Does a High School Diploma Matter?
Evidence Using Regression Discontinuity Design

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The current study explores whether education raises productivity (human capital theory) or just reflects it (sorting theory) by estimating earnings returns to a high school diploma. For this purpose, we compare earnings of students who barely passed and barely failed standardized high school exit exams in the Netherlands. These students have similar levels of human capital but different diploma status. Using a regression discontinuity design on administrative population data, we find that a diploma raises hourly net earnings by about 4%. Thereby, the results indicate that a high school diploma serves as an important signal on the labour market. (JEL I26, J24, J31).

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1. Introduction

It is well documented that more educated people tend to earn higher wages and that the correlation between education and wages has remained relatively stable over time (Psacharopoulos and Patrinos 2018). The reason for this education premium, however, has been a source of considerable debate. To explain the positive correlation between education and wages, two dominant economic theories have emerged: the human capital theory and the sorting theory.

The concept of human capital and its relevance to education and productivity was first pioneered by Schultz (1961) and Becker (1962). According to the human capital theory, people invest in education to raise their level of productivity. In turn, the employers reward this increased level of productivity by offering higher wages. In contrast to the human capital theory, the sorting theory was pioneered by Arrow (1973) and Spence (1973), and suggests that the education has no impact on the level of productivity. Confronted with imperfect information about workers' productivity, employers may use education as a filter to screen workers into more productive (more educated) and less productive (less educated) groups. With this grouping of workers based on the level of productivity, the employers pay higher wages to the more educated workers. In turn, more productive people will choose higher levels of education not to raise, but to signal their productivity.[1]

In practice, it becomes challenging to distinguish between the human capital and the sorting theory as both the theories predict a positive effect of education on wages. Nonetheless, it is an important question for economic policy to understand whether education raises productivity or just reflects it. This is because the human capital theory and the sorting theory have different policy implications. According to the human capital theory, the education raises the productivity, which further leads to social returns to education as reflected by the private returns. If this theory holds, then the policy should aim to increase workers' education levels by removing barriers that prevent people from acquiring their desired level of education. On the other hand, if the sorting theory holds and education is merely a signal of productivity, then the aggregate income may remain

[1] As suggested by Weiss (1995), we will use the term "sorting" to refer to both screening and signalling of workers. In addition, we abstract from different versions of the two theories such as weak versus strong sorting and pure human capital theory versus human capital theory that allows sorting. In this paper, "human capital theory" refers to the pure human capital theory, and "sorting theory" refers to the pure sorting theory, meaning that one theory excludes the other.

unchanged even if all workers raise their education levels. This implies that, under sorting, the social returns may be lower than the private returns, calling into a question the rationale for public investment in education.[2]

In this paper, we aim to estimate whether education raises productivity or just reflects it by estimating the earnings returns to a high school diploma. As opposed to years of schooling, a high school diploma is unlikely to affect the productivity, as it is essentially only a piece of paper (Clark and Martorell 2014). Therefore, if we were to randomly assign a high school diploma, we could capture the sorting value of a diploma by estimating the difference in earnings between students who obtained a diploma, and students who did not. To approximate the random assignment of diplomas, we exploit the standardized exit exams which the students must take at the end of the final year of secondary education to obtain a high school diploma in the Netherlands. These exit exams are the last obstacle before graduation. Using a fuzzy Regression Discontinuity (RD) design (Hahn, Todd and Van der Klaauw 2001), we compare the earnings of students who barely passed and barely failed the standardized exit exams. If the assumptions of a fuzzy RD are satisfied, these students are likely to have similar levels of human capital, but different diploma status.

At first, our results suggest that there is no earnings effect of a high school diploma because most students who passed exit exams continued their schooling in post-secondary education. However, once we focus on students who immediately entered the labour market upon leaving secondary education, we find that a high school diploma increases earnings by about 0.34 euros per hour or about 4% in the first year after high school. Further, this effect persists two and three years after leaving secondary education. Although the effect remains positive regardless of gender, ethnicity, or track, we find a larger positive effect for girls and students who have completed a program in the pre-university track. Moreover, the results also indicate students with a high school diploma are 2 to 4 percentage points more likely to find a job. Therefore, we conclude that a high school diploma is likely to have a positive impact on earnings and employment. We contemplate that this effect can be interpreted as a diploma sorting effect as the students who barely failed and barely passed standardized exit exams have a different diploma status but are likely to have similar levels of human capital.

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[2] Although the social returns to education may be lower than the private returns under sorting, this is not necessarily the case. For instance, sorting may improve the match between workers and jobs (Stiglitz 1975). As a result, the social returns may even exceed the private returns to education under sorting.

Most early studies that aimed to distinguish between the human capital and the sorting theory suffered from omitted variables bias and therefore produced only correlational evidence (see Section 2 for an overview). To solve this selection bias, recent studies have attempted to find exogenous variation in sorting status of a degree among workers with similar levels of human capital. Tyler, Murnane, and Willett (2000) estimated the sorting value of the General Educational Development (GED) by exploiting different passing standards across the U.S. states in a difference-in-differences framework. Similarly, Jepsen, Mueser, and Troske (2016) used the GED passing threshold in a fuzzy RD design. Other studies used RD designs to study the earnings returns to degree classification such as graduating with honors (Di Pietro 2017, Feng and Graetz 2017, Khoo and Ost 2018).

To the best of our knowledge, only one study estimated the sorting value of a high school diploma quasi-experimentally (Clark and Martorell 2014). Using a similar empirical strategy as in this paper, the authors compared the earnings of students that barely passed and barely failed the high school exit exams in Texas. They found no evidence of diploma sorting effects and no heterogeneity by gender nor race. However, this study suffers from an important limitation. In Texas, the students take exit exams for the first time in 10th grade and can further retake the exams several times before the 10th and 12th grade. The scores on the 10th grade exit exams are endogenous as the scores could influence the length of schooling or the curriculum in later years. As a result, Clark and Martorell (2014) focused on a small proportion (4.83%) of students that took exit exams at the end of 12th grade. These students have already failed the exam at least once, and often several times. Moreover, the study found that these students had a lower socioeconomic status than students who took exit exams only once (Clark and Martorell 2014). Therefore, the results in this study are unlikely to hold for the majority of the population.

In the current study, we can solve this problem using the Dutch administrative data for the entire population of non-vocational education students. In the Netherlands, standardized exit exams take place at the end of the final grade of secondary education for most students.[3] Therefore, in the study, we can include all students who have taken standardized exit exams in 12th grade. Moreover,

[3] The Netherlands includes three main tracks: pre-university track, general track and a vocational track. Exit exams take place at the end of the 12th grade for students in the pre-university track and the general track. Students in the vocational track take standardized exit exams in the 8th grade. Therefore, in this study, we only consider students in the pre-university track and the general track (74% of students) to avoid selection issues.

our large administrative data include scores on the exit exams between the school year 2005-2006 and school year 2016-2017 for each student, which possesses two major advantages. First, we can identify students who have retaken exit exams in later school years. Second, we can use initial scores on the standardized exit exams instead of the final scores in a fuzzy regression discontinuity design. This is particularly important, as Jepsen et al. (2016) have shown that usage of the final scores in an RD design leads to biased estimates of the earnings returns to a credential. In addition, unlike the final scores, the initial scores on the standardized exit exams in the Netherlands have been found not to be subjected to manipulation (Cornelisz, Meeter and Van Klaveren 2018).

