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High-Stakes Exams, Parental Shocks, and Human Capital Outcomes

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Abstract

This paper examines the role of standardized high school exam performance in shaping educational attainment and labor market outcomes, and how household shocks immediately prior to these exams affect both short- and long-run student outcomes. We show that stronger exam performance significantly increases enrollment in and completion of tertiary education, and that crossing key grade thresholds raises university attainment by up to 5–10 percent in core subjects. We then study the effects of parental shocks—death, plant closure, and unemployment—and find that they reduce exam performance and worsen later-life outcomes. However, these longer-term effects do not appear to operate primarily through narrowly defined timing effects on exam performance.

Keywords: High School, Standardized Tests, Parental Shocks, Human Capital, Labor Market Outcomes

JEL codes: I21, I24, J24

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1 Introduction

Academic standardized tests play a central role in higher education admissions and often serve as the primary, or even sole, criterion in student admission decisions (OECD 2019). These examinations are typically administered within a narrowly defined time frame, such as the SAT in the United States or the matriculation examination in Finland. A growing body of literature demonstrates that performance on such high-stakes exams has substantial and persistent consequences for subsequent educational attainment and long-term labor market outcomes, including earnings and employment (see e.g. Bensnes 2016; Canaan and Mouganie 2018; Ebenstein et al. 2016; Machin et al. 2020).

As these tests are often held at a fixed point or short period in time, test performance may be sensitive to transitory shocks that are unrelated to students' underlying ability or knowledge. Unexpected household-level events, such as parental death, unemployment, or other sudden economic distress, may impair students' capacity to perform under exam conditions. When such shocks coincide with high-stakes testing, they may lead to lower test scores even in the absence of any change in true academic ability.

These short-run performance effects may also have long-lasting consequences. Given the strong link between standardized test scores and transition to subsequent education (see e.g. Chang and Padilla-Romo 2023; Stans 2022), temporary shocks at the time of examination can also alter students' access to higher education and ultimately scar students' future careers. Understanding the extent to which transitory shocks distort performance on high-stakes exams is therefore crucial for assessing both the efficiency and equity of education systems.

Our detailed data from Finland provide a unique opportunity to study both the short- and long-term consequences of performance in standardized matriculation exams (high school final exams). The data cover all students who took the Finnish matriculation exams between 1990 and 2019 and include both detailed point scores and final grades. This information can then be linked to rich post-exam outcomes, including subsequent educational attainment and long-term labor market outcomes such as employment and labor earnings.

We employ these data in two steps. First, we document that matriculation exam scores have strong correlation with later educational choices and long-term labor market outcomes. Exploiting sharp thresholds in exam points that determine discrete grade categories, we then show that grades – beyond underlying test scores – play an important role in shaping future educations choices.

Second, we examine how unexpected household-level shocks occurring close to the exam date affect students' exam performance and subsequent outcomes. Specifically, we study three types of parental shocks: i) death, ii) plant closure, and iii) unemployment. By linking the precise timings of these shocks to those of the matriculation exams, we assess how these adverse events unrelated to students' ability or preparation affect high-stakes test performance and whether these effects persist into later educational and labor market outcomes.

To our knowledge, this is the first study to combine exact exam timing with multiple types of unexpected household shocks to analyze both immediate effects on standardized test performance and longer-run consequences for education and labor market outcomes. Together, our results highlight the sensitivity of high-stakes academic assessments to transitory shocks and demonstrate how short-run disruptions at critical educational junctures can have lasting effects.

Our first results demonstrate and verify that high school matriculation exams have a significant role in shaping subsequent educational trajectories. Higher test scores are generally very significantly associated with an increased likelihood of both university enrollment and graduation, a pattern that holds particularly in our baseline subjects, English and Advanced Mathematics. We also document sharp increases in university enrollment probabilities at several grade thresholds, indicating that grades themselves exert a discontinuous effect on post-secondary educational outcomes beyond underlying general test performance. Overall, our findings suggest that the highest grades carry particularly high returns in terms of human capital accumulation, raising the probability of university enrollment by as much as 5–10%.

The second part of the paper examines how household-level shock—parental plant closure, unemployment, or death—occurring within twelve or three months prior to the exam date affects the performance of students in matriculation exams. Our identification strategy compares exam scores of students whose households experience a shock to those of otherwise similar students whose households do not. Because exposure to such shocks is not likely to be completely unrelated to the household characteristics, we apply a coarsened exact matching procedure to match and balance households based on pre-shock variables.

Our results show substantial heterogeneity across shock types and subjects. Plant closures have relatively limited effects on exam performance, whereas parental death and unemployment generate sizable declines in test scores in several subjects. These effects are subject-specific: the largest impacts are observed in STEM subjects' exams, particularly in Mathematics and Natural Sciences (physics, chemistry, and biology), while language subjects' exams—such as the native language (i.e., Finnish or Swedish) and English—are largely unaffected. The most pronounced effects amount to declines of almost 5% in Advanced Mathematics scores following parental death or unemployment. Shocks such as parental unemployment and death translate into measurable effects on other subjects as well, but the impacts are consistently smaller than those observed in STEM fields.

What explains the observed heterogeneity across shock types and academic subjects? First, the nature and severity of the shock are likely to matter. In our setting, parental death and job loss may generate not only financial hardship but also – perhaps more importantly – emotional stress and instability. As discussed by, for example, Kristiansen (2021) and Rege et al. (2011), such shocks may impair students' concentration and effort, thereby adversely affecting educational performance. There is also extensive educational psychology literature, drawing on Self-Determination Theory (Ryan and Deci 2000; 2020), suggesting that intrinsic motivation partly arises from the need for relatedness—a sense of belonging and connection to relevant others. If family-level hardships weaken this sense of belonging to peers or school, educational achievement may consequently decline.

Plant closures, as a specific form of parental job loss, are often gradual and potentially anticipated income shocks, which may be partially mitigated by severance payments or subsequent employment opportunities. Moreover, plant closures frequently affect many households simultaneously, which may reduce their social and psychological impact from the student's perspective. Nevertheless, a potentially surprising finding is that parental unemployment generates effects that match—or even exceed—the magnitude of those observed with parental death. One possible explanation is that unemployment operates as a persistent source of stress and uncertainty rather than as a discrete event. Furthermore, although parental death constitutes an extremely severe shock, it may in some cases be less unexpected when preceded by prolonged illness. Consistent with this interpretation, Aaskoven et al. (2022) show that the educational effects of parental health shocks depend importantly on the severity of the diagnosis.

Second, exam subjects differ in their cognitive demands. STEM exams rely heavily on sequential reasoning and time-constrained problem solving, whereas languages and humanities emphasize cumulative knowledge and long-term exposure. Consistent with this distinction, Bingley et al. (2023) find that parental plant closures have larger negative effects on mathematics than on language outcomes. Our findings similarly suggest that household shocks primarily affect academic performance through channels that impair short-run cognitive capacity and focused effort, rather than through a general decline in ability.

Our heterogeneity analysis further indicates that household income plays an important role:

higher income systematically attenuates the effects of all shocks on exam outcomes. While prior evidence is limited, Heissel et al. (2021), for example, show that students from low-income families experiencing larger stress responses (measured by cortisol changes) perform worse in high-stakes exams. In contrast, other dimensions of heterogeneity—such as student gender, whether the shock affects the mother or father, or residence in the capital region—do not appear to systematically drive the results.

We also examine whether household-level shocks affect the probability of failing the entire high school degree, the likelihood of retaking exams, and the total number of exams taken. Parental plant closures have no economically or statistically significant effects on these outcomes. In contrast, parental death increases the probability of failing the degree by 1.4 percentage points—approximately a 15% increase relative to the baseline failure rate of 9.5%. Parental unemployment produces a similar increase in failure risk and reduces the probability of retaking exams by about 5%.

While several studies document positive long-term effects of obtaining a diploma or achieving higher grades in key examinations (e.g., Björk and Karhunen 2023; Canaan and Mouganie 2018; Machin et al. 2020; Böckerman et al. 2026), others find relatively small or negligible effects (e.g., Clark and Martorell 2014). In addition, Tan (2023) examines how university grades influence post-graduation labor market outcomes. We contribute to this literature by demonstrating a strong association between matriculation examination performance and subsequent educational attainment. In particular, we show that certain grade thresholds generate discrete increases in the probability of enrolling in and completing tertiary education several years after the examination.

The existing literature provides limited evidence on how negative shocks shortly preceding or coinciding with high-stakes exams affect long-term outcomes. A growing body of research from the United States examines the consequences of middle- or high-school shootings on academic performance and finds substantial adverse effects, although evidence regarding on their persistence remains relatively limited (e.g., Deb and Gangaram 2024; Cabral et al. 2026).[1] However, this literature focuses on extreme and highly salient events that affect the entire schools or communities, rather than shocks experienced by individual students during examination periods. In contrast, more common and localized household-level shocks—while being less severe and involving fewer spillovers—may operate through different mechanisms and therefore have distinct implications for educational outcomes.

[1]Poutvaara and Ropponen (2018) study school shootings that coincided with Finland's national matriculation examinations and document negative effects on cognitive performance, particularly among male students.

In addition to the above-mentioned literature on the effects of violent attacks, an increasing number of studies have examined how various disruptions—including pollution exposure (e.g., Ebenstein et al. 2016), pollen exposure (e.g., Bensnes 2016; Hugg et al. 2026), high temperatures (e.g., Graff Zivin et al. 2018; Park 2022), psychological stress (e.g., Heissel et al. 2021), and the timing of food-purchasing assistance (e.g., Bond et al. 2022)—affect cognitive performance in high-stakes examinations across different countries. Overall, this literature suggests that adverse circumstances can meaningfully impair test performance. In contrast, Riudavets-Barcons and Uusitalo (2024), studying COVID-19-related high-school closures in Finland, find that the duration of online instruction did not reduce performance in the matriculation examination. A seminal contribution in this literature is Ebenstein et al. (2016), who show that pollution exposure during Israeli matriculation examinations negatively affects not only exam performance but also subsequent educational attainment and later earnings.[2] We contribute to this literature by examining a broader set of household-level (parental) shocks and by analyzing their implications not only for examination performance but also for subsequent educational and labor market outcomes.

We also contribute to the broader literature on household-level shocks and their intergenerational effects on children's outcomes. An extensive body of research has examined the consequences of parental death for cognitive development, educational attainment, and labor market outcomes (e.g., Chen et al. 2009; Gimenez et al. 2013; Kane et al. 2010; Kristiansen 2021; Daly et al. 2026), as well as the effects of plant closures and parental job loss on children's educational and economic trajectories (e.g., Oreopoulos et al. 2008; Rege et al. 2011; Coelli 2011; Hilger 2016; Carneiro et al. 2022). We extend this literature by exploring how the timing of such shocks—specifically, their occurrence before high-stakes examinations—shapes students' outcomes.

Our results suggest that, conditional on a shock occurring within the one- to two-year period preceding the examination, its precise timing is not a key determinant of outcomes. When comparing students who experience the same type of shock within 12 months preceding high-stakes examinations (our baseline group) with those exposed 12–24 months before the examinations, we find no systematic differences in examination performance or subsequent labor market outcomes between the two groups. This finding—that is largely absent from the existing literature—is both policy-relevant and reassuring, as it indicates that shocks occurring immediately before high-stakes examinations do not disproportionately restrict

[2] In addition, Stans (2022) examines both the immediate effects on high-stakes examination performance and the longer-term educational consequences of grandparental death during the transition to tracked secondary education in the Netherlands.

future opportunities.[3] Nevertheless, experiencing a household-level shock during adolescence remains associated with poorer long-term outcomes on average, although these effects do not appear to operate primarily through narrowly defined timing-related impacts on examination performance.

This paper proceeds as follows. Section 2 provides an overview of the Finnish schooling system. Section 3 describes the data used in the empirical analysis. Section 4 examines the effects of matriculation examination grades on subsequent educational choices and short-term labor market outcomes, while Section 5 analyzes the effects of household-level shocks on examination performance. Finally, Section 6 concludes.

2 Institutional setting

We begin by providing an overview of the Finnish schooling system. Figure I provides a simplified description of the main features. After completing the nine-year comprehensive school (i.e., basic education), students can choose between two upper secondary education paths: the general academic track ('lukio' in Finnish; commonly referred to as high school), which culminates in the matriculation examination, and the vocational track. Some students also pursue a double degree, completing both the general and vocational tracks, but this is relatively rare. Unlike primary and lower secondary schools, where student placement is primarily determined by residential location, most high schools select students based solely on their ninth-grade grade point average. As a result, there is considerable variation across high schools in terms of students' prior academic performance and other characteristics, especially when compared to basic education institutions in Finland.

The Finnish education system is tuition-free at all levels of education. For upper-secondary students, the only direct costs are the purchase of study materials and modest fees associated with taking the matriculation examination.[4]

Students typically begin high school in the calendar year they turn 16 and complete the program over the course of three years. Nationally standardized matriculation examinations are held each fall (September/October) and spring (February/March), with students usually taking them during their final academic year. For most of our observation period from 1990 to 2019, students were required to pass a minimum of four exams within a maximum of three semesters to obtain the matriculation examination certificate. Specifically, all students had

[3] An exception is Bond et al. (2022), who show that the timing of food assistance affects SAT scores and college attendance among low-income students.

[4] Private schools are rare in the Finnish primary and secondary education system; they are non-profit and operate with limited autonomy under national regulation.

to complete a native language and literature exam (in Finnish or Swedish, as Finland has these two official languages) along with three additional exams selected from the following subject groups: i) the second national language (Finnish or Swedish), ii) a foreign language, iii) Mathematics (Intermediate or Advanced), and iv) Humanities and Natural Sciences. At least one of the exams had to be taken at the advanced syllabus level. In addition to the four mandatory exams, students could take one or more elective exams. Students were also permitted to retake exams, with only the highest grade in each subject counted toward the final certificate.

A major reform to the matriculation examination during our study period (1990–2019) was implemented in 2006, when one combined exam was replaced by subject-specific examinations. Prior to 2006, subjects such as biology, chemistry, geography, history, and physics were combined into a single exam, which we refer to as Humanities and Natural Sciences. In this format, students selected and answered a subset of questions from across subjects, and grading was based on these responses with equal weight. From 2006 onward, each subject has been examined separately, with distinct exams administered on different days.

Although the Finnish matriculation exams in different subjects are evaluated according to fixed criteria, the question formats do not confine to multiple-choice questions. The subject-specific tests consist of several parts, and each of these parts may consist of different types of tasks. This wide variation in question formats can be seen beneficial due to their ability to measure skills more broadly than, for example, multiple-choice format allows, as discussed by Griselda (2024).

The Matriculation Examination Board is responsible for assessing all exams, ensuring fair and consistent grading nationwide. Based on the points earned in each subject, results are awarded on a seven-grade scale, ranging from highest to lowest: laudatur (L), eximia cum laude approbatur (E), magna cum laude approbatur (M), cum laude approbatur (C), lubenter approbatur (B), approbatur (A), and improbatur (I), which denotes a failed exam. Until 1995, the exams had only six-grade scale and grade E was introduced in 1996.[5]

After completing upper secondary education, students may apply to post-secondary institutions, including universities and universities of applied sciences. Although higher education institutions have over time increasingly shifted toward using matriculation examination grades as the primary selection criterion, two alternative methods were more common during our observation period. These methods were i) selection based solely on entrance exam performance and ii) selection based on a combination of entrance exam scores and matriculation

[5] Typically, ∼5% receive laudatur and ∼5% improbatur (see e.g. Matriculation Examination Board 2024).

exam results. The size of these admission quotas, the relative weighting of entrance exam and matriculation grades, and the specific weight assigned to each matriculation subject varied by university, field of study, and year. The target completion time for bachelor's and master's degrees is three and two years, respectively.

Admission to different university tracks depends on a weighted combination of matriculation exam grades across several subjects, with substantial variation across fields in how subjects are valued. In general, however, grades in Advanced Mathematics, advanced foreign languages (most commonly English), and mother tongue (Finnish or Swedish) play a particularly important role in admission criteria, although the exact weight placed on each subject differs across disciplines and institutions. Out of these three, Advanced Mathematics has been particularly relevant for educational attainment and future opportunities because it is widely regarded as one of the most challenging subjects and is, generally, heavily weighted in the selection criteria of tertiary-level institutions.

The academic track is the primary path into university: in our data (described in detail below), 81% of university entrants hold this upper secondary school certificate, whereas only 3% enter with a vocational qualification, 8% have both qualifications and for 8% of entrants have missing information, likely due to their qualifications from abroad. For university of applied sciences, the corresponding shares are 52%, 25%, 16% and 7%, respectively.

In this paper, we focus exclusively on students who choose the general upper secondary track and are required to complete the Finnish matriculation examination to graduate.

3 Data

Matriculation Points and Grades. Our primary dataset contains individual-level information on matriculation examination grades and point scores for all Finnish high-school students between 1990 and 2019. The data include unique student identifiers, the subject(s) in which the student took an exam, the year and semester of the exam, the name and municipality of the school, whether the exam was mandatory or elective, and the points earned in each subsection of the exam.

Individual-Level Education and Labor Outcomes. The individual-level data from Statistics Finland provide detailed information on students' post-secondary educational pathways, including enrollment in university or vocational education following high school, as well as graduation outcomes from these institutions.

An additional dataset on income allows us to observe several key labor market outcomes, such as employment status (employed, unemployed, or outside the labor force), as well as annual labor earnings and a variety of other income sources such as dividends, capital gains, and other forms of earned and capital income. Crucially, we can link these data to a rich set of individual-level background variables, including age, gender, place of residence, marital status, and number of children.

We also utilize a dataset containing detailed information on job and unemployment spells at the daily level from January 1987 to December 2019. The job-level spell data include individual-, firm-, and plant-level identifiers and the unemployment data include individual-level identifiers. These data, which record the precise start and end dates of employment and unemployment spells, allow us to define plant closure and unemployment shocks for individuals, as described in detail in Section 5.1. By linking the timing of these shocks to the exact dates of the matriculation examinations, we can determine whether a student's parent experienced such a shock during the exam period.

All of the datasets described above cover the entire population of individuals living in Finland from 1987 to 2019 at the end of each year, and include unique individual-year identifiers that enable linkage to the matriculation examination data.

A key component of our analysis is the FOLK child-parent dataset, which contains information on biological or adoptive parents for each child. This dataset covers all individuals born after 1952 who are permanently residing in Finland and allow us to link children to their parents.

Cause of Death. We also use data on causes of death from Statistics Finland in our empirical analysis. This database contains annual statistics on causes and conditions of death and includes all individuals who have died in Finland or abroad since 1971. The dataset includes individual identifiers, the cause of death, and the exact date of death. These data are crucial for identifying the precise timing of death-related shocks in relation to the matriculation examinations, as detailed in Section 5.1.

Sample Restrictions. Our baseline data sample contain all students who took the matriculation examination between 1990 and 2019. However, for estimating the returns to matriculation examination grades, we restrict the sample to students who participated in the exam from 1996 onward, as that was the first year in which the new second-highest grade (E) was introduced.

