
Panel D: Unscaled Measures of Luck				
GPA luck (unscaled)	0.0238*** (0.0008)	0.0018 (0.0013)	0.0002 (0.0018)	0.0064** (0.0029)
Diploma luck (unscaled)	0.0022*** (0.0007)	0.0280*** (0.0018)	0.0013 (0.0019)	0.0059* (0.0032)
Panel E: Including Students with Zero Exam Draw Variance				
GPA luck	0.0191*** (0.0007)	0.0045*** (0.0011)	0.0011 (0.0017)	0.0066** (0.0027)
Diploma luck	0.0052*** (0.0007)	0.0124*** (0.0012)	-0.0003 (0.0017)	0.0025 (0.0028)
Mean	0.020	0.820	0.745	12.649
N	129917	129917	129917	96734
Panel F: Excluding Students with a Failing Course Grade				
GPA luck	0.0181*** (0.0008)	0.0085*** (0.0012)	0.0011 (0.0018)	0.0063** (0.0028)
Diploma luck	0.0061*** (0.0007)	0.0078*** (0.0011)	-0.0004 (0.0018)	0.0025 (0.0029)
Mean	0.170	0.897	0.753	12.675
N	89493	89493	89493	67344

NOTE: The table refers to the same sample as Table 1. The table report similar results as Table 3 and 5. Panel A replicates the main analyses with a restricted set of baseline demographic controls selected by double lasso. Panel B report p-values from permutation tests for GPA luck or diploma luck. Panel C replicates the main analyses with non-winsorized standardized measures of luck. Panel D replicates the main analyses with unscaled measures of luck. Panel E includes students whose GPA and diploma probability are unaffected by the random draw of exams. Panel F focuses on a restricted sample which excludes the students who obtained a failing course grade. Students' high school GPA in third year is standardized to mean zero and unit variance in the universe of full time high school students. Each regression—except 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%.