The remainder of the paper is structured as follows. In Section 2, we offer a comprehensive review of the approaches adopted in the literature to separate the human capital effect from the sorting effect of education. In Section 3, we explain the Dutch education system with an emphasis on high school exit exams. In Section 4, we construct and describe the sample. In Section 5, we formulate the fuzzy RD model based on global polynomial methods and provide evidence that the assumptions underlying this model are likely to hold. In Section 6, we present the results and estimate several alternative specifications, such as a local linear and a local quadratic RD model. Towards the end of the paper, in Section 7, we present the discussion of the results and we explore the limitations of the study.

2. Identification of Sorting Effects in the Literature

Dating back to 1970s when sorting theory was first introduced by Arrow (1973) and Spence (1973), many attempts to separate the productivity-enhancing effect from the sorting effect of education have been conducted. Nonetheless, the methods applied were often unconvincing and the results were thereby, mixed. The vast majority of studies could not control for productivity differences between workers with higher and lower levels of education that are observable to firms, but not to the econometrician. As a result, these studies are correlational in nature. In the earliest approach, Taubman and Wales (1973) estimated earnings regressions within occupational categories, and used these regressions to predict the earnings of the workers if they had been employed in other occupations. The study concluded that many workers in occupations with low educational requirements earn less than the predicted wage in occupations with higher educational requirements. This phenomenon was interpreted as evidence for the sorting hypothesis. In a similar approach, Wiles (1974) proposed a method to distinguish between the human capital and the sorting theory by comparing the earnings of equally educated workers employed in occupations related and unrelated to their qualifications. According to this method, if a wage premium is paid to workers employed in occupations related to their qualifications, the sorting hypothesis is rejected. On the other hand, if a worker with a qualification receives a wage premium irrespective of whether the qualification is relevant for the job, the sorting hypothesis is accepted. Therefore, using this method, Miller and Volker (1984) found evidence in favor of sorting, while the results in Arabsheibani (1989) supported the human capital theory. Nonetheless, none of these studies could control for potential selection bias arising from workers choosing their occupations.

Several previous studies emerged in an attempt to improve the approaches by Taubman and Wales (1973) and by Wiles (1974) which compared the returns to education for a “screened” and an “unscreened” group. The screened group includes workers who are likely to benefit from signalling their ability as determining productivity by employers is costly. The unscreened group includes workers who are unlikely to benefit from signalling their ability as employers can determine productivity at a low cost. Adopting this method, Riley (1979), in an early attempt, divided occupations based on his subjective judgment into screened and unscreened groups and found support for the sorting hypothesis. Psacharopoulos (1979), on the other hand, compared the rates of return to education in the private (unscreened) and the public (screened) sectors. From the study conducted, he found that returns to education were higher in the private sector, rejecting the sorting hypothesis. Similarly, Wolpin (1977) observed higher returns to education among the self-employed (unscreened) than among the privately employed workers (screened). Finally, Albrecht (1981) found that the returns to education were similar between workers who were hired through informal channels such as employee recommendations (unscreened) and workers who were hired through formal channels such as advertisements (screened). As a result, Albrecht (1981) concluded that these findings provided evidence for the human capital hypothesis. However, similar to the studies that used the Wiles (1974) approach, none of the studies which compared screened and unscreened groups of workers were able to control for potential selection into the two groups. Therefore, the validity of these studies is questionable.

Another strand of literature that produced correlational evidence has focused on employer learning. These studies estimate the returns to education and the returns to ability over time. As employers obtain better information about their employees’ real productivity, the returns to education should fall and the returns to ability should rise with experience, if the sorting hypothesis holds. Using this approach, Layard and Psacharopoulos (1974) found that returns to education did not decrease, but increase with experience. Similarly, Lange (2007) estimated that employers learn quickly and most expectation errors in productivity decline by 50% within three years. Therefore, Lange (2007) concluded that the sorting is rather limited. By contrast, the findings in Farber and Gibbons (1996), Altonji and Pierret (2001), Arcidiacono, Bayer, and Hizmo (2010), and Kahn and Lange (2014) are consistent with the predictions of the sorting hypothesis. However, similar to previous studies, these studies are merely correlational and are therefore not able to control for unobserved factors that may be influencing the rate of return to education over time such as on-the-job training. Moreover, falling returns to education and rising returns to ability with experience are also consistent with the human capital theory if skills acquired during education become less relevant for the job over time.

Other correlational studies focused on the measures of education used in the wage regression. Most of these studies estimated sheepskin effects. These sheepskin effects occur if wages rise faster with extra years of education, when the extra years also include a credential (for instance, the final year of secondary education). Positive sheepskin effects are then interpreted as evidence for the sorting hypothesis. Adopting this method, Hungerford and Solon (1987), Belman and Heywood (1991) and Jaeger and Page (1996) found that the largest returns to education occur when the additional year of schooling was accompanied by a credential. However, these findings cannot be interpreted as support for the sorting hypothesis, as sheepskin effects are also consistent with the human capital theory (Flores-Lagunes and Light 2010). Human capital models can generate sheepskin effects if good learners are more likely to stay in school long enough to earn a credential, or if students acquire more skills in the years in which they receive a degree rather than in other years of schooling. Therefore, the ability of these studies to distinguish between the two competing theories is limited.

Two related approaches are also worth mentioning that focused on the measures of education. Groot and Oosterbeek (1994) divided actual years of schooling into effective years (number of formally required years to obtain a degree), repeated years, skipped years, inefficient routing years (number of years students switched programs inefficiently), and dropout years (years spent in education without obtaining a degree). Under the sorting hypothesis, more rapid completion of a degree should signal greater ability and should therefore increase earnings. Moreover, years spent in education without obtaining a degree (dropout years) should not increase earnings. On the other hand, Kroch and Sjoblom (1994) included both an absolute and a relative measure of education in a wage regression. The former includes grade level, and the latter the student's rank in the distribution of educational attainment for the entire cohort. If the sorting hypothesis holds, the returns to a student's rank would be positive while the returns to grade level should be zero. Both studies found little support for the sorting hypothesis. Nonetheless, these studies are prone to omitted variables bias and bias arising from measurement error in the different schooling variables.

To further distinguish between the human capital and the sorting hypothesis, more advanced empirical approaches have used policy changes, although not with quasi-experimental methods. Lang and Kropp (1986) proposed that in a sorting model, an increase in the minimum compulsory schooling age would raise educational attainment of students not directly affected by the law. For instance, consider a law which increases minimum compulsory schooling age from 16 to 17 years. If a student who would have left education at the age of 16 is now forced to stay in school until the age of 17, the average ability of all 17-year-old students who remained in school will fall. Consequently, the most able of these students will remain in school until the age of 18. Thus, under sorting, although the compulsory schooling law was meant to affect 16 year-old-students, it also affected high ability 17-year-old students who are now studying longer to signal their ability. Lang and Kropp (1986) provided evidence supporting the sorting hypothesis in the United States. By contrast, using the same approach, Chevalier et al. (2004) observed no additional evidence of sorting in the United Kingdom. An increase in the compulsory schooling age, however, might affect students not directly affected by the law even if no sorting. This can occur if forcing students to stay in school longer teaches them that school is important, or if having weaker students in class lowers the quality of education. Therefore, this approach is unlikely to separate human capital effects from sorting.