To ensure sufficient follow-up time for labor market and educational outcomes, up to age 25 or 30, depending on the outcome, we further restrict the sample in some analyses to students who completed the exam no later than 2013 or 2008, respectively. In most of the analysis, we also restrict the data to include only the highest grade achieved by each student in each subject, as this is the most relevant measure for predicting future outcomes, especially entry into tertiary education.

For analyzing the effects of parental shocks on exam performance, we use data from 1991 to 2016 and focus primarily on students' first exam attempts, interacting with the timing of the shock, either within 3 or 12 months prior to the exact exam date. In addition, we show how such shocks affect the probability of failing the matriculation degree, the likelihood of retaking at least one exam, and the total number of exams taken.

Descriptive Statistics. Panel A of Table I reports the overall number of exams in the data, the share of retakes, the share of mandatory exams and the average score (in percent) by subject. Appendix Figure A.I displays in more detail the distributions of exam scores. Columns (5) and (6) of Table I report the number of students we can follow until age 25 and until age 30. The low numbers for biology, chemistry, and physics in column (5), and the absence of observations for these subjects in column (6), are attributable to the 2006 reform described above, which altered the exam structure for these subjects. The final column reports the gender composition of these students. Panel B shows that in the full sample, the average age at the time of the exam is 19, and 58% of students are female (standard deviations in italics).

Panel C of Table I summarizes average household characteristics two years before students take the matriculation exam (standard deviations in italics) and the number of observations. We define households based on child–parent links rather than actual co-residence, as our data contain parental information at the individual-parent level rather than the household level. The first column reports statistics for the full sample, and then separately for the subgroups used in Section 5 to study the effects of parental death, plant closures, and unemployment shocks on student performance. "Death" refers to households experiencing parental death, followed by a matched comparison group ("Benchmark"); similarly, "Plant Closure" and "Unemployment" columns show the affected households and their respective comparison groups.

4 Effects of Grades on Education and Labor Outcomes

In the first part of our empirical analysis, we examine the value of matriculation examination grades across a range of educational and labor market outcomes. The objective of this analysis is first to show that matriculation exam performance is positively correlated with human capital accumulation and later labor-market success. We also aim to demonstrate that crossing some grade thresholds—particularly in key subjects such as Advanced Mathematics and English—leads to discontinuous improvements in these outcomes.

To identify the effects of crossing grade thresholds, we employ a regression discontinuity design (RDD), comparing students with scores just above a given grade cutoff to those just below it. We estimate the effects separately for each subject-grade pair.

The estimated equation is as follows:

$$y_i = \beta_0 + \beta_1(P_i - T_i) + \beta_2 D_i + \beta_3 D_i(P_i - T_i) + \epsilon_i, \tag{1}$$

where y_i is the outcome of interest for student i, P_i is the number of points the student earned on the matriculation exam in a specific subject, T_i is the subject-specific point threshold above which the grade increases (this threshold varies by different exam implementations), D_i is a binary indicator equal to 1 if the student's score exceeds the threshold, and 0 otherwise. The term ϵ_i is the error term. The coefficient of interest, β_2, captures the magnitude of the discontinuous change in the outcome variable at the grade point threshold.

We employ two alternative procedures for bandwidth selection. First, we estimate a local linear model using a fixed bandwidth ranging from -3 to -1 points below threshold and from 0 to $+2$ points above the threshold. Second, we apply the robust bias-corrected method proposed by Calonico et al. (2014), using both triangular kernel weights and the optimal symmetric bandwidths suggested by their procedure. To assess the robustness of our results, we conduct a series of sensitivity checks using alternative bandwidths for our two main subjects. These results are presented in Appendix Figure A.III. All specifications are estimated with robust standard errors.

Our baseline analysis focuses mainly on the English and Advanced Mathematics matriculation exams for three key reasons. First, the English exam is taken by nearly all students, resulting in a large number of observations. Second, the English exam includes nearly 300 unique point scores, providing a favorable setup for RDD analysis with a continuous running variable. Third, we include Advanced Mathematics exam due to its importance in the admission criteria of tertiary-level institutions. While the analysis primarily focuses on these two exams, we additionally provide RDD estimates for the remaining matriculation subjects.

We begin by analyzing human capital accumulation outcomes, specifically whether students scoring above a grade threshold are more likely to enroll in university or any form of tertiary education by age 25, and whether they obtain a degree by age 30. We then turn to labor market outcomes, estimating whether surpassing the grade threshold increases the likelihood of being in the top quartile of the earnings distribution or leads to higher absolute earnings by age 30.

To visualize these relationships, we plot exam scores against four key outcomes in Figure II: probability of university enrollment by age 25 (top panel), probability of university graduation by age 30 (second panel), likelihood of being in the top quartile of the earnings distribution at age 30 (third panel), and absolute earnings at age 30 (bottom panel). We observe a clear upward-sloping trend for educational outcomes: higher scores in both English and Advanced Mathematics are associated with a greater likelihood of university enrollment and graduation. The highest grades, in particular, appear to yield the greatest returns in terms of human capital accumulation. Similarly, higher test scores are positively correlated with better labor market outcomes. As hypothesized above, Advanced Mathematics scores exhibit a stronger association with both educational and earnings outcomes compared to English scores.

Figure II also suggests that some grades have a greater impact on future educational outcomes than others. In particular, grades M and E in both English and Advanced Mathematics appear to correspond with noticeable upward jumps in the likelihood of university enrollment by age 25. These discontinuities at specific grade thresholds suggest that the grades themselves may influence further educational outcomes. By contrast, the lower panels of Figure II show little evidence that grade thresholds generate discrete jumps in the probability of belonging to the top quartile of the earnings distribution. However, grades C and M appear to have discontinuous increases in income at age 30 in Advanced Mathematics. Overall, despite the absence of strong grade threshold effects for most labor market outcomes, the association between exam scores and later earnings remains clearly positive.

Figure III provides a closer examination of the impact of matriculation exam grades on university enrollment by age 25. This figure presents RDD estimates for the effect of a grade in the English exam (top panel) and Advanced Mathematics exam (bottom panel) on the probability of university enrollment. The analysis uses a local linear approach by comparing students who scored just below the grade threshold (1–3 points below) to those just above it (0–2 points above). The figures display the average enrollment probability for each score point as well as two separate RDD point estimates without (bolded above fitted slopes) and with controls (below fitted lines), estimated using a linear model with a fixed bandwidth that compares three points below the grade threshold to those scoring three points above it. The control variables include the scores from all other matriculation exam subjects, excluding the subject of interest in the figure. These estimates with and without controls are broadly similar across thresholds. Accordingly, we use the specifications without controls as our baseline for the remainder of the analysis.

The results indicate that certain grade thresholds have statistically significant effects on university enrollment. Specifically, receiving an M or L in the English exam, and a C or M in the Advanced Mathematics exam, significantly increases the likelihood of enrolling in university. Relative to baseline probabilities, receiving an M in English increases the enrollment rate by approximately 10%, and an L increases it by about 5%. In Advanced Mathematics, crossing the C and M thresholds is associated with relative increases of 6.6% and 4%, respectively. These effects are substantial, especially given that the RDD approach identifies highly localized treatment effects. It is important to also note that these results pertain to scores in a single subject. In practice, admission to many university programs depends on the combination of grades across multiple subjects, not just one. Appendix Figure A.III shows that these estimates are also very robust to alternative bandwidth choices.

Tables II and III present the full set of RDD estimates for our main subjects, English and Advanced Mathematics, but also other other subjects, Swedish, Intermediate Mathematics, and Humanities and Natural Sciences that had a combined exam in 1996–2005. Finally, as the structure of the matriculation exam changed in 2006, after which subjects such as biology, physics and chemistry were examined separately, we pool Natural Sciences exams into a single category for the period 2006–2019.

While Figure III focused solely on university enrollment at age 25, these tables summarize effects also on tertiary level enrollment, including universities of applied sciences, university graduation and being in the top-quartile of the income distribution at age 30. These tables include both the simple linear RDD estimates and the estimates based on the robust bias-corrected approach of Calonico et al. (2014) (CCT). Overall, the results are consistent across the two methods, suggesting that the findings are robust to the choice of estimation strategy—whether using a narrow, fixed bandwidth near the threshold or the CCT-optimal bandwidth.

Table II demonstrates that grades in English and Advanced Mathematics are strong predictors of university enrollment, particularly at the M threshold. In contrast, Swedish grades show no systematic effects. Table III indicates that grade thresholds in other subjects generally do not produce large enrollment impacts, except in Natural Sciences. Because Humanities and Natural Sciences were combined into a single exam prior to 2006, we report those results separately. For both periods before and after 2006, Natural Sciences, comprising physics, chemistry, and biology, and Humanities show positive effects on university enrollment for most grades except the lowest threshold (A). We do not report RDD estimates for the Finnish exam because the test score distribution is highly coarse and heavily concentrated at a few points (see Appendix Figure A.II). This pattern largely reflects the structure of the exam, which relies extensively on essay-based questions and yields limited, uneven scores variation. Such a distribution does not provide a credible basis for the use of RDD approach.

Since Tables II and III reveal substantial heterogeneity in the RDD estimates at different grade thresholds, some suggesting large positive effects and others even negative, we do not report a single summary estimate. Any such average estimate would provide a misleading view of the underlying patterns. In some subjects, such as Advanced Mathematics where the score distribution is relatively coarse, there is an additional complication for this type of analysis as a student can appear in the sample more than once, being above one threshold and below another, even when a narrow bandwidth is applied. Finally, constructing an average effect would require deciding how to weight thresholds despite the highly skewed distribution of test scores, adding further arbitrariness to this type of exercise.

Both tables also show that matriculation grades are only weakly associated with overall tertiary enrollment (including universities and universities of applied sciences), reinforcing that matriculation exams matter far more for university entry than for enrollment in universities of applied sciences.

Furthermore, the evidence in the tables indicates that, somewhat unexpectedly, the highest English grades (M, E, and L) have the strongest and most consistent effects on university graduation. In contrast, grades in Advanced Mathematics and other subjects do not show similarly clear or systematic effects on graduation outcomes, although Advanced Mathematics had very clear effects on university enrollment. Finally, the bottom panels of the tables show that none of the subject grade thresholds have a strong or consistent effect on our final labor market outcome—whether the student is in the top 25% of the earnings distribution at age 30. However, Figure II already shows that these test scores, particularly those in Advanced Mathematics, have strong overall predictive power for later labor earnings, even if the RDD estimates at individual grade thresholds do not yield statistically significant effects for these outcomes.[6]

Another way to assess the effect of grades on university enrollment is to conduct a difference-

[6] It is important to note that the income distribution used in the analysis is based on the overall population in Finland for each respective year, not limited to individuals who participated in the matriculation examination.

in-differences type of analysis that compares students scoring just below and just above each grade threshold across age distribution. In our setting, the control group consists of students scoring 1–3 points below a given grade threshold, while the treatment group includes those scoring at the threshold or maximum of two points above it. Figure IV reports these "DiD" estimates for English separately by grade and additionally presents "placebo" estimates, where groups are defined using scores further down the distribution that do not change the grade. These placebo estimates capture the general increase in university enrollment associated with modest score improvements. The figure shows that grades M, E, and L have the strongest effects on university enrollment, consistent with the earlier RDD results, and that the gap between DiD and placebo estimates is sizable and persistent across age.

The patterns for Advanced Mathematics in Figure V differ. Here, placebo estimates without grade changes imply a larger increase in enrollment likelihood, suggesting that this test captures more of underlying skills rather than just marginal grade improvements. The figure again aligns with the RDD evidence, indicating that grades M and E in Advanced Mathematics yield the largest gains in university enrollment.

Appendix Figures A.IV and A.V show the effects on university graduation using the same difference-in-differences approach as Figures IV and V. The results are consistent with the RDD estimates: somewhat unexpectedly, English grades have greater predictive power for university graduation than grades in Advanced Mathematics.

Overall, the evidence suggests that the effects of matriculation grades are strongest for university enrollment but tend to diminish when examining subsequent outcomes such as university graduation or later labor-market performance. Nevertheless, matriculation exam points and grades clearly play a critical role in shaping students' educational opportunities following high-school graduation and later labor-market outcomes.

Böckerman et al. (2026) provide complementary evidence from Finland, showing that students who perform better in the matriculation exam attain higher levels of tertiary education and earn higher incomes. In addition, Machin et al. (2020) find, for younger students in England, that narrowly failing to achieve a sufficiently high grade (grade C) in a key national examination at the end of compulsory schooling has persistent consequences, as these students are less likely to enroll in tertiary education by age 19.[7]

[7] A broader literature has examined tertiary-level outcomes and the signaling value of academic performance in the labor market (see e.g., Tan 2023; Hansen et al. 2024).

5 Effects of Shocks on Grades and Labor Outcomes

5.1 Empirical Strategy

Defining Shocks. The second part of this paper exploits variation from three distinct types of household-level shocks to examine how they affect students' performance in the standardized exams. First, we use the cause-of-death dataset to identify the most severe shocks: the death of a parent during the matriculation examination period. In this analysis, all parental deaths are treated as shock events occurring at the daily level.

Second, we adopt a plant closure approach, following Huttunen and Kellokumpu (2016), to define parental job loss shocks using monthly data from 1990 to 2019. Specifically, we first restrict the sample to individuals with at least one year of continuous tenure in a private-sector plant, using information from the job-spell dataset, which includes both individual and plant-level identifiers. We then calculate the number of workers in each plant at the end of each month and define a plant closure if either (1) the plant no longer appears in the dataset in the following month or ever thereafter, or (2) the plant retains fewer than 70% of its workforce in the following month. A worker is defined as displaced if they are laid off between the current and the following month from a plant that meets one of these closure criteria.

Third, we examine the effects of parental unemployment on exam performance. We exploit daily-level unemployment spell data to identify shocks for parents whose children are taking the matriculation exams in a given year.

Importantly, all three types of household-level shocks are aligned with the timing of the matriculation examinations. We vary the intensity and proximity of the shocks by using two time windows: whether they occur within twelve or three months before the exam date. The method for linking shock timing to exam dates differs slightly across shock types. For parental deaths, we observe the exact date of death and use it directly to assign shocks. For plant closures, we use the above described monthly information from closed plants to determine the timing of displacement. For unemployment shocks, we use the exact starting date of the unemployment spell. In this analysis, using these criteria, we pool all three types of shocks separately for matriculation exam results from 1991 to 2016. We consider unemployment constitute a more severe shock, as it may entail unexpected job loss and prolonged monetary and non-monetary hardship for affected households.

Coarsened Exact Matching (CEM). To estimate how household-level shocks—parental death, plant closure, and unemployment—affect students' matriculation exam performance, we need to establish a credible counterfactual: students from similar households who did not experience a shock. Because these shocks may be systematically correlated with household characteristics that also influence academic outcomes, it is essential to account for differences in baseline levels and trends. For instance, lower-income households may face a higher risk of unemployment or plant closure, while the risk of parental death is more likely among older parents.

To address this concern, we employ a CEM approach to construct a comparison group of students from non-shock households. CEM improves covariate balance between treated (shock) and control (non-shock) groups by matching units on coarsened versions of key observable characteristics. The method restricts the sample to only those treated and control units that fall within the same categories or predefined intervals of the selected matching variables. Weights are then assigned to units based on the relative frequency of matches across these strata, ensuring greater comparability between the groups.

Importantly, households for which no adequate counterpart can be found are excluded from the analysis. This is likely to improve the validity of our estimates by ensuring that comparisons are only made between households with similar observed characteristics. For further details on the CEM methodology, see Iacus et al. (2012).

Four important aspects of our matching strategy warrant further discussion. First, we use information from two years prior to the shock events in the matching procedure. That is, for all three household-level shocks—plant closures, unemployment, and parental death—we apply the CEM approach separately using data from two years before the observed shock. This ensures that the matching variables are not influenced by the shocks themselves.

Second, we exploit the richness of the administrative register data to select an extensive set of matching variables. Following the literature on plant closures (e.g., Huttunen and Kellokumpu 2016), we include both continuous and binary variables. Among the continuous variables, we match on annual total household-level market income, disposable income, and the ages of the mother and father separately—which are to capture household income levels and life-cycle stage. Among the binary indicators, we include whether the mother and father were employed two years prior to the child's matriculation exam.[8]

[8] We also conducted robustness checks using additional variables, including whether the parents were married, whether the child had only one parent alive or residing in Finland (separately for mothers and fathers), and whether the mother or father held a high school diploma or a tertiary-level degree, providing robust results but narrowing the sample size considerably.

Third, we perform the CEM procedure within the population of households in which at least one child has participated in the matriculation examination during the observation period. Moreover, we always match students within the same matriculation cohort—that is, we compare students taking the exam in a given year only to others from the same exam year. This controls for cohort-specific factors that may influence both shock exposure and exam performance.

Finally, to reduce the potential confounding effects of earlier adverse events, we restrict the sample for the parental death, plant closure and unemployment analyses to households that did not experience either type of shock during the four years preceding the child's matriculation exam. In specifications using a narrower three-month window before the exam, we include households experiencing a shock between twelve and four months prior to the exam in the benchmark group. This choice likely attenuates the estimated effects, making our results conservative.

We implement the matching exercise to construct a comparable group of households—particularly in terms of income levels and trajectories—that can serve as a valid benchmark for evaluating the effects of household-level shocks. For our purposes, we argue that the CEM approach can provide a reasonable benchmark group for households that did not experience a shock. As described above, the matching is conducted at the household level, which is the level at which the shocks occur. Due to the lack of sufficiently detailed data over time on students prior to the matriculation exam such as GPAs from primary school or high school, we are constrained to examine household-level pre-trend outcomes. However, our primary interest lies in assessing student performance on the matriculation exams as a function of whether or not a shock occurred in the household.

As briefly discussed in Section 3, Panel C of Table I presents the CEM-matched samples for each shock. Column (1) reports descriptive statistics for the full sample, while columns (2) and (3) display the matched "Death" group and its corresponding benchmark. Columns (4) and (5) present the matched comparison for "Plant Closure" and columns (6) and (7) for "Unemployment" along with their respective benchmark groups. The summary statistics indicate that CEM matching produces treatment and comparison groups that are highly comparable across a range of household-level characteristics.