A similar approach was proposed by Bedard (2001) based on increased university access. In her study, she argued that an expansion of the university system would lower the cost of entering a university under the sorting hypothesis, but also increase the high school dropout rate. In particular, because of the increased university access, high-ability graduates who were previously constrained from entering a university due to high cost would now enrol in a university. This would decrease the average quality of high school graduates and the employers would realize this. As a result, low-ability students would have less incentive to pool themselves with the high-school graduates group and would leave school. This is in contrast with the human capital hypothesis that predicts only an upward movement in educational attainment. Bedard (2001) indeed found evidence supporting the sorting hypothesis in the US. However, the decision to drop out from high school, graduate, or enrol into a university is not random. Therefore, the results in Bedard (2001) suffer from selection bias.

It is clear that most studies in the literature produced correlational results, prone to selection bias. Several studies, however, attempted to find exogenous variation in sorting status of a degree among workers with similar levels of human capital. Tyler et al. (2000) estimated the sorting value of the General Educational Development (GED) credential in the United States, by exploiting different passing standards across states. In particular, they compared workers from different states with equal GED scores, but different GED status because of differences in the stringency of the passing standards in their state of residence. The results from their difference-in-differences analysis suggest that GED has a large sorting value for white dropouts, but not for minority dropouts.

Other quasi-experimental studies used regression discontinuity designs. Jepsen et al. (2016) exploited the GED passing threshold in a fuzzy RD design and found sorting effects for men right after graduation, but not for women. Other studies used RD designs to study the returns to degree classification (Di Pietro 2017, Feng and Graetz 2017, Khoo and Ost 2018). These studies generally found positive sorting effects. Finally, in the only study to estimate the sorting value of a high school diploma, Clark and Martorell (2014) used an RD design to compare the earnings of workers who barely passed and barely failed high school exit exams in Texas. They found no evidence of diploma sorting effects.

3. Institutional Setting

3.1. The Dutch Education System

The Dutch education system provides for compulsory education beginning at the age of five and continuing either until the age of 18 or until a younger age if a student has already obtained a high school diploma (Government of the Netherlands 2019). Primary education lasts for 7 years, from the age of five until the age of 12. Nonetheless, most parents already enrol their children into primary education at the age of four. In the last year of primary education, pupils take a standardized cognitive test also called as the Cito test. This test includes multiple choice questions testing pupils' Dutch and comprehension skills, mathematics, world orientation (which involves geography, biology and history) and study skills. In general, this test is compulsory for all the pupils, although small deviations exist such as for students in special education. However, this test is not an exam; pupils cannot pass or fail the test. Instead, the goal of the test is to advise the pupils' parents on a secondary education track in which they should enrol their children and also to advise the schools on the ability of pupils. In addition to the cognitive test, pupils also receive an advice of the primary school teacher on which track to follow in secondary education.

At the age of 12, after attending the primary education, the students enter a tracking system in secondary education. Secondary schools decide on whether to accept students based on the advice of the student's primary school teacher and the cognitive test conducted at the end of primary education. In general, secondary schools do not set their own entrance exams, except in exceptional circumstances, such as dance, music, or sports programs. There are three tracks: pre-university track (VWO), general track (HAVO) and pre-vocational track (VMBO). The pre-university track (VWO) lasts for six years and is attended by pupils aged 12 to 18 years (average) thereby, preparing students for university education (WO). A pre-university track diploma provides access to university education, although universities may set their own admission criteria. This track is perceived as the most prestigious track and mainly includes high-performing students. At a university, an academic bachelor's degree program typically lasts for three years. The general track (HAVO) lasts for five years and prepares students for higher professional education (HBO) at a university college. A professional bachelor's degree program at a university college typically lasts for four years. Students who successfully finished a general track program cannot enrol in a university, but have to complete a higher professional education program first. Furthermore, students who did not obtain a high school diploma cannot enrol into a university nor a university college. Nonetheless, school dropouts can continue studying in an adult education (VAVO) program.

The pre-vocational track (VMBO) lasts for four years, from the age of twelve to sixteen and prepares students for the vocational track (MBO). The pre-vocational track combines vocational training with theoretical education in languages, mathematics, history, arts and sciences. This track is typically perceived as the least prestigious track. After four years in the pre-vocational track, students can enrol in the vocational track (MBO) which is oriented towards vocational training. This track prepares students for a certain occupation and lasts for up to four years, depending on the level of training. There are four levels offered to the students undergoing MBO. The MBO level 1 is the "assistant training" level which lasts for 1 year and is focused on simple executive task. Level 2 is the "basic vocational training" which lasts for one or two years depending on the specific program and is focused on executive tasks. “Professional training” forms the level 3 training and lasts for two or three years in which students are taught to complete their tasks independently. Finally, the “middle-management training” (level 4) lasts for three or four years and prepares for jobs with higher responsibility, thereby opening the gates to higher professional education at a university college. The students need to have completed a theoretical, combined, or middle-management vocational program in the pre-vocational track to enrol in professional and middle-management training.

3.2. High School Exit Exams and Diplomas in the Netherlands

In the Netherlands, a student must successfully complete a program in either pre-university track, general track, or in basic vocational training (vocational track, level 2) to obtain a high school diploma. Thus, high school dropouts in the Netherlands are those students who left secondary education before completing a program in one of these three tracks. According to the reports from Government of the Netherlands (2019) the dropout rate in school year 2016-2017 was 6.95%. Most students drop out from the vocational track (9.89%), followed by the general track (6.53%). Least students drop out from the pre-university track (4.11%). This is unsurprising as the pre-university track is the most prestigious track and therefore, mainly includes high performing students.

To successfully complete a program in secondary education, all students need to pass the minimum number of required courses set by the national law. In the final year of the pre-university track, the general track, and the pre-vocational track, students conduct two exit exams per course for most courses: a school exit exam and a standardized exit exam.[4] School exit exams are set by the schools and therefore differ per school. These exit exams can be oral, practical, or written and are graded by the school teachers. By contrast, the standardized exit exams are the standardized national exams compiled by the Dutch Ministry of Education, Culture and Science. One standardized exit exam is administered per course for all pupils in the same track. This exit exam is mostly written[5] and can contain both multiple-choice as open questions. It is either graded by a computer or by appointed external examiners. Standardized exit exams are conducted in the pre-university track, the general track, and the pre-vocational track. Reader should note that the

4 Nonetheless, some elective courses include only a school exit exam.

[5] Some courses in the pre-vocational track include a “practical” test in which students go to a separate examination centre and perform practical tasks in front of an examiner. These tests are also graded out of possible 10 points.

vocational track does not include standardized exit exams, but only school exit exams. As mentioned previously, students can only obtain a high school diploma in the pre-university track, the general track, and in basic vocational training (vocational track, level 2). Therefore, students enrolled in the pre-vocational track need to continue their studies in at least basic vocational training to qualify for a high school diploma and this track does not include standardized exit exams.

Both school exit exams and standardized exit exams are graded out of possible 10 points. The final grade for a course is generated by the average number of points on the school exit exam and the standardized exit exam. None of the scores are made public.[6] Although school exit exams and standardized exit exams are rounded to 1 digit after the comma, final grades are rounded to whole digits. To complete a program, a necessary requirement is that the average score on the standardized exit exams for all courses should be at least 5.5 out of possible 10 points. However, this requirement is not sufficient, and several other criteria need to be taken into consideration (see Government of the Netherlands (2019) for a detailed list of criteria). Therefore, for the purpose of this paper, it is important to note that it is possible that a student with an average score on the standardized exit exams of 5.5 or higher does not receive a high school diploma. On the contrary, it is legally not possible that a student with an average score on the standardized exit exams of less than 5.5 still receives a high school diploma.

The school exit exams and the standardized exit exams are conducted at the end of the final school year. The students are informed about the scores on their school exit exams before the start of the standardized exit exams. Thus, although both the exit exams are conducted at the end of the final school year and can therefore, not determine the curriculum studied, school exit exams precede standardized exit exams. Therefore, standardized exit exams are the last obstacle before program completion. In general, students can take a standardized exit exam in all subjects only once per year, in the second half of May. However, students can retake a standardized exit exam in one course in the second half of June. In exceptional circumstances such as illness, students can also take standardized exit exams in the second half of August. Furthermore, some students who are not enrolled in a school anymore such as older school dropouts from earlier school years, students in the military and imprisoned students can also take the so-called state exam in August.

[6] In Section 7, we delve deeper into the issue of whether employers can acquire information about the exam scores.

This exam is equivalent to a standardized exit exam for regular students. In all cases, the highest of the three scores counts. In school year 2016-2017, it was observed in our population data (see below) that 99.98% out of 203,310 students took standardized exit exams in May for the first time. Furthermore, 82.90% took standardized exit exams only once and 17.10% retook a standardized exit exam for one of the courses in later periods (June or August).

As mentioned previously, students can only complete a program if they obtain an average score for the standardized exit exams of at least 5.5 out of possible 10 points. If a student does not reach this threshold, this student needs to retake standardized exit exams for all courses again in the next school year, regardless of whether the student passed an individual course. Students are eligible to retake standardized exit exams in later school years at most twice. For instance, from the students who took an exit exam in school year 2011-2012 for the first time and failed, 37.49% retook standardized exit exams once in the next school year and 0.14% retook standardized exit exams twice. Moreover, students who failed to obtain a diploma but passed several courses do not receive a certificate as an alternative, except in rare circumstances such as students in the military or imprisoned students who failed the state exam.

4. Data

4.1. Sample Construction

We use the administrative education records collected by the Statistics Netherlands that cover the entire Dutch population of students. Thereby, we observe all educational enrolments starting from school year 2000-2001 until school year 2016-2017. Each student has been given a unique personal identification number, allowing us to follow a student's educational path over the school years. Per student/school year record, we observe the specific program and the track a student was enrolled in (secondary education, higher education and adult education) as well as the high school graduation status coded as *dropped out*, *graduated*, *continued to the next school year*. Moreover, for school years ranging from 2005-2006 until 2016-2017, we also observe (a) whether a student took standardized exit exams, (b) when the student took standardized exit exams (May, June, or August), (c) the score on the standardized exit exams for each time period averaged over the courses, (d) the score on the school exit exams averaged over the courses, and (e) the final score calculated as the average of the school exit exams and the standardized exit exams over all the courses.

Using personal identification numbers, we link these data to population registers that contain demographic characteristics of the entire Dutch population. This allows us to observe the date of birth, gender, neighbourhood of residence, and birth country of the student as well as the birth country of the parents. Furthermore, we link these data to labour market information from tax authorities. Moreover, these data further include the job history of the entire Dutch population between 1999 and 2016 as well as gross earnings per job per day, and taxes paid. Therefore, we observe earnings after leaving high school for most students. Finally, we also construct a measure of a student's socioeconomic status. For this purpose, we use the population registers to link students to their parents. Subsequently, to calculate annual earnings of the parents, we merge these parental data with tax records.

The obvious strengths of our administrative dataset are a very large sample (entire population) and likely little measurement error in the variables of interest compared to survey data. Additionally, we observe the average score on the standardized exit exams per school year, allowing us to identify students who have retaken standardized exit exams in later years. A limitation of the dataset is that we only observe the average score on the standardized exit exams, but not the score on the standardized exit exam for each course. An additional limitation is that we cannot observe long-run outcomes.

To study earnings returns to a high school diploma, we restrict the sample in three ways. First, we solely consider students in the pre-university track and the general track. Therefore, students who took standardized exit exams in the pre-vocational track are not taken into consideration. This is because of two reasons. First, this track does not lead to a high school diploma. Students who successfully complete a program in the pre-vocational track need to continue their studies to at least basic vocational training (vocational track, level 2) to obtain a high school diploma. However, as mentioned previously, the vocational track does not include standardized exit exams. Therefore, at least two years have passed since the moment these students took their initial standardized exit exams and the moment they left secondary education. As a result, students with an equal average score on the standardized exit exams may have accumulated a different amount of human capital in the years after the standardized exit exam. The second reason we do not consider students in the pre-vocational track is that standardized exit exams are equal for all students within the same track. Therefore, comparing scores within a track is warranted. However, for students in the pre-vocational track, the average score on the standardized exit exams often serves as a mechanism to choose which level in the vocational track to follow, leading to selection effects. As a result, including a variable for both the average score on the standardized exit exams and a variable for the track would lead to post-treatment bias (Rosenbaum, 1984). In sum, the results in this paper do not allow us to draw conclusions about the value of a high school diploma for students in vocational education. Furthermore, it is unclear whether our results can be generalized for this population of students as these students have a higher dropout rate than students in the other two tracks.

As a second sample restriction, we study cohorts who took their initial standardized exit exams between the school year 2007-2008 and school year 2012-2013. Before 2007-2008, we do not observe whether a student took standardized exit exams multiple times. Similarly, after, 2012-2013, we cannot study labour market outcomes. Consider, for instance, a student who took standardized exit exams for the first time in the school year 2013-2014 and failed two times. This student is allowed to try one more time, in 2015-2016. If the student passes the exit exams and obtains a high school diploma, this student will enter the labour market in 2017.[7] However, we observe labour market outcomes until the year 2016. Therefore, we restrict the sample to observe students' labour market outcomes one year after leaving school. Lastly, we remove a small percentage of students (0.24%) with missing values on the outcomes, variables of interest, or one of the covariates. The final sample includes 435,768 students who took initial standardized exit exams between school year 2007-2008 and school year 2012-2013. We observe the outcomes of these students one year after leaving school. However, we will also consider outcomes two years after leaving school for cohorts who took their initial standardized exit exams until school year 2011-2012, and three years after leaving school for cohorts who took their initial standardized exit exams until school year 2010-2011.