To further support the validity of this approach, we examine the evolution and levels of household-level variables before and after the shock events. This serves three key purposes: (1) to demonstrate that households with and without shocks were on similar trajectories prior to the event (i.e., parallel pre-trends), (2) to show that the shocks lead to clear and measurable changes in key observable outcomes, and (3) to illustrate how comparable the household groups are in levels. A key variable in this analysis is household-level total market income, which we first examine in levels. To visualize these trends, we plot the estimates from the following event study specification:

$$w_{it} = \sum_{k=-5,\, k\neq -2}^{5} \psi_k D_{it}^k + \lambda_t + \upsilon_{it}, \tag{2}$$

where w_{it} denotes the outcome variable—specifically, the household-level total market income for parents of student i in year t, measured relative to the timing of the shock. We omit the event time dummy D_{it}^k at $k = -2$, so that the estimated event-time coefficients ψ_k capture changes in the outcome relative to two years prior to the shock across groups exposed to the shock with those not exposed. The analysis is restricted to households in which at least one child takes the matriculation exam in both groups in a particular year. The term λ_t represents year fixed effects that flexibly control for overall time trends and υ_{it} is the error term. We present estimates for the period spanning four years before to five years after the shock.[9]

The left panel of Figure VI plots the evolution of average gross household market income for households experiencing a shock, separately for parental death, plant closure, and unemployment, and their matched benchmark households, from four years before to five years after the shock. These averages are computed using CEM weights. The right panel presents the dynamic difference-in-differences estimates across groups for each shock type, based on Equation (2).

The figure provides strong evidence that pre-shock income trends are largely parallel across treated and matched control groups, lending support to the validity of our matching strategy. For parental death (panels a and b of Figure VI), the drop in average household income exceeds €20,000 from the average of €50,000 following the event, a large and expected change given the severity of the shock. It is notable that the income trajectory begins to slightly diverge from the benchmark group approximately one year before the death, likely reflecting some deteriorating health or other precursors to the death event. However, this

[9]This approach is conceptually similar to a staggered difference-in-differences framework. As noted by Roth et al. (2023), such designs are subject to well-documented issues related to variation in treatment timing and treatment effect heterogeneity, which may influence the magnitude of the estimates. However, our setting differs from typical cases in the recent literature, as our benchmark group, the ”no shock” group, consists exclusively of never-shock households, which is likely to mitigate some of these concerns. Also, as our interest in this analysis is not in precisely identifying the effects of the shocks on household outcomes, but rather in estimating their impact on children’s test performance, these concerns are further alleviated.

pre-trend deviation is relatively small, especially compared to the magnitude of the post-shock income decline.

The plant closure shock (panels c and d of Figure VI) leads to a more modest decline in income, with household income falling by approximately €2,000 in the year of the shock. For the unemployment shock (panels e and f), household-level income declines more clearly, by more than €5,000 in the first year following the shock.

Overall, Figure VI demonstrates that our CEM procedure effectively balances household-level characteristics prior to the shock, both in levels and trends. These empirical patterns support the credibility of our approach in constructing valid counterfactual groups for each shock type, thereby allowing for meaningful estimation of the causal effects of these shocks on students' matriculation exam outcomes.

To examine the effects of household shocks on matriculation examination performance (g_i) for student i, we estimate the following equation:

$$g_i = \eta Shock_i + X_i'\gamma + \nu_i. \tag{3}$$

We first compare the matriculation exam outcomes of students who took the same exam implementation (defined by year and semester) at the same school, separately for each subject, focusing on differences between those students whose household experienced a shock ($Shock = 1$) to those whose household did not face a shock ($Shock = 0$). A shock can occur to either the mother or father (or, in very rare cases, both parents) within a specified time window of three or twelve months prior to the exact exam date. All shocks are pooled by type, regardless of timing. η is the coefficient of interest, capturing the average difference in exam scores between students in shock-affected and non-affected households. We report baseline estimates without CEM weighting, and present all corresponding results using CEM weights derived from household-level characteristics in the Appendix.

The vector of covariates X_i includes controls used in alternative specifications to assess robustness. All specifications include indicators for examination timing to account for differences across examination cohorts. We further consider specifications that additionally include school indicators and student-level controls for gender and age. The error term is denoted by ν_i and standard errors are clustered at the level of the CEM strata, which correspond the groups defined by the matching variables.

We apply a similar framework to a range of additional educational outcomes, including the percentage of points earned across all matriculation examinations at the student level, the total number of examinations taken, the probability of failing to complete the degree, and the probability of retaking at least one examination. We also use this framework to estimate effects on longer-term outcomes, including university enrollment by age 25, university graduation by age 30, employment at age 30, and log income at age 30.

5.2 Effects on Test Results

Parental Death. Table IV presents the estimates from Equation (3), comparing the percentage difference in matriculation exam scores between CEM-matched students whose household experienced a parental death shock and those whose household did not. The analysis is conducted separately for different subjects: Panel A reports results for Advanced Mathematics, Intermediate Mathematics, and Humanities and Natural Sciences, while Panel B presents the corresponding estimates for English, Finnish and Swedish. For each subject, we estimate the effects using two shock timing windows, within twelve and three months prior to the exam. Within each timing window and subject, we provide results from three model specifications, which progressively add control variables, allowing us to assess the robustness of the estimates to increasingly rich set of covariates.[10]

The results in Panel A of Table IV indicate that parental death adversely effects students' matriculation exam performance in both levels of Mathematics and also in Humanities and Natural Sciences. All point estimates are negative and most are statistically significant. The magnitudes are sizable: in our preferred specification, a parental death occurring twelve months before the exam reduces, for example, Advanced Mathematics scores by 1.4 percentage points, corresponding to a 2.5% decline relative to the average score of 47.8%. The effects are generally larger in absolute terms when the shock occurs closer to the exam (within three months), with the except of Intermediate Mathematics. Estimates are very similar across specifications within subject and time window, suggesting strong robustness.

Panel B of Table IV reveals a markedly different pattern for English, Finnish, and Swedish. For English, the estimates are consistently positive but very close to zero across all specifications and timing windows. In our preferred specification, we can rule out declines larger than 0.35 percentage points following a parental death twelve months prior to the exam, a relative effect below 0.5% given the average score of 74.9%. For Finnish, the twelve-month window shows small negative and insignificant effects, but a death within three months of the exam leads to a roughly one-percentage-point decline in our preferred estimate that is

[10] Appendix Table A.I reports the results using the CEM weighting strategy in the same symmetric format as Table IV. The findings remain qualitatively similar and robust. However, the CEM-weighted estimates are generally smaller in absolute magnitude compared to the unweighted baseline results.

statistically significant. For Swedish, the estimates are sizable and consistently close to a one-percentage-point reduction across timing windows and specifications, but yet smaller in absolute magnitude in comparison to results in Panel A.

Taken together, the results suggest clear differences across subjects: STEM exams and the combined Humanities and Natural Sciences exam show larger responses to parental death shocks, whereas language exams—particularly English—appear far less affected. This pattern likely reflects differences in the nature of these exams. STEM subjects typically require problem-solving and concentration, which may be more vulnerable to emotional stress, whereas language exams may rely more on accumulated knowledge and long-time exposure.

The existing economics literature provides limited evidence on the effects of parental death on the children's performance in high-stakes exams. More broadly, however, evidence suggest a negative association between parental death and educational achievement. For example, Gertler et al. (2004), studying Indonesian households, document adverse effects on school enrollment, particularly during transitions between primary and secondary education. Most evidence on parental death and educational outcomes in a Nordic context comes from Denmark. Aaskoven et al. (2022) examine younger children and find that parental cancer-related health shocks, including deaths, negatively affect children's educational performance. Similarly, Kristiansen (2021) reports adverse effects of parental health shocks, including deaths, on ninth-grade test scores and school enrollment. Importantly, Kristiansen is among the few studies to examine subject-specific outcomes, reporting broadly similar effects for mathematics and written Danish. Concurrently with our study, Daly et al. (2026) analyze a broad set of short-term educational outcomes, including high school completion and university enrollment by age 20. Our paper contributes to this literature by providing new evidence on the effects of parental death on performance in high-stakes examinations, while also examining subject-specific heterogeneity in greater detail than previous studies.

Plant Closure. Next, we examine how parental plant closures affect students' performance in the matriculation examination. Prior research has shown that plant closures can have substantial consequences across a wide range of outcomes, including earnings losses (see e.g. Bertheau et al. 2023, Athey et al. 2026), labor mobility (see e.g. Huttunen et al. 2018), local labor market dynamics (see e.g. Foote et al. 2019), mental health (see e.g. Marcus 2013; Tsai et al. 2024), fertility (see e.g. Huttunen and Kellokumpu 2016), and crime (Rege et al. 2019). Given the potential stress induced by plant closures, such events may also affect children's academic performance, particularly when they occur close to high-stakes examinations.[11]

[11] Very recently, Carneiro et al. (2022), using Norwegian data, reported that early adolescence (ages 11–16) constitutes a particularly sensitive period during which firm closures or mass layoffs can adversely affect

Table V mirrors the structure of Table IV, reporting the effects of parental plant closure shocks by subject, shock timing window, and specification, using the same empirical approach as for parental death shock. The overall conclusion is straightforward: plant closures appear to have substantially smaller impacts on matriculation exam performance than parental deaths. It is also clear that the number of affected households is very limited when using the three-month shock window, making those estimates imprecise and difficult to interpret. Using the twelve-month window, we find statistically significant negative effects for Intermediate Mathematics, Humanities and Natural Sciences, and Swedish. However, these effects are relatively modest in magnitude and not consistently statistically significant across specifications. We therefore conclude that, while plant closures may modestly disrupt student performance, the impacts are considerably weaker and less systematic than those resulting from parental death.[12]

Unemployment. We then proceed to examine the effects of parental unemployment on exam scores. We treat unemployment as a more severe household-level shock relative to plant closure as discussed above, since many workers affected by closures may find new employment relatively quickly, limiting the overall disruption for the household.

Table VI presents the estimates, again following the same estimation strategy and structure as in the previous tables. The results indicate that parental unemployment has a negative impact on students' test performance. For Advanced Mathematics, our preferred specification shows a 0.9 percentage point decline in scores with twelve month timing window, corresponding to a relative decrease of approximately 1.9%. Across subjects and specifications, the estimates are consistently negative and relatively stable in percentage terms, corresponding to approximately a one–percentage-point reduction. However, the magnitudes vary in relative terms due to differences in baseline averages across subjects. The results further show that the effects are systematically larger the closer the shock occurs to the exam date (from twelve months to three months prior), which is consistent with expectations. These increases are particularly pronounced in the most demanding exams—Advanced Mathematics and Humanities & Natural Sciences—which require sustained concentration and problem-solving skills.[13]

human capital accumulation. In the Finnish context, this age range broadly corresponds to the transition from basic to upper secondary education, which closely aligns with the timing examined in the present study.

[12] Appendix Table A.II reports the results using the CEM weighting strategy in the same symmetric format as Table V. The findings are very similar and robust between these two approaches.

[13] Appendix Table A.III reports the results using the CEM weighting strategy in the same symmetric format as Table VI. While the CEM-weighted estimates are systematically smaller in absolute magnitude than the unweighted baseline results, they yield qualitatively similar conclusions.

The effects of an unemployment shock on exam performance are surprisingly similar in magnitude to those of a parental death shock presented in Table IV. Moreover, the unemployment shock yields more consistently negative effects across subjects and specifications. This highlights that even relatively modest household-level economic shocks that imply 5000 euro income loss in the shock year, can meaningfully affect the exam performance of students. At the same time, it is reassuring that a shock as severe as the death of a parent does not appear to lead to large declines in children's exam outcomes on average.

Furthermore, Appendix Table A.IV presents results from a more restrictive specification that requires households to experience both a plant closure and an unemployment spell prior to the exam. These estimates indicate clearly negative effects on test scores. While these findings support the expectation that combined shocks impose larger impacts on students, the number of observations in this subgroup analysis is very limited and the estimates based on the three month shock window cannot be credibly interpreted due to the very small number of observations in the shock group. As a result, these findings should be interpreted with caution.

Although the economics literature provides extensive evidence on the effects of parental job loss on children's educational outcomes, previous studies have typically focused on outcomes such as GPA, graduation, or continuation into further education (e.g., Coelli 2011; Pan and Ost 2014; Hilger 2016; Rege et al. 2011; Mörk et al. 2020; Carneiro et al. 2022), rather than detailed subject-specific performance in high-stakes examinations. The broad conclusion from this literature is that parental unemployment adversely affects children's educational outcomes, although the magnitude of the effects varies across settings and is sometimes modest.

Focusing on somewhat earlier stages of childhood in the Danish context, Bingley et al. (2023) examine the effects of plant closures on children at different ages and find that the negative impacts are more pronounced in mathematics than in language subjects, a pattern that is consistent with our findings. One possible explanation is that these examinations rely on different cognitive skills and may therefore differ in their sensitivity to family-level shocks.

Additional Exam Performance Outcomes. Furthermore, we examine the effects of household-level shocks on three additional student-level outcomes: (1) the probability of failing to complete the high-school degree, (2) the probability of retaking at least one matriculation exam, and (3) the total number of exams taken. A degree is considered failed if the student does not pass at least one of the mandatory subject examinations. Table VII summarizes the results, focusing on our preferred specification in which shocks are defined as occurring within twelve months prior to the exam, and all control variables are included, namely examination, school, age, and gender fixed effects. Unlike the subject-level analysis presented earlier, these estimates are based on student-level data.[14]

Panel A of Table VII shows that parental death increases the probability of failing the degree by 1.4 percentage points, which is a sizable effect given the baseline failure rate of 9.5%. Somewhat surprisingly, however, parental death does not have a statistically or economically significant effect on either the likelihood of retaking an exam or the total number of exams taken.

Consistent with earlier findings on exam scores (Table V), Panel B shows that plant closures do not significantly affect any of the three outcomes: the probability of failing the degree, the likelihood of retaking an exam, or the total number of exams taken. This further supports the conclusion that plant closures occurring close to exam dates do not appear to harm students' educational performance.

Finally, Panel C of Table VII reveals that parental unemployment occurring close to the matriculation exams increases the probability of failing the high school degree. The estimated effect is 1.4 percentage points and is statistically significant. Column (2) also shows that parental unemployment decreases the probability of retaking at least one exam by more than 2 percentage points. Similarly, the total number of exams taken is significantly lower among students whose parents experienced unemployment before the exams.

These findings indicate that, in addition to the negative effect of parental unemployment on average exam scores, students are also more likely to fail the entire degree and less likely to retake exams compared to their benchmark group. The estimated effects of parental unemployment are sizable, and those for retake probability and the number of exams are even larger than the corresponding effects of parental death prior to the matriculation exams, which is somewhat surprising. Previous literature does not provide this type of comparison over different shock types.

Heterogeneity. We next examine heterogeneity in the effects by student gender, the affected parent (mother or father), whether the student attends exams in school in the capital region, and whether household income is above or below the median. Table VIII reports estimates from specifications that interact the main shock indicator with these subgroup

[14] Appendix Table A.VII reports the results using the CEM weighting strategy in the same symmetric format as Table VII. The CEM-weighted estimates convey the same overall message as the baseline results, although the magnitudes of the coefficients and their statistical significance vary somewhat between the two approaches.

characteristics. The outcome is the percentage score averaged across all exams, so the coefficients reflect the baseline effect of the shock and the additional differential effect for each subgroup.

Overall, the results reveal heterogeneity across subgroups as we will discuss below. As a common thread, however, the adverse effects appear significant for all shock types for below-median-income households.

Panel A shows that even the plant closure shock has statistically significant effects for certain groups, namely male students, cases where the father experiences the shock, students who reside outside the capital region, and students who are from below-median-income households. While the differences by gender, affected parent, and region are relatively modest in magnitude, the heterogeneity by household income is substantial: the negative effects are much larger among lower income families, whereas there is virtually no response among students from higher-income households.

Panel B presents corresponding results for parental unemployment shocks, and it similarly indicates pronounced heterogeneity. The average effect is slightly smaller in absolute terms for male students and does not differ meaningfully depending on whether the unemployed parent is the mother or the father. However, the effects are considerably larger for students outside the capital region and markedly smaller for those from above-median-income households.

The existing economics literature has documented heterogeneous effects of parental job loss depending on whether the mother or the father experiences the labor market shock. Evidence from Nordic countries similarly points to potentially different mechanisms operating across parental gender. For example, Rege et al. (2011) find that paternal displacement negatively affects children's school performance in Norway and argue that this pattern is consistent with earlier evidence suggesting that job displacement generates greater psychological distress among men than women. In contrast, using Swedish data, Mörk et al. (2020) report modest negative effects of maternal job loss, which they relate to the strong dual-earner norm and institutional incentives supporting female labor force participation. More recently, Carneiro et al. (2022) find, using Norwegian data, that children below age 16 are more strongly affected by maternal labor market shocks. Our finding that the adverse effects of parental job loss are larger among below-median-income families is also consistent with the evidence reported by Bingley et al. (2023) for somewhat younger children in Denmark.

Panel C further shows that the effects of parental death are generally less heterogeneous across these dimensions, with household income representing the most notable exception. As with the other shocks, students from higher-income households appear largely unaffected, whereas students from lower-income families experience substantially more pronounced negative effects.

Previous research has suggested that the gender of the deceased parent may influence children's educational outcomes. For example, Chen et al. (2009) report that unexpected maternal death has particularly detrimental effects on college enrollment in Taiwan. Using Danish data, Kristiansen (2021) examines the immediate effects of parental health shocks, including death, on ninth-grade students and finds some evidence of gender differences, although the estimated effects are not statistically distinguishable across mothers and fathers. In relatively egalitarian societies such as Denmark and Finland, gender-based differences in these effects may therefore be less pronounced than in other institutional settings. Nevertheless, Kristiansen also reports that Danish boys' mathematics performance is more sensitive to adverse parental health shocks than girls' performance.

5.3 Long-Term Impacts

Our data and empirical strategy also allow us to examine longer-term outcomes. We begin by estimating the overall effects of the different shocks on the percentage score averaged across all exams. We then analyze subsequent outcomes, including the probability of university enrollment by age 25, university graduation by age 30, employment at age 30, and (log) income at age 30. Table IX reports the corresponding estimates.

Panel A of Table IX shows that parental plant closures have small but negative and statistically significant effects on exam performance. However, these effects do not appear to translate into meaningful differences in longer-term educational or labor market outcomes.

Panel B indicates that parental unemployment shocks have relatively sizable effects on exam performance, reducing average test scores by approximately 1.3 percentage points. These negative impacts persist into adulthood: students whose parents experience unemployment are significantly less likely to enroll in or graduate from university, and they also exhibit worse labor market outcomes at age 30, both in terms of employment probability and income.

Panel C presents the effects of parental death. While the estimated impact on exam performance is modest (-0.004 percentage points), the longer-term educational and labor market outcomes are negative. Notably, however, these effects are smaller in absolute magnitude than those associated with parental unemployment shocks.

These long-term estimates may, however, capture both the direct effects of shocks on exam performance and broader impacts on children's subsequent outcomes. To better assess the role of shock timing relative to the exam, we conduct an additional comparison between students who experience a shock 12–24 months before the exam and those in our baseline group, who experience a shock within 0–11 months prior to the exam. Table X summarizes the results of this analysis.

The average estimates show no systematic differences between these timing groups, suggesting that the precise timing of the shock relative to the exam is not a key determinant of exam performance or longer-term educational and labor market outcomes. This finding is reassuring, as it indicates that the interaction between shocks and exam timing does not appear to substantially limit students' opportunities to perform in these exams. Nevertheless, experiencing a household-level shock during this vulnerable age stage is still associated, on average, with worse average longer-term outcomes, though not primarily through timing-related effects on exam performance.