4.2. Variable Construction

Outcome Variables. We aim to distinguish between the human capital and the sorting hypothesis by estimating the returns to a high school diploma. Therefore, the outcome of interest is productivity, proxied by the average net earnings per hour in the first year after graduation. The calculation of this variable takes place in three steps. In the first step, we calculate total net earnings per year as the sum of gross earnings over all jobs within a year minus the amount of taxes paid. Second, to obtain the number of Full Time Equivalents (FTE), we multiply the number of days

[7] Technically, a student can also enter the labour market at the end of 2016.

worked by a part-time factor (for instance, 0.5 means employed at 50% and 1 means employed full time). In the last step, we divide the net earnings per year by the number of FTE worked and by 7.6 (usual number of working hours per day based on a 38 hours working week). Furthermore, we also reproduced our results using the net earnings per year instead of per hour, log of net earnings per hour, log of net earnings per year, log of gross earnings per hour, and log of gross earnings per year in **Table A1** in the Appendix. As an additional labour market outcome, we consider an indicator for employment given value of 1 if the person had at least one paid job and 0 otherwise. These results are provided in **Table A2** and **Figure A1** in the Appendix. Due to data restrictions, we mainly study outcomes one year after students finished their last exit exam. Nonetheless, for earlier cohorts, we also study outcomes two and three years after students finished their last exit exam. Thus, this paper focuses on immediate returns to a high school diploma.

Standardized Exit Exam Score. The average score on the school exit exams, the average score on the standardized exit exams and the final score form the three exit exam scores at the end of secondary education. The final score is defined as the unweighted average of the school exit exam score and the standardized exit exam score. We have chosen for the average standardized exit exam score as the exam score of interest given that it is nationally determined, externally graded and includes a clear threshold of 5.5 out of 10 points, which students need to obtain to receive a high school diploma. School exit exams, on the other hand, are set by schools, teacher graded and thus could be manipulated, and do not include a clear cut off. Similarly, the final score also does not contain a clear cut off and it would ignore the minimum requirement students need to attain on the standardized exit exams. Furthermore, to account for students retaking the standardized exit exams, we follow Jepsen et al. (2016) and solely consider the average score on the initial standardized exit exams a student took. We construct two variables. The first is a continuous variable for the average score on the initial standardized exit exams a student took, centred to be zero at passing threshold. The second variable is an indicator given value of 1 if a student scored at or above the threshold and 0 if the student scored below the threshold.

High School Diploma, Track, and Year of Exam. Our data include an indicator for high school dropout per school year, which comprises three categories: dropped out, graduated, or continued to the next school year. Therefore, we measure high school diploma as an indicator given value of 1 if a student graduated in the school year of taking the standardized exit exams, and 0 if a student dropped out. If students continued their studies in high school, we follow them for two more school years as they are allowed to retake standardized exit exams twice. If students still continued their studies in high school after these two school years without graduating, they are counted as school dropouts (this is less than 0.01% of students). Furthermore, we include a variable for the track student took standardized exit exams in, because standardized exit exams are equal for all students within the same track. However, they may differ across tracks. We code this variable as an indicator given value of 1 for the pre-university track and value of 0 for the general track. Finally, we also include indicators for the year students took their initial standardized exit exams to account for exams differing by year.

Control Variables. Several control variables are constructed, although not strictly necessary for our empirical strategy (see below). We include an indicator for gender (1 is boy, 0 is girl), a continuous variable for age at initial standardized exit exams, and age squared. In addition, we include three variables as a measure of socioeconomic background. First, we construct a variable for child's ethnicity based on parental birth country. It is given value of 1 if at least one parent was born outside the Netherlands and value of 0 if both parents were born in the Netherlands. Second, we include indicators for neighbourhood of residence. Third, we include a continuous measure for parental annual net income in 10,000 euros one year before taking standardized exit exams. We calculate this variable as the total annual net income of the father and the mother. Both neighbourhood of residence as parental income are measured one year before taking standardized exit exams to avoid potential endogeneity arising from post-treatment bias (Rosenbaum 1984).

4.3. Descriptive Statistics

From the descriptive statistics presented in **Table 1**, we observe that 34,426 students (7.9%) dropped out from high school after their last exit exams. It was further observed in **Table 1** that about 79% passed the initial standardized exit exams. Moreover, about 41% retook at least one standardized exit exam either in the same school year or in one of the following school years from the students that failed the initial standardized exit exams. We also observe that students who obtained a diploma are more likely than dropouts to be a girl, and to have a higher socioeconomic status in terms of having Dutch parents, older parents, and more parental income.

It further appears from descriptive statistics that students who obtained a diploma are not significantly more likely to be employed or to earn more than dropouts. However, a large proportion of students, about 73%, went to post-secondary education immediately after their last exit exam. These findings will have an important consequence on our analysis as students who enter post-secondary education are often not employed and thereby do not have earnings on the labour market. As a result, our results will be driven downward. This also explains why the net earnings may appear low at only about 4 euros per hour. Given that many students who entered post-secondary education are not employed and have zero earnings or only work in low paying jobs for a short period of time, these low hourly earnings are not surprising.

If we compare students who immediately entered the labour market after secondary education and therefore, did not enrol into post-secondary education with the full sample, several important differences are worth mentioning. First, students who immediately entered the labour market are typically more disadvantaged than students in the full sample. They are more likely to be from foreign ethnicity, to be older (due to grade repetition), to have younger parents, and less parental income. They are also more likely to be boys who typically have a higher dropout rate. As a result, the dropout rate for these students is at about 27%, significantly higher than the dropout rate of 7.9% for the full sample.

TABLE 1 – DESCRIPTIVE STATISTICS

	Full sample			Students not in post-secondary education		
	Total	Diploma	Dropout	Total	Diploma	Dropout
	(1)	(2)	(3)	(4)	(5)	(6)
Gender (1=boy, 0=girl)	0.449	0.441	0.537#	0.533§	0.521	0.564#
Ethnicity (1=foreign, 0=Dutch)	0.126	0.119	0.211#	0.227§	0.209	0.277#
Age at first std. exit exam	17.333	17.315	17.548	17.985§	17.981	17.995
Age of the mother	46.969	47.298	43.132#	42.530§	43.001	41.258#
Age of the father	49.603	49.881	46.357#	45.238§	45.764	43.815#
Parental annual income (10,000)	3.958	4.012	3.330#	3.156§	3.210	3.009#
Passed initial std. exams (1=yes)	0.738	0.794	0.091#	0.528§	0.701	0.059#
Retook std. exam (1=yes)[a]	0.414	0.419	0.353#	0.308§	0.318	0.281#
Net earnings per hour in EUR[b]	3.985	3.991	3.910	6.659§	6.748	6.419#
Employment (1=employed)[b]	0.784	0.759	0.767	0.849§	0.851	0.812#
Number of students	435,768	401,342	34,426	118,446	86,466	31,980

Notes.

# indicates that the coefficient for dropouts is significantly different from the baseline coefficient for graduates at the 5% level using a t-test.