Our findings on long-term effects extend the existing economics literature on the consequences of adverse shocks during childhood and adolescence. For example, the growing literature on school gun violence in the United States documents persistent negative effects on educational attainment, employment, and earnings in early adulthood (e.g., Deb and Gangaram 2024; Cabral et al. 2026). Similarly, Ebenstein et al. (2016) exploit transitory variation in pollution exposure in Israel and show that exposure during matriculation examinations is adversely related to both post-secondary educational attainment and later earnings.

More broadly, the literature on the long-term consequences of parental shocks—although not focused specifically on high-stakes examination performance—provides insights into the mechanisms through which such shocks may affect children's outcomes. In addition to reductions in household income, several studies emphasize the importance of nonfinancial channels, particularly psychological stress and disruptions to the family environment (e.g., Oreopoulos et al. 2008; Chen et al. 2009; Rege et al. 2011; Pan and Ost 2014; Hilger 2016; Daly et al. 2026). A common conclusion across these studies is that family-level shocks during childhood or adolescence tend to have adverse intergenerational consequences for later educational and labor market outcomes, although the estimated magnitudes are sometimes modest. At the same time, the broader literature suggests that the dominant mechanisms may vary substantially across institutional settings, reflecting differences in health care systems, social insurance, and educational institutions (see e.g. Aaskoven et al. 2022; Daly et al. 2026).

6 Conclusions

This paper first demonstrates that high school matriculation exams play a pivotal role in shaping students' educational and labor market trajectories. Test scores strongly predict university enrollment and completion, particularly in core subjects such as English and Advanced Mathematics. Moreover, the presence of sharp grade thresholds reveals that grades themselves have discontinuous and meaningful effects on post-secondary outcomes. The highest grade categories yield especially large returns, increasing the probability of university enrollment by 5–10 percent, underscoring the high stakes embedded in these assessments.

The analysis further shows that unexpected household-level shocks occurring shortly before the exams, namely parental death, plant closure, and unemployment, can significantly affect exam performance and subsequent outcomes. While plant closures have limited measurable effects, parental death and unemployment lead to clear declines in test scores, particularly in STEM subjects. These impacts are largest in Advanced Mathematics and Natural Sciences, where sustained concentration and short-term cognitive effort are crucial. The findings suggest that acute emotional and financial stress impairs short-run performance rather than long-term ability, with effects attenuated or no effects in higher-income households.

In sum, the results highlight the sensitivity of high-stakes academic assessments to transitory but severe household disruptions. Short-run shocks at critical educational junctures can generate persistent consequences for degree completion and future opportunities, including increased failure rates following parental death or unemployment. By combining precise exam timing with multiple types of unexpected shocks and rich long-term outcomes, this study provides new evidence that temporary adverse events can have lasting educational and economic effects, reinforcing the importance of institutional awareness and potential policy responses around high-stakes testing environments.

However, the broader results show that experiencing a household-level shock just before the exact exam timing during this vulnerable stage of a student's life is associated with poorer longer-term outcomes on average. Importantly, these adverse consequences do not appear to operate primarily through narrowly defined timing effects on exam performance. Rather, they likely reflect more persistent disruptions linked to the shock itself.

Finally, our study illustrates the impacts of household-level shocks in a Nordic country characterized by a relatively generous welfare system, including universal health care, comprehensive social security programs, and tuition-free education, which may partially cushion individuals against such adverse events. Similar perspectives have been emphasized by Mörk et al. (2020) in the Swedish context and by Aaskoven et al. (2022) in Denmark. Nevertheless, our findings suggest that even in a Nordic welfare-state setting, the need for support extending beyond purely financial assistance remains evident.

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Figures and Tables

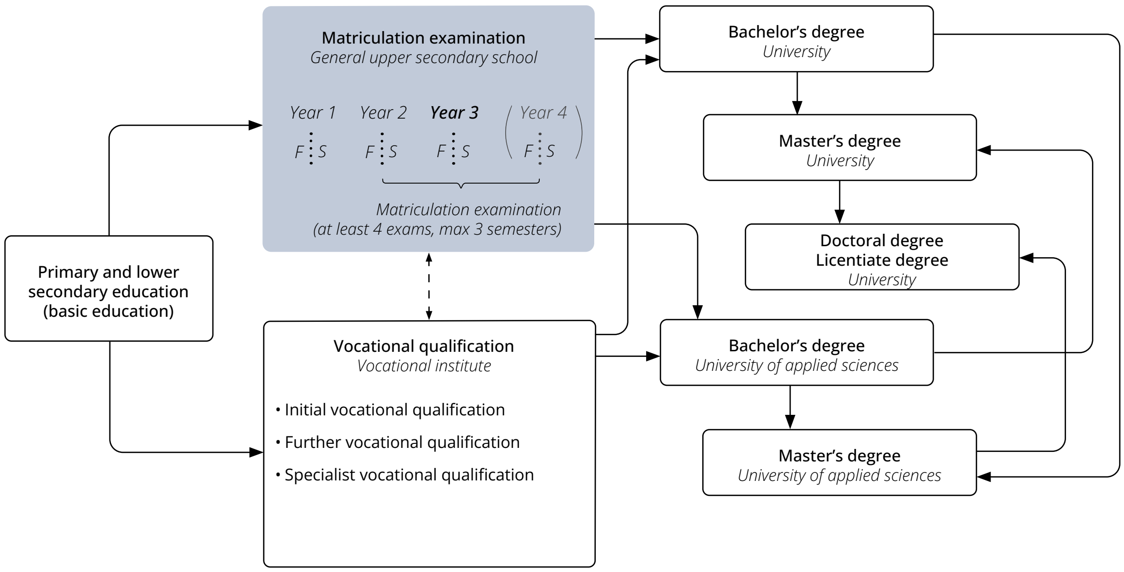


Figure I: Finnish education system

Notes: The figure illustrates the structure of the Finnish education system. After finishing the basic education (around the age of 16), students can choose between a general and a vocational track. In this paper, we focus on students who choose to go to the general upper secondary school and are required to complete the Finnish matriculation examination to obtain the degree. Typically, students complete the upper secondary school in three years (sometimes in four) and they take the matriculation exams during the last two or three semesters. Exams are held twice a year, every fall (F) and spring (S). After the general upper secondary school or vocational institute, students can apply for a tertiary level education.

Table I: Summary Statistics

Panel A:
Exam Statistics

	Exams				Students		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Subject	N	Retakes (%)	Mandatory (%)	Avg. score (%)	N (obs. till 25)	N (obs. till 30)	Male (%)
English	1 019 804	17.3	98.1	73.7	588 916	433 567	42.6
Advanced Math	360 245	12.5	71.5	46.2	216 531	159 841	57.3
Intermediate Math	453 334	13.1	59.3	45.2	278 652	205 298	40.4
Swedish	702 853	10.0	91.6	66.0	440 963	358 244	39.1
Humanities & Natural Sc.	547 841	13.6	66.5	48.2	314 897	314 897	41.9
Biology	80 009	14.9	56.6	52.8	45 022	0	34.2
Chemistry	64 546	15.5	30.4	51.1	36 966	0	58.3
Physics	63 819	9.9	43.9	49.8	41 492	0	77.9

Panel B:
Student Statistics: in the year of matriculation exam

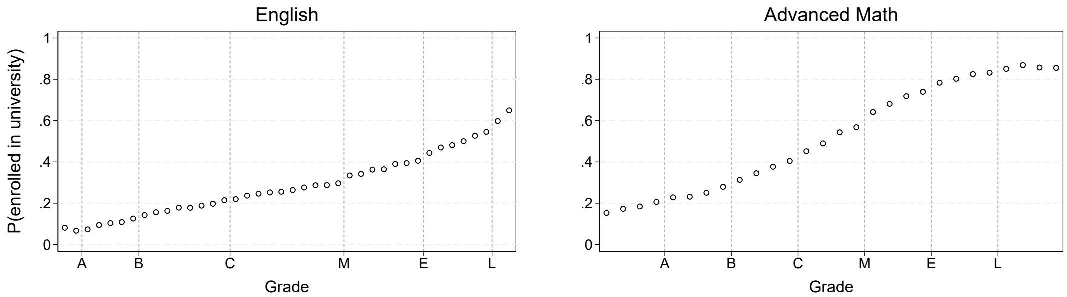
	(1) All
Age	19.06
	0.551
Female (%)	0.575
	0.494
N	879 354

Panel C:
Household Statistics: two years prior to the matriculation exam

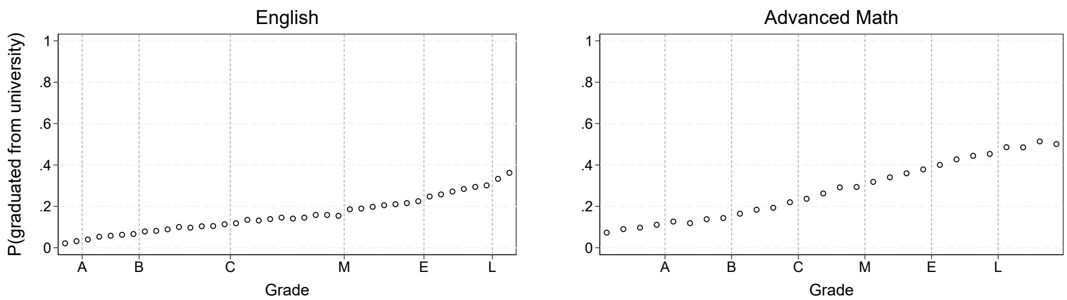
	(1) All	(2) Death	(3) Benchmark	(4) Plant closure	(5) Benchmark	(6) Unemployment	(7) Benchmark
Total Market Income	72 265	53 588	51 930	80 572	79 834	56 304	54 363
	189 588	*70 740*	*64 634*	*64 380*	*61 633*	*51 287*	*39 689*
Disposable Income	51 472	43 481	42 211	47 021	46 986	29 336	27 159
	137 097	*48 550*	*47 210*	*47 545*	*47 022*	*43 028*	*31 543*
Age: Mother	45.58	47.57	47.49	45.11	45.30	44.83	44.64
	6.74	*5.53*	*5.72*	*5.79*	*5.74*	*6.86*	*6.72*
Age: Father	46.02	50.38	50.24	46.24	46.46	44.92	45.20
	11.29	*7.57*	*7.68*	*8.29*	*8.30*	*11.92*	*11.16*
P(working): Mother	0.80	0.71	0.69	0.88	0.87	0.78	0.75
	0.40	*0.46*	*0.46*	*0.33*	*0.34*	*0.42*	*0.43*
P(working): Father	0.74	0.54	0.58	0.89	0.85	0.70	0.70
	0.44	*0.50*	*0.49*	*0.32*	*0.36*	*0.46*	*0.46*
High School degree: Mother	0.45	0.38	0.36	0.44	0.45	0.30	0.31
	0.50	*0.48*	*0.48*	*0.50*	*0.50*	*0.46*	*0.46*
High School degree: Father	0.31	0.25	0.23	0.33	0.33	0.21	0.22
	0.46	*0.43*	*0.42*	*0.47*	*0.47*	*0.41*	*0.42*
N	1,030,925	3,746	398,500	8,299	752,749	15,197	447,334

Notes: Panel A reports the exam statistics: first, the total number of exams in the data, the share of retakes and mandatory exams by subject group. Columns (5) and (6) shows the sample sizes in the RDD analysis, i.e. the number of students we can follow until age 25 and 30 by subject group. Panel B reports the overall number of unique students in our sample, their average age and share of females (standard deviations in italics). Panel C summarizes average household characteristics two years before students take the matriculation exam. The first column reports statistics for the full sample, and then separately for the subgroups used in Section 6 to study the effects of parental death, plant closures, and unemployment shocks on student performance. "Benchmark" columns refer to a matched comparison group.

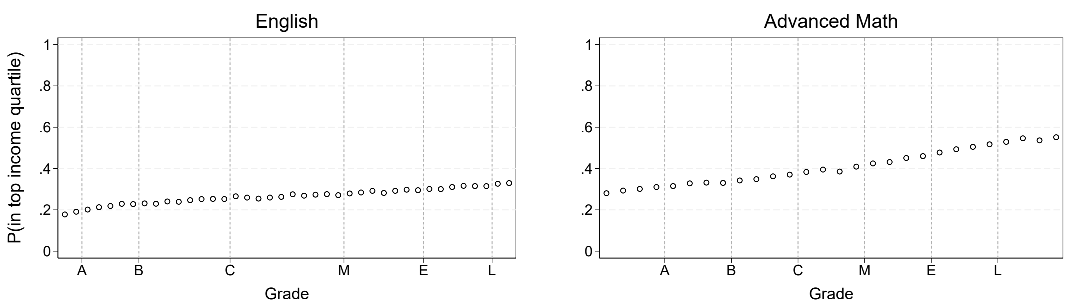
(a) University enrollment by age 25



(b) University graduation by age 30



(c) Top income quartile at age 30



(d) Income at age 30

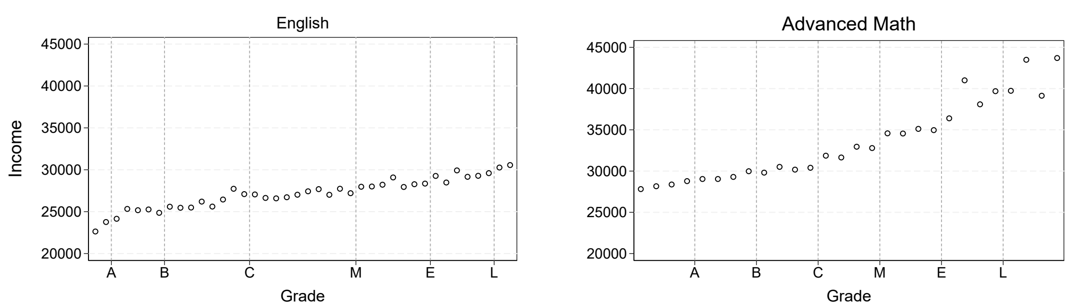


Figure II: Exam results and education and labor market outcomes

Notes: The figures illustrate how matriculation exam grades are associated with four educational and labor market outcomes. L represents the highest grade, while Grade A is the lowest; scores below the Grade A threshold indicate a failed exam. Students are divided into subgroups based on their exam scores such that within each grade, a subgroup (bin) contains an approximately equal number of students. For English, this even distribution of students across bins not only holds true within each grade but also across all grades, because the grade distribution follows a bell curve — grades in the middle are the most common ones. For math, drawing a similar figure is not feasible due to the lack of a sufficient number of unique scores within a single grade.

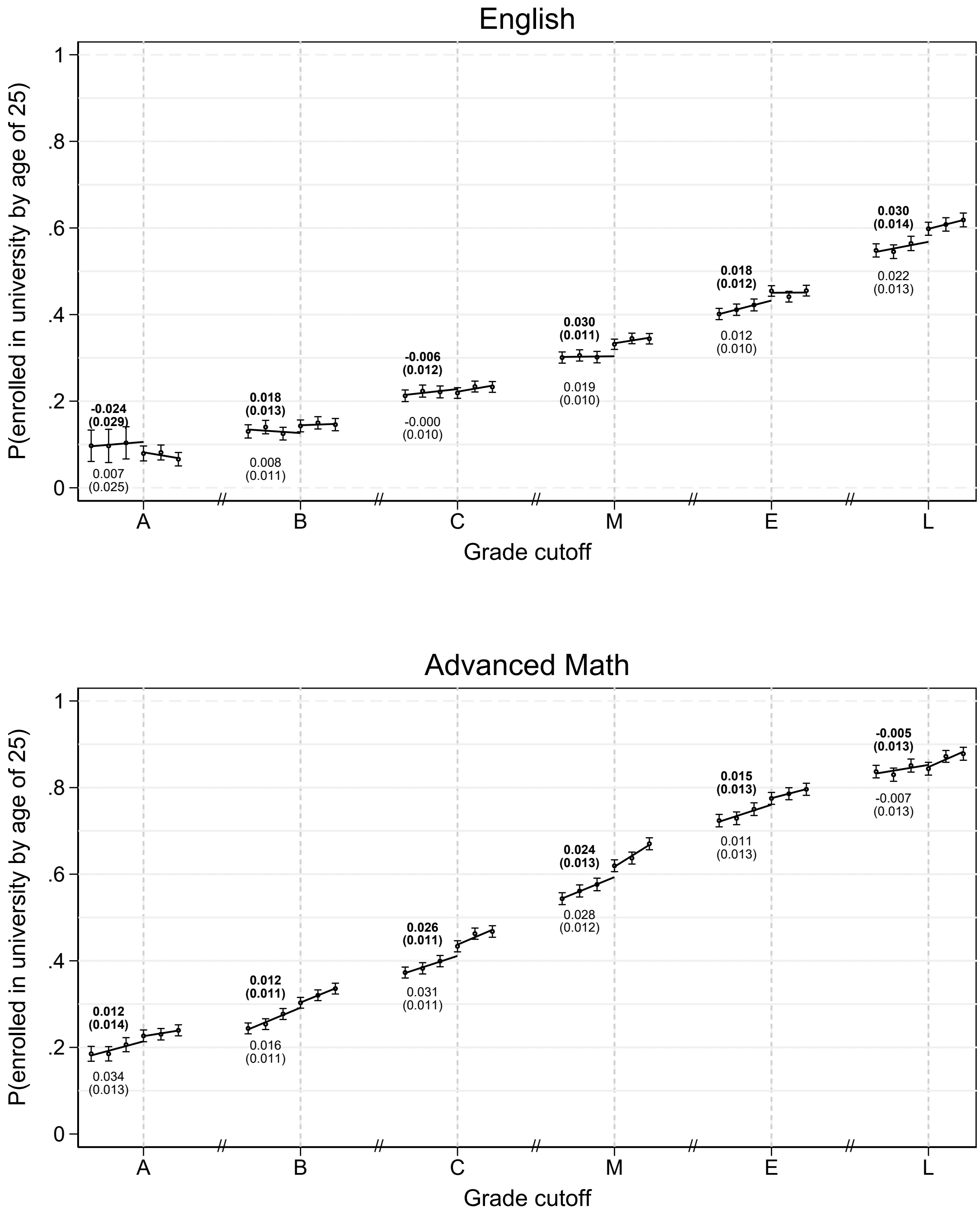


Figure III: The effect of grades on university enrollment probability

Notes: The figures show the RD estimates (standard errors in parentheses) of the effect of a higher grade in the English and Advanced Math tests on the probability of being enrolled in university by age 25. Bolded estimates are from models without any controls. Estimates in the lower row are from models that control for the student's other exam results. We compare students who have scored 1–3 points below a certain grade threshold to those on the threshold or 1–2 points above it, and use a linear fit in the RD specifications. L represents the highest grade, while Grade A is the lowest; scores below the Grade A threshold indicate a failed exam. Figures also show the mean probabilities of being enrolled in the university with 95% confidence intervals.