§ indicates that the coefficient for total in column (4) is significantly different from the baseline coefficient for total in column (4) at the 5% level using a t-test.

[a] Share of students who retook at least one standardized exit exam from the total number of students who failed the initial standardized exit exams.

[b] This variable was measured one year after students finished their last exit exam.

5. Empirical Methodology

5.1. Fuzzy Regression Discontinuity Design

The goal of the paper is to compare earnings of students with and without a high school diploma among students with similar levels of human capital. Therefore, we use the average score on the standardized exit exams as a running variable in a fuzzy regression discontinuity design for this purpose (Hahn, Todd and Van der Klaauw 2001). The fuzziness of the RD design arises from two sources. First, it is possible that a student with an average score on the standardized exit exams of 5.5 or higher does not receive a high school diploma due to an insufficient score on the school exit exams. Second, we use the average score on the *initial* standardized exit exams as a running variable as recommended by Jepsen et al. (2016). Although legally students cannot obtain a diploma if they did not reach the threshold on the standardized exit exams on average, it is possible to retake one standardized exit exam in a second period within the same school year, and to retake all standardized exit exams in later school years. Thus, the students can obtain an insufficient average score on the initial standardized exit exams, but then still pass once they retake the exams. It is important to note, however, that although students can retake the exams, these exams take place at the end of the final year of secondary education. Therefore, students are unlikely to influence the length of schooling or the curriculum in later years unlike in previous studies (e.g. Clark and Martorell (2014)). In sum, the fuzziness of our approach arises from students who passed the standardized exit exams and still dropped out of high school as well as from students who failed the standardized exit exams and still obtained a diploma.

Intuitively, we study the earnings difference between those students who barely passed and barely failed on the high school standardized exit exams. More formally, Hahn at al. (2001) show that fuzzy RD design can be formulated as a parametric Instrumental Variables (IV) model estimated by Two-Stage Least Squares (2SLS). Therefore, we use passing status on the standardized exit exams as an instrumental variable for diploma status in models that control for various polynomial orders of the average standardized exit exam scores (Clark and Martorell 2014). The outcome equation is formulated as follows:

$$(1)\ Y_i = \beta_0 + \beta_1 \widehat{D}_i + \beta_2 S_i + \beta_3 T_i + g(p_i) + \boldsymbol{\delta} \boldsymbol{X}_i + \epsilon_i$$

The corresponding first stage equation is formulated as follows:

$$(2)\ D_i = \alpha_0 + \alpha_1 P_i + \alpha_2 S_i + \alpha_3 T_i + f(p_i) + \boldsymbol{\gamma} \boldsymbol{X}_i + \varepsilon_i$$

In **Equation (1)** and **Equation (2)**, Y_i represents a labour market outcome, i.e. net earnings per hour for student i, D_i is the high school diploma status (1=diploma, 0=dropout), P_i is an indicator for passing the standardized exit exams (1=passed, 0=failed), S_i is an indicator for the track (1=pre-university track, 0=general track), T_i is an indicator for the year a student took the initial standardized exit exams, X_i is a set of control variables as specified above, and p_i is the average score on the initial standardized exit exams, centred at 0 for the threshold score if 5.5 out of 10 points. Furthermore, $g(p_i)$ captures the relationship between the earnings and the average score on the initial standardized exit exams and $f(p_i)$ captures the relationship between the high school diploma status and the average score initial on the standardized exit exams. The parameter of interest is β_1 which identifies the causal effect of a high school diploma on earnings under the assumptions of a fuzzy regression discontinuity design (see Section 5.2).

As stated by Lee and Lemieux (2010), it is not possible to know whether a parametric or nonparametric approach to RDD produces more reliable estimates in finite samples. Therefore, to enable comparisons with other seminal papers in this literature (Clark and Martorell 2014, Jepsen, Mueser and Troske 2016), we use parametric global polynomial methods to model the relationship between the earnings and the standardized exit exam scores on the one hand, and diploma status and the standardized exit exam scores on the other. Nonetheless, In Section 6.4, we reanalyze the data using local linear and local quadratic methods with a triangular kernel for various bandwidths.

Gelman and Imbens (2018) advise against the use of higher order polynomials in RD designs because they may lead noisy estimates, sensitivity to the degree of the polynomial, and poor coverage of confidence intervals. Therefore, we will only use polynomials of order one and two consistent with Jepsen et al. (2016) in the main specifications.[8] Furthermore, to allow different functional forms on the two sides of the threshold, we also interact test scores with the indicator for passing standardized exit exams. As recommended by Lee and Lemieux (2010), we use the

[8] Nonetheless, the results are robust to the use of higher order polynomials (available upon request).

same functional form for both the first-stage and the second-stage (outcome) equation (Gelman and Imbens 2018).

5.2. Validity Checks

If the fuzzy RD assumptions hold, the variation in treatment near the threshold is randomized as though from a randomized experiment for the group of compliers (Lee and Lemieux 2010). In this section, we consider each of the fuzzy RD assumptions in turn which include: (a) a sizeable discontinuity in the exam scores (said otherwise, passing standardized exit exams should be a *strong instrument* for diploma attainment), (b) the passing status should only influence earnings through a high school diploma (*exclusion restriction*), and (c) there should be no defiers (*monotonicity*).

Strong Instrument. In **Figure 1**, we show diploma status as a function of the average score on the initial standardized exit exams. As bin size, we consider the full range of scores as suggested by “optimal” bin sizes (Calonico, Cattaneo and Titiunik 2014). We observe a large jump in diploma attainment at the threshold suggesting that the instrument is strong. Moreover, in Section 6.1, we present the empirical results for the first stage equation including the Kleibergen and Paap (2006) *F*-statistic. All first stage *F*-statistics are well above the weak instrument thresholds of Montiel Olea and Pflueger (2013).