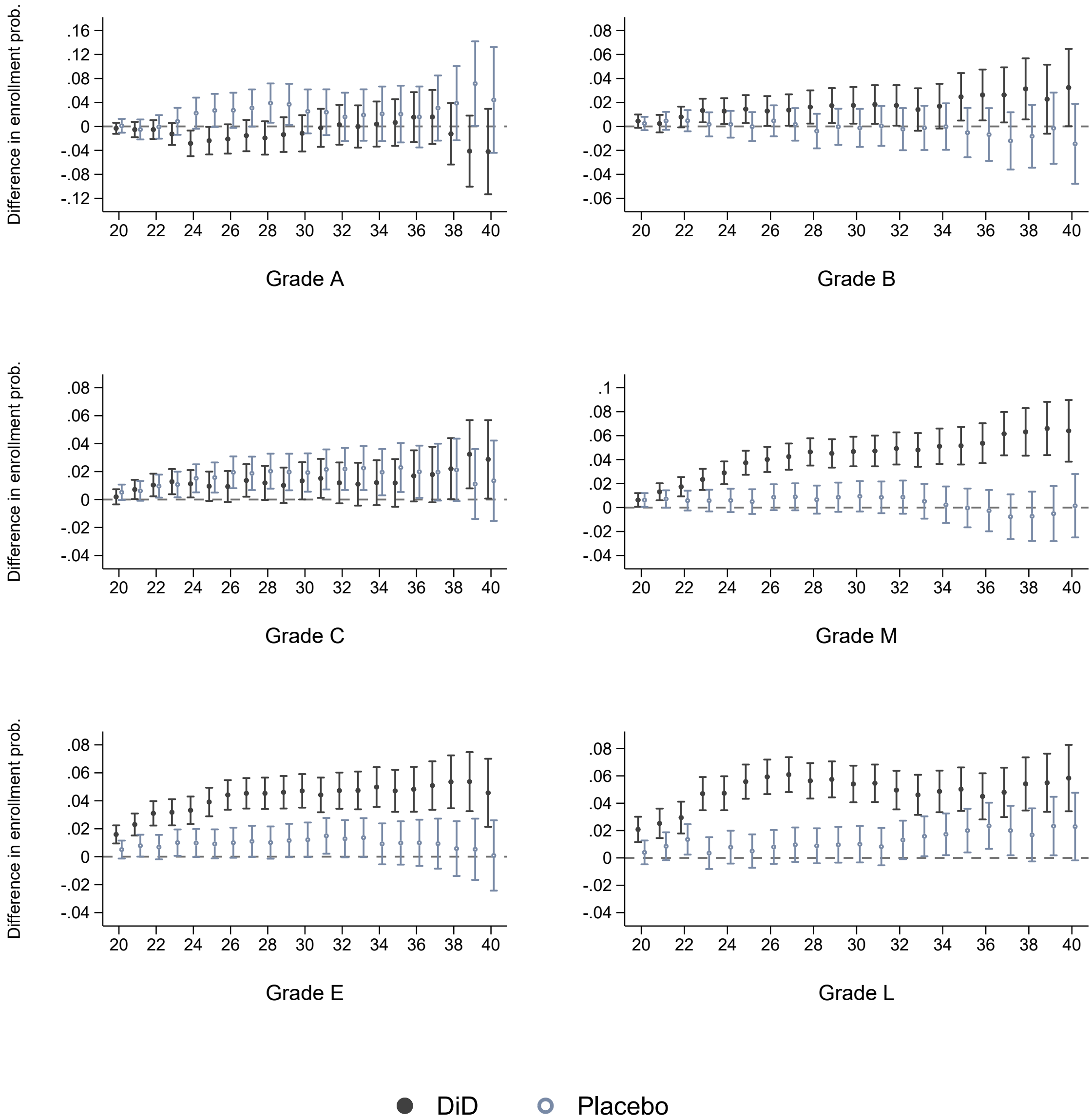


Figure IV: DiD estimates on the likelihood of university enrollment across ages: English test grades

Notes: The figures display difference-in-differences (DiD) estimates (with 95% confidence intervals) for the effect of earning a specific English test grade on the likelihood of university enrollment across ages. For each age cohort, the control group consists of students scoring 1–3 points below the grade threshold, while the treatment group includes those scoring at the threshold or 0–2 points above it. The ”placebo” analysis compares individuals scoring 4–6 points below the threshold with those scoring 1–3 points below it.

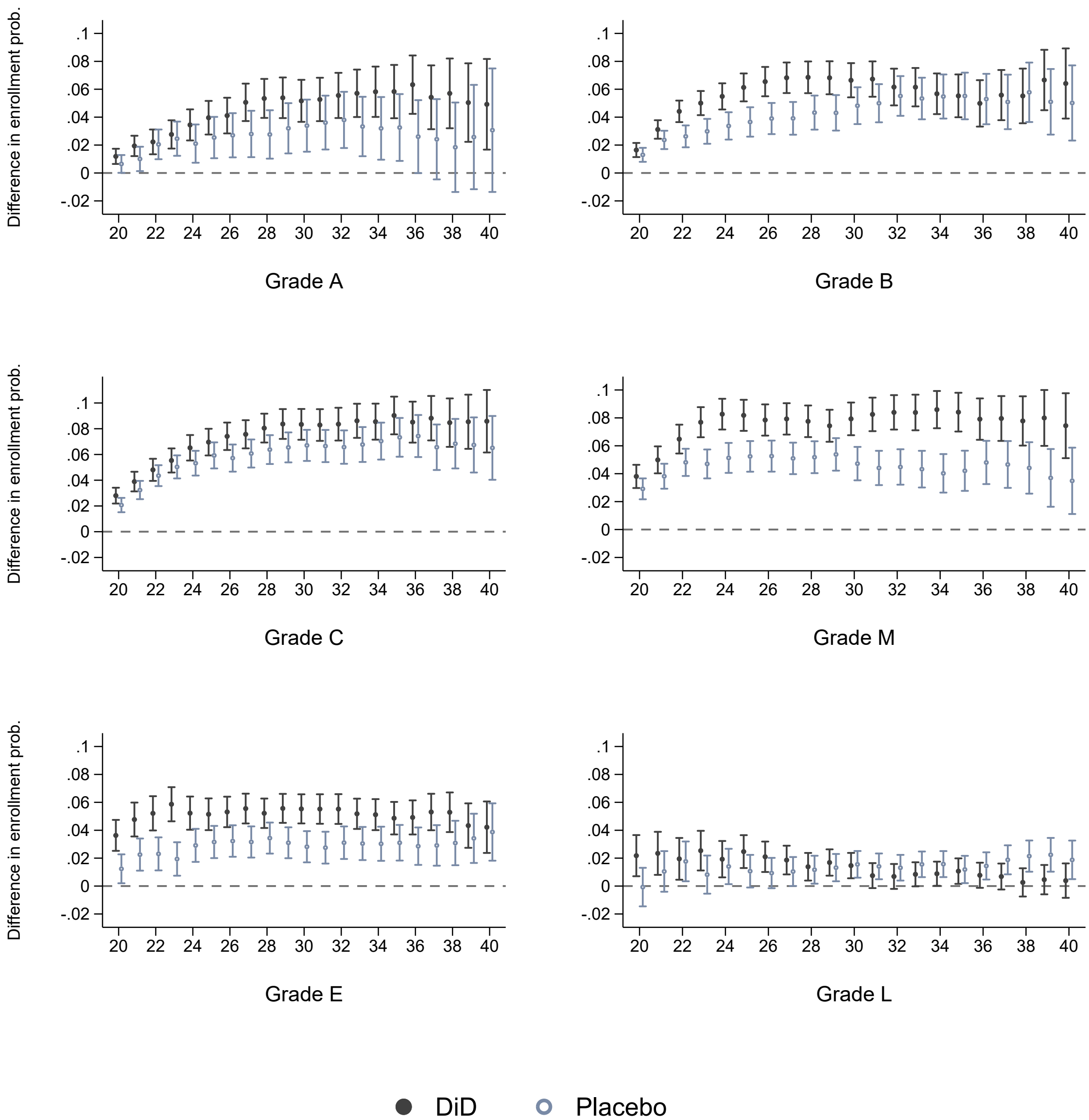


Figure V: DiD estimates on the likelihood of university enrollment across ages: Advanced Mathematics test grades

Notes: The figures display difference-in-differences (DiD) estimates (with 95% confidence intervals) for the effect of earning a specific Advanced Math test grade on the likelihood of university enrollment across ages. For each age cohort, the control group consists of students scoring 1–3 points below the grade threshold, while the treatment group includes those scoring at the threshold or 0–2 points above it. The ”placebo” analysis compares individuals scoring 4–6 points below the threshold with those scoring 1–3 points below it.

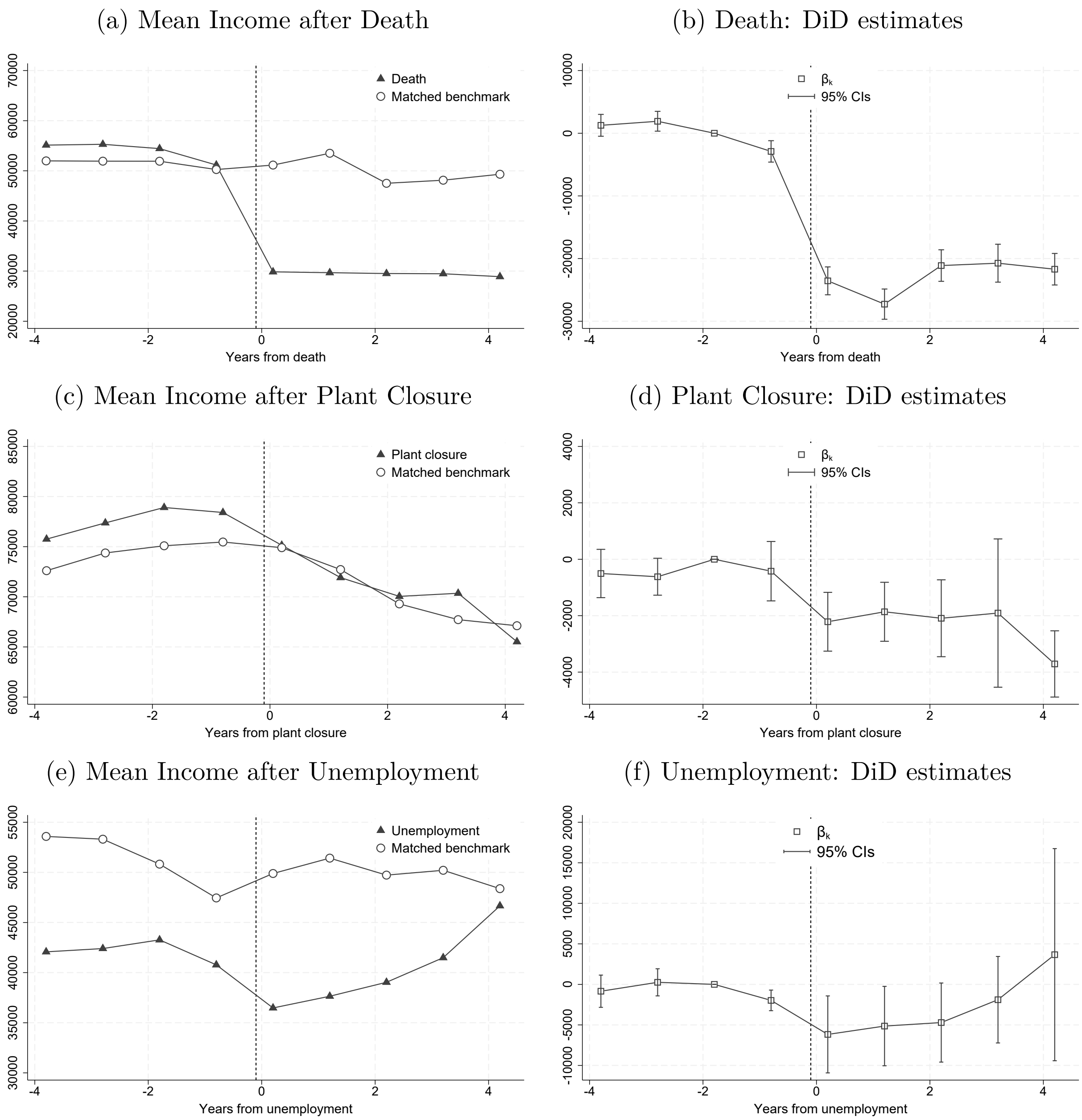


Figure VI: Household-level market income trends before and after the plant closure, death and unemployment among affected and CEM matched control group

Notes: This figure illustrates the evolution of household-level market income trends among households where either parent faced a shock (Death, Plant Closure or Unemployment) and among similar households around the same time (CEM Matched). Panels in the left illustrate levels of outcomes, while panels in the right illustrate the difference in these levels. Panels (a), (c) and (e) display the development of gross market incomes, panels (b), (d) and (f) illustrate the difference across groups relative to two years before the shock, respectively. The figures in the right illustrate the ψ_k coefficients and 95% confidence intervals obtained from estimating specification Equation (2). Standard errors are clustered at the CEM-matching strata level.

Table II: RDD results

	English						Advanced Math						Swedish					
	A	B	C	M	E	L	A	B	C	M	E	L	A	B	C	M	E	L
University enrollment																		
RDD	-.0236	.0183	-.00646	.03	.0177	.0301	.0117	.0117	.0262	.0238	.0147	-.00529	-.0702	.0169	.0224	.000387	.0153	-.0164
	.0293	.0129	.0119	.0114	.0117	.0142	.0140	.0112	.0115	.0126	.0128	.0132	.0242	.0125	.0131	.0146	.0165	.0197
N	3797	13599	24648	33484	36258	23808	19044	31466	34698	29543	21579	14008	5101	14025	18742	19613	17707	10955
CCT	-.0385	.0265	-.00819	.0307	.0125	.0385	.00412	.00027	.0289	.0297	.00606	-.0382	-.0593	.0102	.0083	-.00468	.0122	-.00833
	.0318	.0144	.0106	.00928	.013	.0151	.0205	.0164	.0168	.0179	.0185	.0236	.0209	.0077	.00825	.013	.0112	.0159
N (cct)	31454	97876	171690	226141	231625	144488	68226	95733	111946	101096	75210	41651	63315	139545	187119	197982	171263	99564
BW (left)	4.91	4.37	6.07	7.27	4.36	4.88	3.79	3.32	3.24	3.42	3.28	2.4	6.36	11.6	11.3	5.71	9.47	7.29
Baseline mean	.104	.125	.221	.302	.422	.564	.206	.277	.399	.576	.75	.851	.114	.122	.197	.322	.473	.66
Ter. level enrollment																		
RDD	.051	-.00354	.0168	.0146	.0144	-.00323	-.00292	.0192	-.00583	-.0038	-.00661	.00172	-.0976	-.0012	.0152	-.00602	.00809	-.0187
	.0488	.0187	.0133	.0108	.0099	.0114	.0149	.0101	.00867	.00881	.0101	.0122	.0399	.0185	.0150	.0131	.0127	.0151
N	3797	13599	24648	33484	36258	23808	19044	31466	34698	29543	21579	14008	5101	14025	18742	19613	17707	10955
CCT	.0321	-.00451	.0235	.0162	.00783	-.00739	.00278	.0307	-.00534	-.00987	-.00473	-.0259	-.0626	.00724	.00204	.00574	.00669	-.0147
	.0414	.0167	.0124	.00867	.00921	.0097	.0221	.0148	.0126	.0127	.0142	.0207	.0309	.0117	.00945	.0103	.00836	.0111
N (cct)	31454	97876	171690	226141	231625	144488	68226	95733	111946	101096	75210	41651	63315	139545	187119	197982	171263	99564
BW (left)	6.35	6.3	5.7	7.37	5.99	6.78	3.71	3.38	3.31	3.25	3.44	2.81	7.7	11	11	7.55	10.1	8.67
Baseline mean	.478	.62	.682	.738	.773	.807	.758	.786	.838	.863	.868	.876	.566	.59	.684	.773	.82	.847
University graduation																		
RDD	.00566	.00388	-.0118	.0366	.018	.0279	.00986	.00535	.0198	-.0014	.0171	.0123	-.0378	.00246	-.00575	.0128	.0236	-.0451
	.0253	.0111	.0107	.0104	.0116	.0151	.0119	.00989	.0110	.0134	.0166	.0225	.0195	.00962	.0108	.0127	.0159	.0217
N	2843	9919	18001	24554	26699	17743	15382	24455	26470	22462	16149	9516	4113	11404	15094	15777	14536	9296
CCT	-.00531	.0028	-.0128	.0562	.019	.0351	-.000279	.00575	.0166	-.0115	.0216	.00791	-.0223	.00211	-.0022	.000324	.0179	-.0388
	.0253	.00961	.00967	.0152	.0117	.0199	.0175	.0141	.0163	.0191	.0233	.0305	.0143	.00655	.00814	.011	.013	.0208
N (cct)	23122	71443	125530	165865	170643	106503	53900	73992	85021	76580	55971	29752	50418	113959	151128	160152	139985	82951
BW (left)	5.18	6.61	5.52	3.06	5.29	3.81	3.7	3.62	3.25	3.44	3.46	3.63	8.34	9.66	8.04	6.34	7.03	5.34
Baseline mean	.0508	.0655	.118	.144	.222	.286	.109	.142	.208	.302	.371	.488	.0588	.0555	.1	.153	.247	.386
Top 25% at 30																		
RDD	.0165	-.0308	.022	.000451	-.0012	.00125	-.0143	.00856	-.0101	-.00674	.00692	.0198	.00394	-.0177	.0129	-.00362	-.0175	-.012
	.0435	.0190	.0144	.0128	.0127	.0155	.0179	.0133	.0130	.0144	.0170	.0225	.039	.0184	.0159	.0156	.0166	.0213
N	2843	9919	18001	24554	26699	17743	15382	24455	26470	22462	16149	9516	4113	11404	15094	15777	14536	9296
CCT	.0349	-.0365	.053	.00556	.00468	.00356	-.0437	.0175	-.0117	-.01	.0155	.00842	-.00518	-.0165	-.0118	-.00971	-.00878	-.0162
	.0372	.0199	.0189	.0127	.0108	.0131	.0267	.0192	.0192	.0212	.0247	.0307	.0145	.0134	.01	.0126	.0138	.0203
N (cct)	23122	71443	125530	165865	170643	106503	53900	73992	85021	76580	55971	29752	50418	113959	151128	160152	139985	82951
BW (left)	6.7	4.47	3.38	5.41	6.5	6.81	3.45	3.49	3.27	3.23	3.3	3.57	10.2	8.37	11.1	7.05	6.78	5.18
Baseline mean	.173	.247	.237	.273	.301	.326	.33	.33	.377	.414	.46	.513	.256	.265	.26	.277	.296	.344

Notes: Full result table of RDD analysis illustrating the effect of a higher grade from Finnish matriculation examination on four outcomes: probability of being enrolled in university and any tertiary level education by the age of 25, average probability of being graduated from university by the age of 30 and average probability of being in the top income quartile at the age of 30. First row of each section provides the RD point estimates and robust standard errors from linear model using a bandwidth from -3 to 2 points. CCT estimates and standard errors refer to bias-corrected RD estimates with robust standard errors, using a triangular kernel and optimal symmetric bandwidths determined following Calonico et al. (2014). N (cct) indicate the number of observations and BW the bandwidth used in the CCT estimation. The baseline mean reports the average probability of being enrolled, graduating, or belonging to the top income quartile for students scoring one point below a given grade threshold.