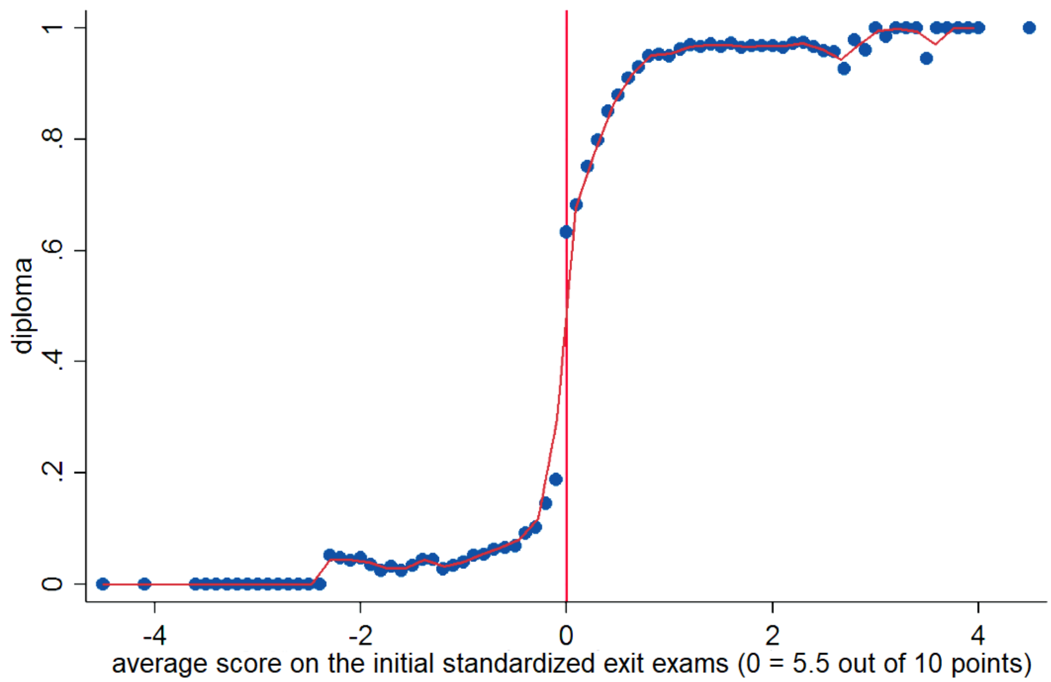

FIGURE 1 – DIPLOMA STATUS BY INITIAL STANDARDIZED EXIT EXAM SCORES.
Notes. Diploma is an indicator given value of 1 if a student obtained a high school diploma and a value of 0 if a student dropped out from high school. Dots represent the share of students who obtained a diploma by initial standardized exit exam scores. The full range of scores is depicted on the x-axis. This bin size was suggested to be the "optimal" bin size (Calonico, Cattaneo and Titiunik 2014).

Exclusion Restriction. Ultimately, the exclusion restriction is empirically untestable. However, we conduct several checks that suggest that the exclusion restriction is likely to hold in our setting. First, students should not be able to precisely manipulate the average score on the initial standardized exit exams. This assumption is very likely to hold in our setting as standardized exit exams are graded either by a computer or by external examiners, not by school teachers. In addition, we use the average score on the standardized exit exams, and students take a standardized exit exam for the majority of courses. Therefore, it is very unlikely that a student's intensity of studying could precisely manipulate this average score. Finally, we use the initial score which has been found not to be subjected to manipulation (Cornelisz, Meeter and Van Klaveren 2018). To confirm this, we show the density of standardized exit exam scores in **Figure 2** as suggested by McCrary (2008). We find that the density of the standardized exit exam scores appears to be continuous near the threshold. Formally, we also use the manipulation test suggested by McCrary (2008) as well as the test suggested by Cattaneo, Jansson, and Ma (2018) and do not reject the null hypothesis of no manipulation in both tests (p-values are 0.361 and 0.488, respectively).

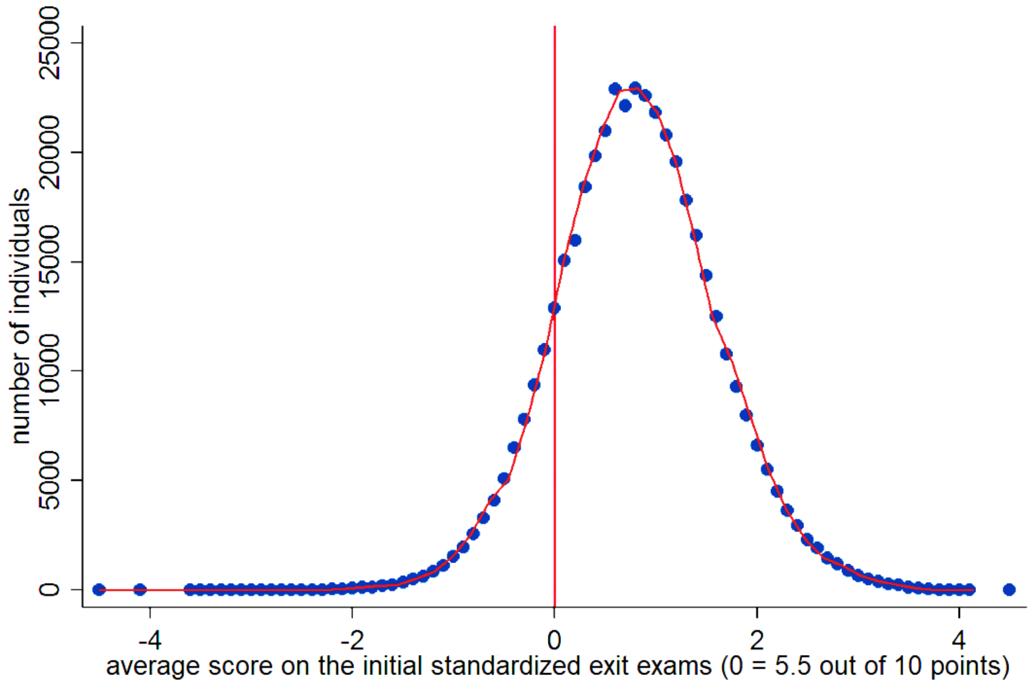

FIGURE 2 – DISTRIBUTION OF INITIAL STANDARDIZED EXIT EXAM SCORES.
Notes. Dots represent the number of students who obtained a given initial standardized exit exam score. The full range of scores is depicted on the x-axis. This bin size was suggested to be the "optimal" bin size (Calonico, Cattaneo and Titiunik 2014).

Second, we seek for potential other discontinuities that may reduce confidence in our model. Nonetheless, in **Figure 1**, we do not observe any discontinuities other than the discontinuity at the passing threshold of 5.5 out of possible 10 points. As a robustness check, we test for discontinuities at two placebo exit exam scores: the median exam score for all scores below the threshold (coefficient: 0.001, standard error: 0.029) and the median exam score for all scores above the threshold (coefficient: 0.009, standard error: 0.033). Neither of the coefficients were significant at the 5% level. Finally, we perform a balancing test on the covariates. Theoretically, it is not necessary to include covariates in an RD model as the variation in treatment near the threshold is as good as randomized if the crucial RD assumptions hold (Lee and Lemieux 2010). Nonetheless, covariates can be used to test whether there is a discontinuity in variables other than the treatment at the passing threshold. If this was the case, students on the left of the threshold would not be similar to students on the right of the threshold, invalidating our RD design. In particular, we run the following model on each covariate:

$$(3)\ X_i = \theta_0 + \theta_1 P_i + \theta_2 S_i + \theta_3 T_i + h(p_i) + \mu_i$$

In **Equation (3)**, X_i represents a covariate, e.g. gender for student i, P_i is an indicator for passing standardized exit exams (1=passed, 0=failed), S_i is an indicator for the track (1=pre-university track, 0=general track), T_i is an indicator for the year a student took the initial standardized exit exams, and h_i is the average score on the initial standardized exit exams centred at 0 for the threshold score of 5.5 out of 10 points. Finally, $h(p_i)$ captures the relationship between the covariate and the average score on the initial standardized exit exams. We use polynomials of order one and two with and without interactions as in the main analyses (higher order polynomials yield analogous results). Results shown in **Table 2** indicate that the discontinuity is not significant in any of the covariates at the passing threshold. This indicates that students near the threshold are similar. In sum, although the exclusion restriction ultimately cannot be tested, our analyses suggest that it is likely to hold in our setting.