Table III: RDD results

	Intermediate Math						Humanities & Natural Sciences 1996–2005						Natural Sciences 2006–2019					
	A	B	C	M	E	L	A	B	C	M	E	L	A	B	C	M	E	L
University enrollment																		
RDD	-.000679	.00311	-.00778	.00874	.0143	.00909	-.0167	.00941	.00647	.0143	.0123	.0171	-.0415	.00275	.0172	.0174	.0219	.0201
	.00918	.00667	.00712	.00836	.0106	.0155	.010	.00509	.00547	.00672	.00843	.0121	.0195	.0144	.0142	.0133	.0120	.0132
N	21582	38736	45919	44606	35212	18194	19770	64813	83997	83355	64384	26142	8975	17787	23569	24795	21866	12343
CCT	.0147	.00173	-.00988	.00308	.0189	-.000841	-.0177	.0179	.0175	.0315	.0329	.0262	-.0214	.0307	.0397	.0399	.0435	.028
	.0183	.01	.0125	.0147	.0157	.0258	.00896	.00486	.00526	.00649	.00815	.0117	.0176	.0128	.0125	.0118	.0108	.0116
N (cct)	73538	113747	138242	134686	106245	55448	47441	120309	148441	146148	112766	45928	21778	37828	50542	52444	44082	24522
BW (left)	2.46	3.42	2.85	2.9	3.27	2.95	2.62	1.91	1.76	1.55	1.96	1.95	1.7	1.93	1.89	1.63	1.51	1.84
Baseline mean	.0766	.0965	.141	.202	.296	.427	.0655	.0905	.155	.276	.446	.688	.169	.247	.415	.621	.779	.853
Ter. level enrollment																		
RDD	-.0544	-.00535	-.0235	.0136	-.0092	.00464	-.0787	.0197	.00276	.001	-.000457	.0152	-.0399	-.0158	.000821	-.00748	.00993	.0114
	.0172	.0112	.00979	.00923	.00947	.0119	.0208	.00873	.00713	.00641	.0067	.00984	.0246	.0140	.0104	.00873	.00840	.0111
N	21582	38736	45919	44606	35212	18194	19770	64813	83997	83355	64384	26142	8975	17787	23569	24795	21866	12343
CCT	-.0145	.011	-.0348	.00514	-.0041	-.000345	-.0499	.038	.0167	.0111	-.00227	.00181	.00998	-.00146	.0159	-.000524	.0092	.00785
	.034	.0213	.0185	.0149	.0142	.0183	.0185	.00815	.00671	.00609	.00644	.00956	.023	.0126	.00924	.00777	.00748	.00966
N (cct)	73538	113747	138242	134686	106245	55448	47441	120309	148441	146148	112766	45928	21778	37828	50542	52444	44082	24522
BW (left)	2.6	2.77	2.34	3.1	3.22	3.12	1.98	2.51	2.17	2.02	2.51	2.34	1.87	1.77	1.84	1.81	1.8	1.9
Baseline mean	.509	.556	.658	.725	.791	.825	.494	.557	.665	.759	.809	.83	.701	.778	.847	.889	.907	.902
University graduation																		
RDD	-.00359	.00236	-.00324	.00994	.0082	.00918	-.00275	.00173	.00631	.0123	.00993	-.00428						
	.00790	.00581	.00636	.00751	.00995	.0159	.00617	.00321	.00364	.00496	.00695	.0126						
N	17496	29780	34470	33345	25929	12963	19770	64813	83997	83355	64384	26142						
CCT	-.00594	-.000913	-.00408	.0136	.00885	.0212	-.00632	.0053	.0119	.0197	.025	.0085						
	.0127	.00873	.0116	.0113	.0147	.0227	.00542	.00307	.00351	.00483	.00677	.0123						
N (cct)	58292	87402	103549	100064	78256	40145	47441	120309	148441	146148	112766	45928						
BW (left)	3.28	3.4	2.83	3.19	3.27	3.35	2.54	1.97	2.3	1.71	1.96	2.43						
Baseline mean	.0484	.0545	.079	.108	.161	.236	.023	.0341	.0604	.123	.209	.363						
Top 25% at 30																		
RDD	-.0215	-.00661	-.000013	.0174	.00216	.00879	-.0421	-.000849	.00158	-.00971	-.0133	-.0071						
	.0140	.0101	.00986	.0103	.0120	.0169	.0174	.00745	.00653	.00672	.00789	.0129						
N	17496	29780	34470	33345	25929	12963	19770	64813	83997	83355	64384	26142						
CCT	-.018	-.000674	.000796	.0276	-.00418	.0102	-.0273	-.00138	.00921	-.00219	-.00703	.0179						
	.0224	.0152	.0153	.0173	.0193	.0253	.0155	.00696	.00619	.00644	.00762	.0126						
N (cct)	58292	87402	103549	100064	78256	40145	47441	120309	148441	146148	112766	45928						
BW (left)	3.31	3.4	3.18	2.86	3.06	3.23	2.6	2.53	2.37	2.4	2.48	2.51						
Baseline mean	.175	.193	.222	.236	.273	.292	.232	.233	.247	.281	.318	.403						

Notes: Full result table of RDD analysis illustrating the effect of a higher grade from Finnish matriculation examination on four outcomes: probability of being enrolled in university and any tertiary level education by the age of 25, average probability of being graduated from university by the age of 30 and average probability of being in the top income quartile at the age of 30. First row of each section provides the RD point estimates and robust standard errors from linear model using a bandwidth from -3 to 2 points. CCT estimates and standard errors refer to bias-corrected RD estimates with robust standard errors, using a triangular kernel and optimal symmetric bandwidths determined following Calonico et al. (2014). N (cct) indicate the number of observations and BW the bandwidth used in the CCT estimation. The baseline mean reports the average probability of being enrolled, graduating, or belonging to the top income quartile for students scoring one point below a given grade threshold.

Table IV: Effects of parental death on exam performance

	Advanced Math			Intermediate Math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Parental death	-1.435*	-1.529**	-1.378*	-1.299**	-1.228**	-1.136**	-1.226***	-1.267***	-1.161***
≤12 months	(0.739)	(0.725)	(0.727)	(0.566)	(0.562)	(0.564)	(0.413)	(0.414)	(0.408)
N	112,336	112,336	112,335	139,449	139,449	139,448	179,495	179,495	179,494
N (treated)	980	980	980	1,318	1,318	1,318	1,675	1,675	1,675
R^2	0.049	0.071	0.086	0.052	0.070	0.086	0.012	0.028	0.056
Baseline mean	47.817	47.817	47.817	47.181	47.181	47.181	49.857	49.857	49.858
Parental death	-2.844**	-2.681**	-2.785**	-1.056	-1.070	-0.976	-2.186***	-2.166***	-1.987**
≤3 months	(1.336)	(1.303)	(1.325)	(1.140)	(1.129)	(1.133)	(0.792)	(0.798)	(0.798)
N	112,336	112,336	112,335	139,449	139,449	139,448	179,495	179,495	179,494
N (treated)	285	285	285	332	332	332	422	422	422
R^2	0.049	0.071	0.086	0.052	0.070	0.086	0.012	0.028	0.056
Baseline mean	47.808	47.808	47.808	47.171	47.171	47.171	49.850	49.850	49.850
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Parental death	0.036	0.022	0.181	-0.142	-0.129	-0.163	-0.897***	-0.876***	-0.751**
≤12 months	(0.286)	(0.270)	(0.263)	(0.233)	(0.233)	(0.231)	(0.337)	(0.330)	(0.324)
N	306,242	306,242	306,242	293,778	293,774	293,772	233,010	233,010	233,010
N (treated)	2,919	2,919	2,919	2,831	2,831	2,831	2,241	2,241	2,241
R^2	0.021	0.060	0.090	0.562	0.570	0.598	0.096	0.117	0.204
Baseline mean	74.865	74.865	74.865	69.081	69.081	69.081	67.694	67.694	67.694
Parental death	0.134	0.154	0.192	-0.905**	-0.907**	-0.892**	-1.152**	-1.152**	-0.861
≤3 months	(0.486)	(0.470)	(0.468)	(0.439)	(0.438)	(0.431)	(0.586)	(0.585)	(0.573)
N	306,242	306,242	306,242	293,778	293,774	293,772	233,010	233,010	233,010
N (treated)	773	773	773	752	752	752	595	595	595
R^2	0.021	0.060	0.090	0.562	0.570	0.598	0.096	0.117	0.204
Baseline mean	74.865	74.865	74.865	69.081	69.081	69.081	67.688	67.688	67.688
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table V: Effects of plant closure on exam performance

	Advanced Math			Intermediate Math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Plant closure	0.853**	0.524	0.550	-0.634*	-0.688*	-0.690*	-0.573**	-0.674**	-0.724**
≤*12 months*	(0.430)	(0.427)	(0.423)	(0.368)	(0.358)	(0.355)	(0.290)	(0.286)	(0.286)
N	247,644	247,644	247,644	296,459	296,459	296,458	357,673	357,673	357,671
N (treated)	2,634	2,634	2,634	3,184	3,184	3,184	3,910	3,910	3,910
R^2	0.053	0.073	0.088	0.050	0.067	0.084	0.009	0.025	0.053
Baseline mean	48.284	48.284	48.284	47.602	47.602	47.602	50.088	50.088	50.088
Plant closure	-0.430	-0.150	-0.258	-1.514	-1.123	-1.245	-1.700	-1.696	-2.022
≤*3 months*	(3.825)	(3.836)	(3.823)	(2.447)	(2.531)	(2.532)	(2.305)	(2.364)	(2.346)
N	247,644	247,644	247,644	296,459	296,459	296,458	357,673	357,673	357,671
N (treated)	32	32	32	57	57	57	41	41	41
R^2	0.053	0.073	0.088	0.050	0.067	0.084	0.009	0.025	0.053
Baseline mean	48.296	48.296	48.296	47.592	47.592	47.592	50.082	50.082	50.082
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Plant closure	0.464**	0.023	0.023	-0.193	-0.200	-0.289*	-0.260	-0.401*	-0.549***
≤*12 months*	(0.191)	(0.175)	(0.172)	(0.153)	(0.151)	(0.149)	(0.215)	(0.208)	(0.202)
N	654,188	654,188	654,187	628,636	628,633	628,632	487,559	487,559	487,557
N (treated)	6,966	6,966	6,966	6,741	6,741	6,741	5,291	5,291	5,291
R^2	0.027	0.067	0.097	0.564	0.573	0.600	0.102	0.123	0.207
Baseline mean	75.189	75.189	75.189	68.147	68.148	68.147	67.839	67.839	67.839
Plant closure	-0.801	-0.726	-0.595	-0.707	-0.599	-1.098	-0.151	-0.206	-1.166
≤*3 months*	(1.358)	(1.356)	(1.328)	(1.144)	(1.122)	(1.105)	(1.520)	(1.547)	(1.467)
N	654,188	654,188	654,187	628,636	628,633	628,632	487,559	487,559	487,557
N (treated)	112	112	112	107	107	107	90	90	90
R^2	0.027	0.067	0.097	0.564	0.573	0.600	0.102	0.123	0.207
Baseline mean	75.196	75.196	75.196	68.151	68.152	68.151	67.840	67.840	67.840
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. Examination years 1990–2016. Standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table VI: Effects of unemployment on exam performance

	Advanced Math			Intermediate Math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Unemployment	-1.385***	-1.008***	-0.923***	-1.535***	-1.374***	-0.969***	-1.607***	-1.458***	-1.274***
≤12 months	(0.298)	(0.289)	(0.286)	(0.227)	(0.226)	(0.220)	(0.213)	(0.207)	(0.209)
N	154,214	154,214	154,213	193,235	193,235	193,234	208,725	208,725	208,723
N (treated)	7,294	7,294	7,294	10,543	10,543	10,542	11,901	11,901	11,901
R^2	0.055	0.077	0.092	0.050	0.067	0.086	0.010	0.027	0.057
Mean (treated)	47.765	47.765	47.765	47.516	47.516	47.516	49.966	49.966	49.966
Unemployment	-2.375***	-2.120***	-2.179***	-1.438***	-1.315***	-1.192***	-1.973***	-1.836***	-1.884***
≤3 months	(0.449)	(0.438)	(0.436)	(0.344)	(0.337)	(0.329)	(0.271)	(0.268)	(0.274)
N	154,214	154,214	154,213	193,235	193,235	193,234	208,725	208,725	208,723
N (treated)	2,623	2,623	2,623	3,858	3,858	3,858	5,144	5,144	5,144
R^2	0.055	0.077	0.092	0.050	0.067	0.086	0.010	0.027	0.057
Mean (treated)	47.731	47.731	47.731	47.467	47.467	47.467	49.914	49.914	49.914
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Unemployment	-1.908***	-1.321***	-0.927***	-0.840***	-0.827***	-0.838***	-1.669***	-1.459***	-1.097***
≤12 months	(0.146)	(0.126)	(0.124)	(0.105)	(0.102)	(0.103)	(0.151)	(0.144)	(0.144)
N	419,957	419,957	419,957	401,893	401,890	401,888	304,871	304,871	304,871
N (treated)	21,868	21,868	21,868	21,411	21,411	21,411	16,647	16,647	16,647
R^2	0.028	0.068	0.102	0.560	0.569	0.597	0.099	0.120	0.204
Mean (treated)	74.796	74.796	74.796	66.891	66.891	66.891	67.172	67.172	67.172
Unemployment	-1.705***	-1.246***	-1.082***	-1.152***	-1.119***	-1.176***	-1.304***	-1.140***	-1.166***
≤3 months	(0.193)	(0.173)	(0.167)	(0.144)	(0.143)	(0.147)	(0.208)	(0.202)	(0.199)
N	419,957	419,957	419,957	401,893	401,890	401,888	304,871	304,871	304,871
N (treated)	8,047	8,047	8,047	7,939	7,939	7,939	6,536	6,536	6,536
R^2	0.027	0.068	0.101	0.560	0.569	0.597	0.098	0.120	0.204
Mean (treated)	74.725	74.725	74.725	66.856	66.856	66.856	67.092	67.092	67.092
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table VII: Effects of shocks on number of exams, probability of retake exam and failed degree

	(1)	(2)	(3)
	P(Failed Degree)	P(Retake)	Number of Exams
Panel A: Death			
	0.014**	-0.002	-0.028
	(0.005)	(0.008)	(0.026)
N	402245	402245	402245
N (treated)	3533	3533	3533
R^2	0.043	0.146	0.408
Baseline Mean	0.095	0.388	5.578
Panel B: Plant Closure			
	0.003	0.002	-0.023
	(0.003)	(0.005)	(0.017)
N	761048	761048	761048
N (treated)	8299	8299	8299
R^2	0.043	0.114	0.209
Baseline Mean	0.097	0.422	5.893
Panel C: Unemployment			
	0.014***	-0.020***	-0.154***
	(0.002)	(0.003)	(0.011)
N	534975	534975	534975
N (treated)	33023	33023	33023
R^2	0.047	0.132	0.364
Baseline Mean	0.101	0.410	5.718

Notes: Outcomes are: the total number of exams in the degree, probability of retake any exam and probability of failed degree. Controls: examination, school, age and gender fixed effects. All the estimates represent the effects of shock within 12 months before the exam. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table VIII: Heterogeneity of the effects of shocks on the percentage of points earned in all matriculation exams

	(1) Male	(2) Shock to Mom	(3) Capital Region	(4) Total Income>p(50)
Panel A: Plant closure				
Plant closure	-0.000	-0.004**	-0.003*	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
Plant closure × subgroup	-0.006**	0.003	0.002	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)
N	702,744	702,744	702,744	702,744
R^2	0.170	0.170	0.170	0.170
Baseline Mean	0.672	0.672	0.672	0.672
N (treated, subgroup = 1)	3,097	3,867	1,969	3,653
N (treated, subgroup = 0)	4,412	3,642	5,540	3,856
Panel B: Unemployment				
Unemployment	-0.015***	-0.013***	-0.011***	-0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment × subgroup	0.004**	-0.000	-0.012***	0.022***
	(0.002)	(0.002)	(0.003)	(0.002)
N	450,752	450,752	450,752	450,752
R^2	0.170	0.170	0.170	0.171
Baseline Mean	0.665	0.665	0.665	0.666
N (treated, subgroup = 1)	12,406	8,304	4,186	15,527
N (treated, subgroup = 0)	18,612	22,714	26,832	15,491
Panel C: Death				
Death	-0.006*	-0.002	-0.004	-0.017***
	(0.003)	(0.004)	(0.003)	(0.003)
Death × subgroup	0.005	-0.003	-0.002	0.025***
	(0.005)	(0.005)	(0.006)	(0.004)
N	330,323	330,323	330,323	330,323
R^2	0.161	0.161	0.161	0.161
Baseline Mean	0.671	0.671	0.671	0.671
N (treated, subgroup = 1)	1,267	2,205	629	1,567
N (treated, subgroup = 0)	1,865	927	2,503	1,565

Notes: Outcome is the percentage of points earned in all matriculation exams over all subjects. Controls: examination, school, number of exams and gender fixed effects. All the estimates represent the effects of shock within 12 months before the exam. Examination years 1990–2016. Standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table IX: Long-term effects of shocks on educational attainment, employment, and income

	(1) Test Scores	(2) P(Enrolled by 25)	(3) P(Graduated by 30)	(4) P(Employed at 30)	(5) Log(income at 30)
Panel A: Plant closure					
Plant closure	-0.003*	-0.008	-0.004	0.001	0.019
	(0.002)	(0.006)	(0.004)	(0.005)	(0.013)
N	702,744	668,479	668,879	486,456	691,425
R^2	0.170	0.067	0.087	0.187	0.406
Baseline mean	0.672	0.343	0.181	0.793	11.398
N (treated)	7,509	7,010	7,136	5,228	7,378
Panel B: Unemployment					
Unemployment	-0.013***	-0.043***	-0.029***	-0.025***	-0.084***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.008)
N	450,752	433,193	429,548	302,424	442,425
R^2	0.170	0.070	0.085	0.173	0.411
Baseline mean	0.666	0.337	0.182	0.793	11.337
N (treated)	31,018	29,976	29,263	21,574	30,232
Panel C: Death					
Death	-0.004*	-0.029***	-0.023***	-0.018**	-0.023
	(0.002)	(0.009)	(0.007)	(0.008)	(0.020)
N	330,323	313,140	313,771	227,299	324,823
R^2	0.161	0.064	0.083	0.146	0.413
Baseline mean	0.671	0.330	0.167	0.803	11.383
N (treated)	3,132	2,978	2,952	2,277	3,080

Notes: First outcome is the percentage of points earned in all matriculation exams over all subjects; second outcome is probability of being enrolled in the university by 25; third outcome is probability of being graduated from university by 30; fourth outcome is probability of being employed at age 30; fifth outcome is log total income at age 30. Controls: examination, school, number of exams and gender fixed effects. All the estimates represent the effects of shock within 12 months before the exam. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table X: Long-term effects of shocks under exclusion restriction

	(1) Test Scores	(2) P(Enrolled by 25)	(3) P(Graduated by 30)	(4) P(Employed at 30)	(5) Log(income at 30)
Panel A: Plant closure					
Plant closure	0.001	0.006	0.002	0.009	0.014
	(0.002)	(0.008)	(0.006)	(0.007)	(0.016)
N	15,425	14,465	14,616	10,674	15,150
R^2	0.175	0.090	0.118	0.193	0.429
Baseline mean	0.674	0.337	0.174	0.795	11.419
Subgroup *N*	7,520	7,022	7,148	5,228	7,391
Panel B: Unemployment					
Unemployment	0.001*	0.006*	0.001	-0.007**	-0.008
	(0.001)	(0.003)	(0.002)	(0.003)	(0.008)
N	78,618	75,055	73,840	54,814	76,822
R^2	0.183	0.065	0.069	0.133	0.371
Baseline mean	0.655	0.273	0.133	0.783	11.305
Subgroup *N*	38,867	36,639	36,542	27,241	38,009
Panel C: Death					
Death	0.002	-0.002	0.001	0.010	0.038
	(0.003)	(0.012)	(0.010)	(0.012)	(0.030)
N	5,910	5,643	5,561	4,241	5,801
R^2	0.200	0.106	0.112	0.218	0.385
Baseline mean	0.663	0.287	0.148	0.757	11.349
Subgroup *N*	3,164	3,008	2,977	2,292	3,110

Notes: First outcome is the percentage of points earned in all matriculation exams over all subjects; second outcome is probability of being enrolled in the university by 25; third outcome is probability of being graduated from university by 30; fourth outcome is probability of being employed at age 30; fifth outcome is log total income at age 30. Controls: examination, school, number of exams and gender fixed effects. All estimates represent the difference between the effects of a shock occurring within 12 months before the exam and a shock occurring 12–24 months before the exam. Subgroup N denotes the number of individuals who experienced the shock 12–24 months before the examination. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A Additional Figures and Tables

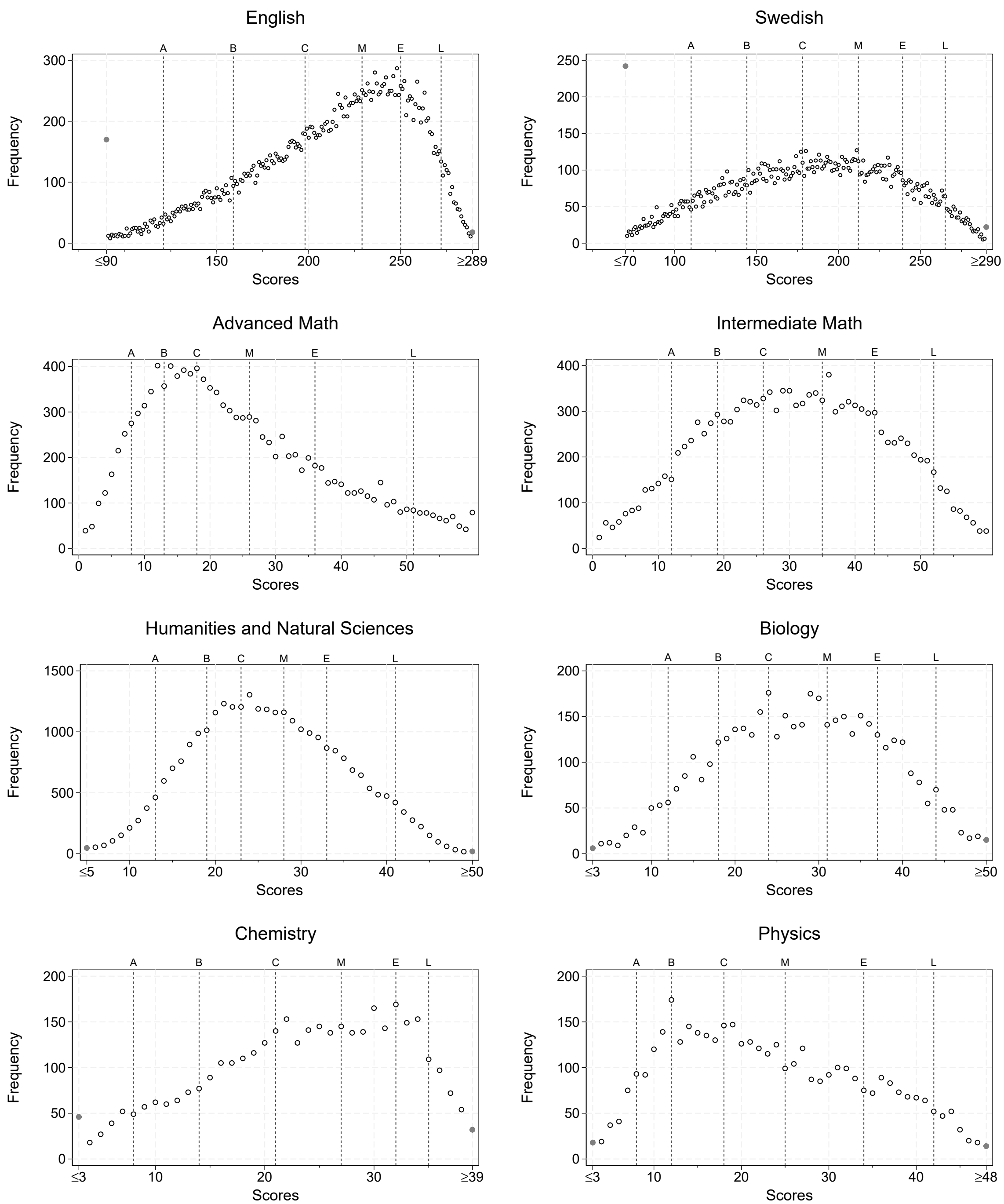


Figure A.I: Distribution of points in matriculation exams

Notes: The figures illustrate the distribution of scores in the matriculation exams. The vertical lines represent the cutoffs for each grade. Since the cutoffs vary by year, the graphs are based on data from spring 2005, except for Biology, Chemistry, and Physics, which are from Spring 2006 (as these subjects were previously part of the general Humanities and Natural Sciences test). End point bins (gray) contains all observations with lower (or greater) scores than the end point.

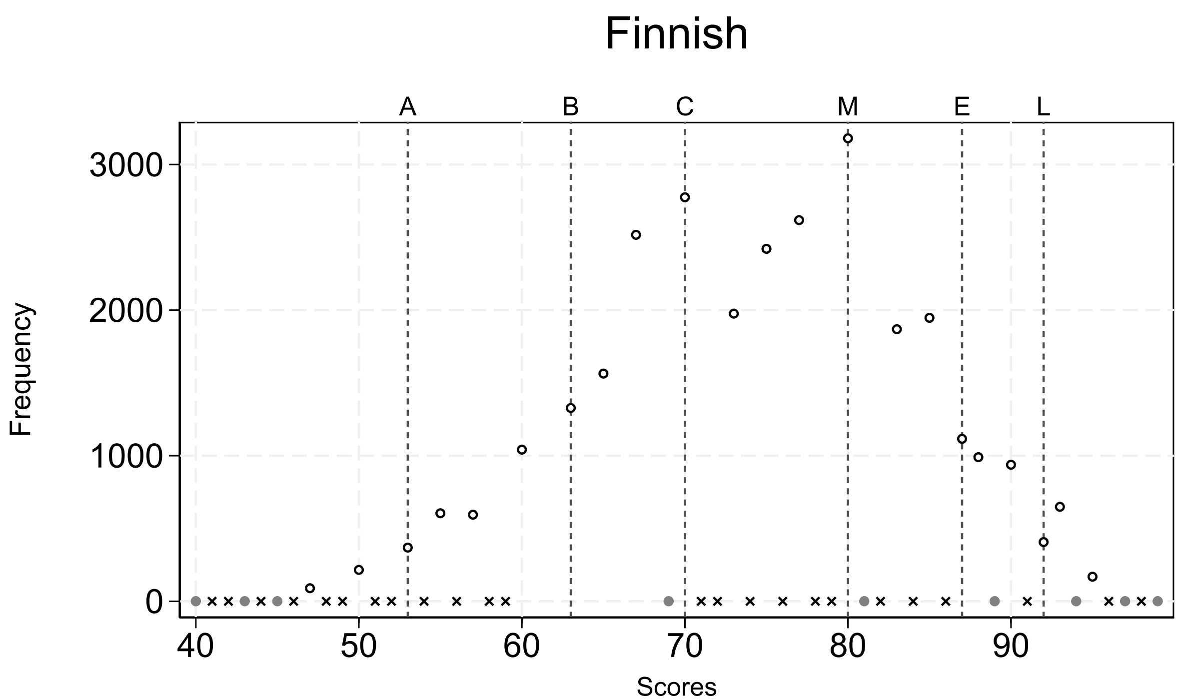


Figure A.II: Distribution of points in Finnish exam

Notes: The figure illustrates the distribution of scores in the Finnish matriculation examinations. Vertical lines indicate the grade cutoffs. Observations with fewer than 50 students are replaced with a gray dot. Points with zero observations are marked with a symbol ”x” to highlight the holes in the distribution.

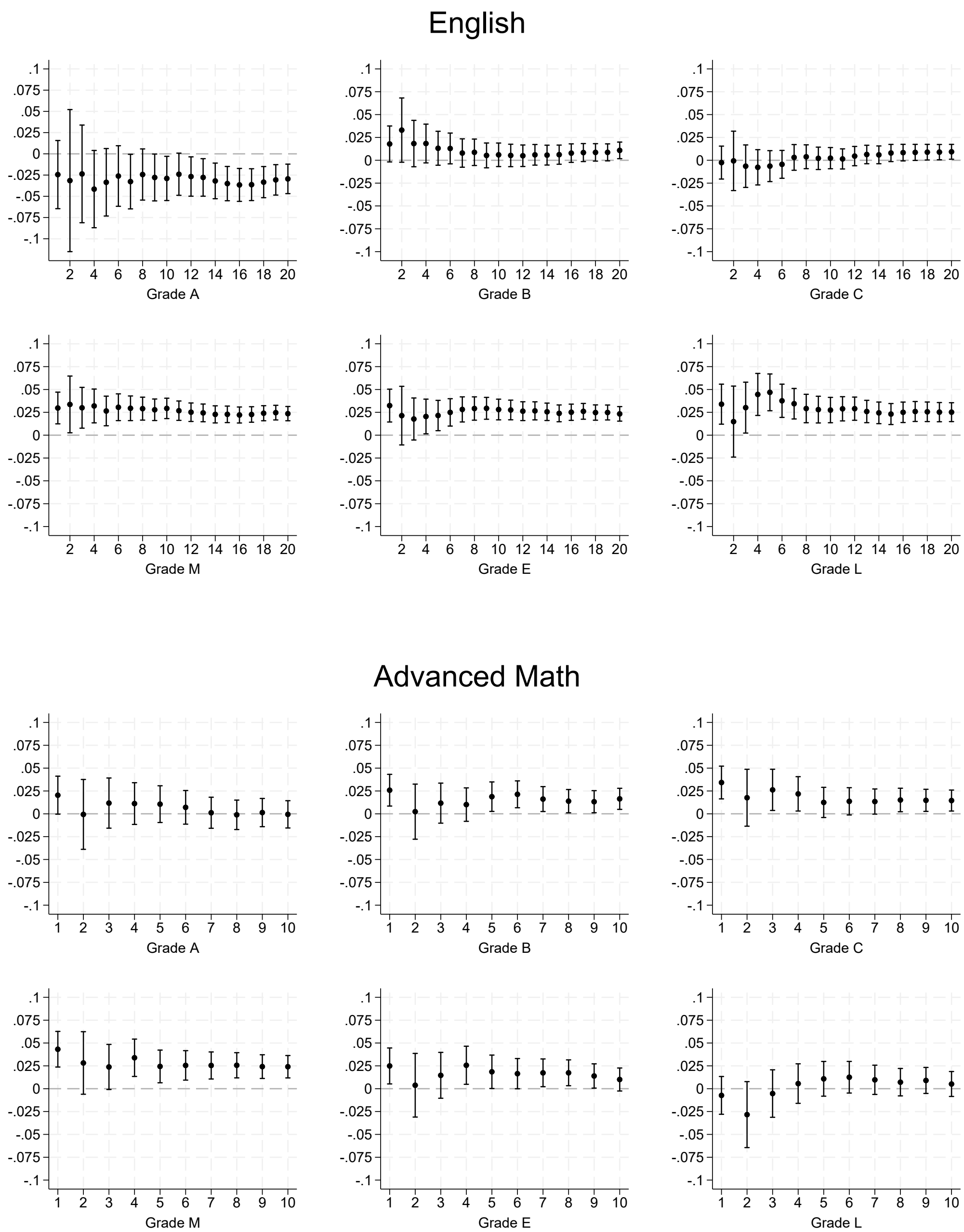


Figure A.III: Robustness check—the effect of grades on university enrollment probability using different bandwidths

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Notes: The figures examine the sensitivity of the RD results to the bandwidth used in the estimation. The RD estimates illustrate the effect of each grade on the probability of being enrolled in university by the age of 25. Both the point estimate and its 95% confidence interval are plotted. For English, we test bandwidths ranging from ± 1 to ± 20 points, as the average difference between grades is around 20 points. Similarly, for Advanced Math we estimate the model using 10 different bandwidths. These ranges are chosen to avoid overlapping with other grade cutoffs above or below (some overlap may still occur at the largest bandwidths because grade cutoffs vary across years).

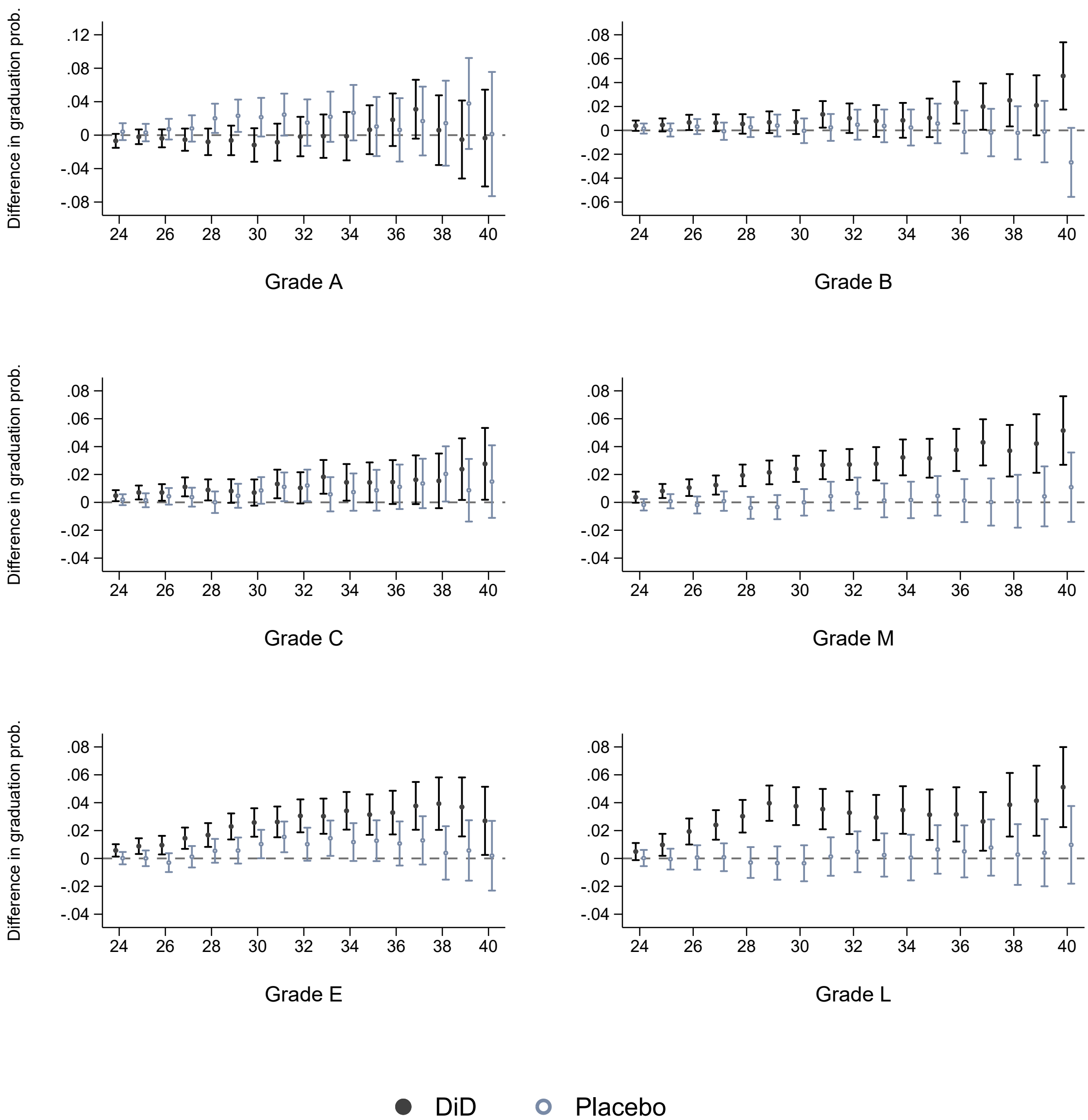

Figure A.IV: DiD estimates on the likelihood of university graduation across ages: English test grades

Notes: The figures display difference-in-differences estimates (with 95% confidence intervals) for the effect of earning a specific English test grade on the likelihood of university graduation across ages. For each age cohort, the control group consists of students scoring 1–3 points below the grade threshold, while the treatment group includes those scoring at the threshold or 1–2 points above it.

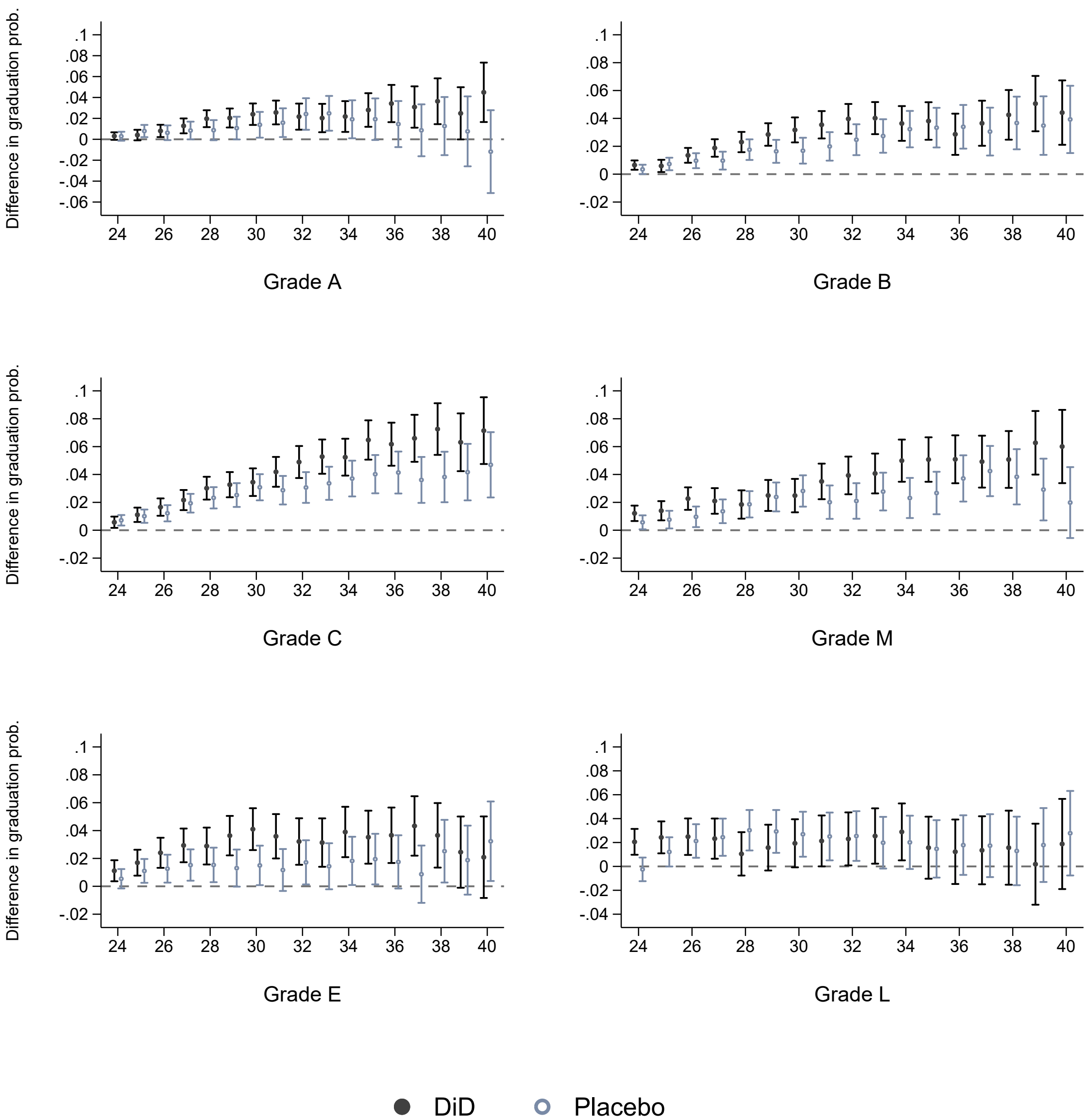

Figure A.V: DiD estimates on the likelihood of university graduation across ages: Advanced Mathematics test grades

Notes: The figures display difference-in-differences estimates (with 95% confidence intervals) for the effect of earning a specific Advanced Math test grade on the likelihood of university graduation across ages. For each age cohort, the control group consists of students scoring 1–3 points below the grade threshold, while the treatment group includes those scoring at the threshold or 1–2 points above it.

Table A.I: Effects of parental death on exam performance (CEM weighted)

	Advanced Math			Intermediate Math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Parental death	-0.673	-0.918	-0.861	-0.806	-0.741	-0.723	-0.997**	-1.063***	-1.000**
≤12 months	(0.743)	(0.737)	(0.741)	(0.577)	(0.577)	(0.579)	(0.396)	(0.402)	(0.397)
N	112,336	112,336	112,335	139,449	139,449	139,448	179,495	179,495	179,494
N (treated)	980	980	980	1,318	1,318	1,318	1,675	1,675	1,675
R^2	0.056	0.088	0.105	0.048	0.076	0.092	0.010	0.033	0.062
Baseline mean	46.674	46.674	46.674	46.525	46.525	46.525	49.582	49.582	49.582
Parental death	-2.049	-2.136	-2.340*	-0.572	-0.633	-0.583	-1.935**	-2.015**	-1.878**
≤3 months	(1.338)	(1.315)	(1.340)	(1.151)	(1.157)	(1.161)	(0.781)	(0.788)	(0.787)
N	112,336	112,336	112,335	139,449	139,449	139,448	179,495	179,495	179,494
N (treated)	285	285	285	332	332	332	422	422	422
R^2	0.056	0.088	0.105	0.048	0.076	0.092	0.010	0.033	0.062
Baseline mean	46.672	46.672	46.672	46.521	46.521	46.521	49.577	49.577	49.577
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Parental death	0.520*	0.277	0.339	0.079	0.085	0.053	-0.505	-0.591*	-0.535*
≤12 months	(0.272)	(0.266)	(0.260)	(0.230)	(0.230)	(0.226)	(0.329)	(0.325)	(0.318)
N	306,242	306,242	306,242	293,778	293,774	293,772	233,010	233,010	233,010
N (treated)	2,919	2,919	2,919	2,831	2,831	2,831	2,241	2,241	2,241
R^2	0.024	0.070	0.106	0.558	0.568	0.596	0.102	0.126	0.213
Baseline mean	74.414	74.414	74.414	69.443	69.443	69.443	67.385	67.385	67.385
Parental death	0.601	0.361	0.296	-0.687	-0.743*	-0.739*	-0.735	-0.876	-0.689
≤3 months	(0.483)	(0.473)	(0.472)	(0.437)	(0.437)	(0.431)	(0.586)	(0.588)	(0.577)
N	306,242	306,242	306,242	293,778	293,774	293,772	233,010	233,010	233,010
N (treated)	773	773	773	752	752	752	595	595	595
R^2	0.024	0.070	0.106	0.558	0.568	0.596	0.102	0.126	0.213
Baseline mean	74.417	74.417	74.417	69.441	69.441	69.441	67.382	67.382	67.382
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. All regressions are weighted using the CEM weights. Examination years 1990–2016. Standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.II: Effects of plant closure on exam performance (CEM weighted)

	Advanced Math			Intermediate Math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Plant closure	0.557	0.290	0.312	-0.673*	-0.731**	-0.735**	-0.664**	-0.752**	-0.775***
≤12 months	(0.431)	(0.426)	(0.422)	(0.372)	(0.363)	(0.360)	(0.301)	(0.295)	(0.297)
N	247,644	247,644	247,644	296,459	296,459	296,458	357,673	357,673	357,671
N (treated)	2,634	2,634	2,634	3,184	3,184	3,184	3,910	3,910	3,910
R^2	0.050	0.070	0.086	0.055	0.073	0.089	0.009	0.026	0.049
Baseline mean	48.692	48.692	48.692	47.338	47.338	47.338	50.046	50.046	50.045
Plant closure	-0.450	-0.114	-0.214	-1.385	-1.029	-1.193	-1.703	-1.766	-2.026
≤3 months	(3.818)	(3.821)	(3.809)	(2.442)	(2.522)	(2.525)	(2.326)	(2.372)	(2.346)
N	247,644	247,644	247,644	296,459	296,459	296,458	357,673	357,673	357,671
N (treated)	32	32	32	57	57	57	41	41	41
R^2	0.050	0.070	0.086	0.055	0.073	0.089	0.009	0.026	0.049
Baseline mean	48.700	48.700	48.700	47.331	47.331	47.331	50.040	50.040	50.040
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Plant closure	0.313	-0.046	-0.038	-0.234	-0.248*	-0.336**	-0.358*	-0.483**	-0.614***
≤12 months	(0.191)	(0.177)	(0.174)	(0.152)	(0.150)	(0.149)	(0.216)	(0.210)	(0.205)
N	654,188	654,188	654,187	628,636	628,633	628,632	487,559	487,559	487,557
N (treated)	6,966	6,966	6,966	6,741	6,741	6,741	5,291	5,291	5,291
R^2	0.028	0.070	0.098	0.567	0.575	0.602	0.112	0.134	0.213
Baseline mean	75.360	75.360	75.360	68.453	68.453	68.453	68.432	68.432	68.432
Plant closure	-0.852	-0.697	-0.595	-0.737	-0.658	-1.146	-0.234	-0.305	-1.228
≤3 months	(1.366)	(1.367)	(1.340)	(1.142)	(1.123)	(1.107)	(1.533)	(1.562)	(1.487)
N	654,188	654,188	654,187	628,636	628,633	628,632	487,559	487,559	487,557
N (treated)	112	112	112	107	107	107	90	90	90
R^2	0.028	0.070	0.098	0.567	0.575	0.602	0.112	0.134	0.213
Baseline mean	75.366	75.366	75.366	68.453	68.453	68.453	68.426	68.426	68.426
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. All regressions are weighted using the CEM weights. Examination years 1990–2016. Standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.III: Effects of unemployment on exam performance (CEM weighted)

	Advanced math			Intermediate math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Unemployment	0.053	0.187	0.263	-0.782***	-0.734***	-0.230	-0.363*	-0.342*	-0.060
≤12 months	(0.297)	(0.293)	(0.288)	(0.241)	(0.243)	(0.232)	(0.186)	(0.185)	(0.186)
N	154,197	154,197	154,196	193,212	193,212	193,211	208,706	208,706	208,704
N (treated)	7,279	7,279	7,279	10,526	10,526	10,525	11,886	11,886	11,886
R^2	0.054	0.077	0.095	0.045	0.063	0.084	0.010	0.028	0.058
Mean (treated)	46.014	46.014	46.014	46.428	46.428	46.428	48.568	48.568	48.568
Unemployment	-1.094**	-1.094**	-1.136***	-0.555	-0.542	-0.407	-0.780***	-0.753***	-0.732***
≤3 months	(0.452)	(0.448)	(0.440)	(0.347)	(0.342)	(0.328)	(0.253)	(0.258)	(0.261)
N	154,197	154,197	154,196	193,212	193,212	193,211	208,706	208,706	208,704
N (treated)	2,623	2,623	2,623	3,856	3,856	3,856	5,142	5,142	5,142
R^2	0.054	0.077	0.095	0.045	0.063	0.084	0.010	0.028	0.058
Mean (treated)	46.033	46.033	46.033	46.395	46.395	46.395	48.557	48.557	48.557
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Unemployment	-0.858***	-0.585***	-0.202*	-0.200**	-0.221**	-0.134	-0.763***	-0.705***	-0.202
≤12 months	(0.126)	(0.119)	(0.114)	(0.098)	(0.098)	(0.098)	(0.142)	(0.139)	(0.134)
N	419,906	419,906	419,906	401,849	401,846	401,844	304,836	304,836	304,836
N (treated)	21,831	21,831	21,831	21,378	21,378	21,378	16,619	16,619	16,619
R^2	0.022	0.060	0.098	0.560	0.570	0.596	0.094	0.115	0.202
Mean (treated)	73.640	73.640	73.640	67.033	67.033	67.032	66.106	66.106	66.106
Unemployment	-0.627***	-0.475***	-0.351**	-0.556***	-0.551***	-0.513***	-0.397**	-0.381*	-0.297
≤3 months	(0.175)	(0.166)	(0.160)	(0.141)	(0.140)	(0.142)	(0.200)	(0.198)	(0.191)
N	419,906	419,906	419,906	401,849	401,846	401,844	304,836	304,836	304,836
N (treated)	8,047	8,047	8,047	7,937	7,937	7,937	6,533	6,533	6,533
R^2	0.022	0.060	0.098	0.560	0.570	0.596	0.094	0.115	0.202
Mean (treated)	73.593	73.593	73.593	66.987	66.987	66.986	66.047	66.047	66.047
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. All regressions are weighted using the CEM weights. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.IV: Effects of plant closure and parental unemployment on exam performance

	Advanced Math			Intermediate Math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Plant closure × unemployment									
≤12 months	-4.379**	-4.145**	-3.968**	-0.623	-0.230	-0.446	-2.091**	-2.005**	-2.094**
	(1.939)	(1.884)	(1.858)	(1.209)	(1.205)	(1.180)	(0.956)	(0.957)	(0.945)
N	236,789	236,789	236,789	278,869	278,869	278,868	338,507	338,507	338,506
N (treated)	132	132	132	236	236	236	252	252	252
R^2	0.053	0.073	0.088	0.050	0.068	0.084	0.009	0.025	0.052
Baseline mean	48.373	48.373	48.373	47.692	47.692	47.692	50.189	50.189	50.189
Plant closure × unemployment									
≤3 months	-2.317	-1.467	-2.138	-1.550	0.360	0.629	8.948***	9.278***	8.674***
	(8.386)	(8.418)	(8.157)	(6.731)	(6.912)	(6.644)	(3.011)	(2.947)	(2.864)
N	240,497	240,497	240,497	286,402	286,402	286,401	345,075	345,075	345,073
N (treated)	8	8	8	13	13	13	11	11	11
R^2	0.053	0.073	0.088	0.050	0.067	0.084	0.009	0.025	0.053
Baseline mean	48.352	48.352	48.352	47.652	47.652	47.652	50.152	50.152	50.152
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Plant closure × unemployment									
≤12 months	-1.487**	-1.108*	-0.993*	-0.226	-0.162	-0.322	-1.665**	-1.370*	-1.545**
	(0.608)	(0.585)	(0.584)	(0.525)	(0.521)	(0.505)	(0.751)	(0.732)	(0.713)
N	613,866	613,866	613,865	595,253	595,251	595,251	454,516	454,516	454,514
N (treated)	535	535	535	479	479	479	425	425	425
R^2	0.027	0.067	0.095	0.564	0.572	0.599	0.102	0.124	0.207
Baseline mean	75.270	75.270	75.270	68.165	68.165	68.165	67.952	67.952	67.952
Plant closure × unemployment									
≤3 months	1.537	2.622	2.607	3.444	3.479*	2.921	6.129**	6.537***	5.943***
	(2.608)	(2.572)	(2.491)	(2.094)	(2.036)	(1.909)	(2.391)	(2.249)	(1.965)
N	632,564	632,564	632,563	607,726	607,723	607,722	470,602	470,602	470,600
N (treated)	20	20	20	23	23	23	21	21	21
R^2	0.027	0.068	0.097	0.564	0.572	0.600	0.101	0.123	0.207
Baseline mean	75.247	75.247	75.247	68.145	68.145	68.145	67.876	67.876	67.876
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. Examination years 1990–2016. Standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.V: Effects of plant closure and parental unemployment on exam performance (CEM weighted)

	Advanced Math			Intermediate Math			Humanities & Natural Sciences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Plant closure × unemployment									
≤12 months	-4.578**	-4.240**	-3.968**	-0.572	-0.093	-0.446	-2.105**	-2.011**	-2.094**
	(1.948)	(1.907)	(1.858)	(1.210)	(1.200)	(1.180)	(0.962)	(0.970)	(0.945)
N	236,789	236,789	236,789	278,869	278,869	278,868	338,507	338,507	338,506
N (treated)	132	132	132	236	236	236	252	252	252
R^2	0.049	0.070	0.088	0.056	0.074	0.084	0.009	0.025	0.052
Baseline mean	48.781	48.781	48.781	47.418	47.418	47.418	50.152	50.152	50.152
Plant closure × unemployment									
≤3 months	-2.096	-0.987	-2.157	-0.332	1.870	1.440	7.037**	7.444**	7.219**
	(8.319)	(8.276)	(8.165)	(6.316)	(6.507)	(6.227)	(3.468)	(3.303)	(3.019)
N	239,143	239,143	239,143	281,552	281,552	281,551	341,896	341,896	341,895
N (treated)	8	8	8	14	14	14	12	12	12
R^2	0.049	0.070	0.088	0.056	0.073	0.084	0.009	0.025	0.052
Baseline mean	48.790	48.790	48.790	47.410	47.410	47.410	50.146	50.146	50.146
	English			Finnish			Swedish		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B									
Plant closure × unemployment									
≤12 months	-1.600***	-1.141*	-0.993*	-0.235	-0.165	-0.322	-1.753**	-1.421*	-1.545**
	(0.607)	(0.586)	(0.584)	(0.527)	(0.523)	(0.505)	(0.754)	(0.736)	(0.713)
N	613,866	613,866	613,865	595,253	595,251	595,251	454,516	454,516	454,514
N (treated)	535	535	535	479	479	479	425	425	425
R^2	0.029	0.070	0.095	0.567	0.575	0.599	0.112	0.134	0.207
Baseline mean	75.457	75.457	75.457	68.482	68.482	68.482	68.553	68.553	68.553
Plant closure × unemployment									
≤3 months	2.105	3.182	3.319	3.700*	3.968*	3.429*	7.366***	7.458***	6.572***
	(2.288)	(2.217)	(2.172)	(2.159)	(2.100)	(2.009)	(2.165)	(2.100)	(1.826)
N	619,706	619,706	619,705	600,981	600,979	600,979	458,923	458,923	458,921
N (treated)	28	28	28	26	26	26	28	28	28
R^2	0.029	0.070	0.095	0.567	0.575	0.599	0.112	0.134	0.207
Baseline mean	75.463	75.463	75.463	68.482	68.482	68.482	68.549	68.549	68.549
Examination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE		✓	✓		✓	✓		✓	✓
Age & gender FEs			✓			✓			✓

Notes: Outcomes are measured as the percentage of points earned in each matriculation exam. The set of control variables expands across columns: first including examination fixed effects, then adding school fixed effects, and finally including examination, school, age, and gender fixed effects. The shock exposure window is defined as either 12 months or 3 months prior to the examination date, with both specifications reported in each panel. All regressions are weighted using the CEM weights. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.VII: Effects of shocks on number of exams, probability of retake exam and failed degree (CEM weighted)

	(1)	(2)	(3)
	Prob. of Failed Degree	Prob. of Retake	Number of Exams
Panel A: Death			
	0.007	0.003	0.001
	(0.005)	(0.008)	(0.026)
N	402245	402245	402245
N (treated)	3533	3533	3533
R^2	0.053	0.132	0.311
Baseline Mean	0.106	0.406	5.717
Panel B: Plant Closure			
	0.003	-0.001	-0.045***
	(0.003)	(0.005)	(0.017)
N	761048	761048	761048
N (treated)	8299	8299	8299
R^2	0.044	0.116	0.127
Baseline Mean	0.097	0.410	5.936
Panel C: Unemployment			
	0.003	-0.011***	-0.085***
	(0.002)	(0.003)	(0.011)
N	534904	534904	534904
N (treated)	32969	32969	32969
R^2	0.053	0.145	0.426
Baseline Mean	0.114	0.400	5.521

Notes: Outcomes are: the total number of exams in the degree, probability of retake any exam and probability of failed degree. Controls: examination, school, age and gender fixed effects. All the estimates represent the effects of shock within 12 months before the exam. Examination years 1990–2016. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.