TABLE 2 – TESTS OF COVARIATE BALANCE

	Discontinuity estimate			
	(1)	(2)	(3)	(4)
Gender (1=boy, 0=girl)	0.005	0.004	0.005	0.006
	(0.007)	(0.007)	(0.008)	(0.007)
Ethnicity (1=foreign, 0=Dutch)	0.002	0.001	0.004	-0.002
	(0.004)	(0.004)	(0.006)	(0.004)
Age at first standardized exit exam	0.002	0.002	0.004	0.003
	(0.010)	(0.009)	(0.009)	(0.007)
Age of the mother	0.028	0.011	0.021	0.020
	(0.061)	(0.055)	(0.078)	(0.081)
Age of the father	0.014	0.012	0.011	0.012
	(0.072)	(0.081)	(0.080)	(0.077)
Parental net annual income	0.041	0.038	0.067	0.032
	(0.043)	(0.044)	(0.058)	(0.068)
Polynomial order	linear	linear interaction	quadratic	quadratic interaction
Number of students	435,768	435,768	435,768	435,768

Notes. Robust standard errors are in parentheses. All specifications include an indicator for the track (1=pre-university track, 0=general track).

Monotonicity. The results obtained by a fuzzy regression discontinuity design solely hold for *compliers* near the threshold (Lee and Lemieux 2010). In our study, these are the students who obtained a high school diploma because they barely passed the standardized exit exams, and who would not have done so if they barely failed the standardized exit exams. By contrast, the results in this paper do not allow us to draw conclusions about the value of a high school diploma for *always-takers*: students who would have obtained a diploma regardless of the passing status, by for instance retaking the standardized exit exams. From our data, we observe that 9.4% of students who first failed standardized exit exams, eventually obtained a diploma by retaking them. Similarly, our results also do not hold for *never-takers*: students who would not have obtained a diploma regardless of whether they barely passed or barely failed the standardized exit exams, by for instance failing the school exit exams. In our data, we find that 11.5% of students who passed standardized exit exams, actually dropped out. Finally, our model assumes the absence of *defiers*: students who obtained a high school diploma because they barely failed standardized exit exams, and who would not have done so if they barely passed standardized exit exams. Evidently, this behaviour would be counterintuitive. Furthermore, according to the Dutch law, students who did not pass standardized exit exams cannot obtain a high school diploma. Therefore, we conclude that the monotonicity assumption is likely to hold.

6. Results

The following sections of the paper present the results. First, we report estimates of the effect of passing the initial standardized exit exams on diploma attainment and on earnings. Then, we report estimates of the effect of a high school diploma on earnings. In addition to this, we also report heterogeneous effects based on gender, ethnicity, and secondary education track. Finally, the section ends by showing that the results are similar when using local linear and local quadratic methods instead of global polynomial methods. All the models have been estimated with covariates included to improve precision of the estimates. Nonetheless, models without covariates yield very similar results.

6.1. The Effect of Passing Initial Standardized Exit Exams on High School Diploma and on Earnings

The effect of passing the initial standardized exit exams on diploma attainment (*first stage*) is reported in **Table 3** (Panel A). As expected from **Figure 1**, we find that students who passed standardized exit exams are much more likely to graduate from high school. This effect is robust to the polynomial order and ranges from 0.229 to 0.529 percentage points. Moreover, all the *F*-statistics are large, suggesting that our instrument is strong. Goodness-of-fit statistics indicate that the second model with linear interaction as polynomial order is the preferred specification.

TABLE 3 – THE EFFECT OF PASSING INITIAL STANDARDIZED EXIT EXAMS ON DIPLOMA ATTAINMENT AND EARNINGS

Panel A: Outcome: Diploma Attainment	(1)	(2)	(3)	(4)
Passed (1=yes, 0=no)	0.529***	0.363***	0.383***	0.229***
	(0.002)	(0.003)	(0.003)	(0.006)
Polynomial order	linear	linear interaction	quadratic	quadratic interaction
Number of students	435,768	435,768	435,768	435,768
F-statistic	258.584	279.339	275.550	284.334
Panel B: Outcome: Net Earnings	(5)	(6)	(7)	(8)
Passed (1=yes, 0=no)	0.002	0.003	0.003	0.005
	(0.007)	(0.007)	(0.008)	(0.009)
Polynomial order	linear	linear interaction	quadratic	quadratic interaction
Number of students	435,768	435,768	435,768	435,768

Notes. Robust standard errors are in parentheses. Net earnings are calculated per hour in the year immediately after students finished their last exit exam. All specifications include an indicator for the track (1=pre-university track, 0=general track) as well as additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income).
*** Significance at the 1% level.

In **Figure 3**, we show earnings by the initial mean standardized exit exam scores. There appears to be a positive association between earnings and initial standardized exit exam scores. This is unsurprising as the initial standardized exit exam scores are predictive of diploma attainment and we expect a positive association between a high school diploma and earnings. Nonetheless, there appears to be no discontinuity at the passing threshold.

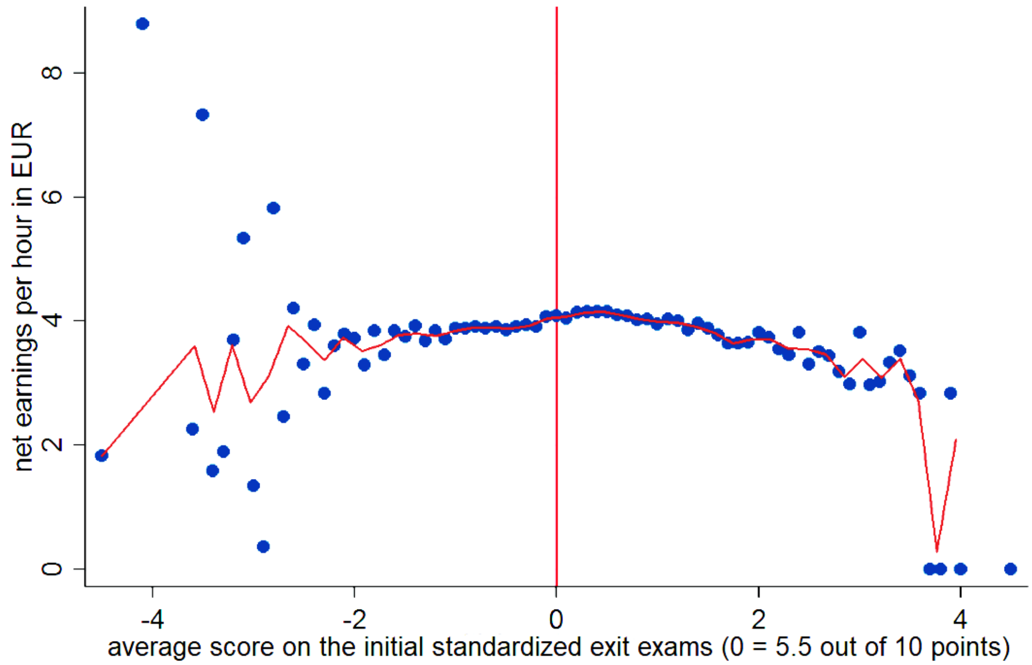

FIGURE 3 – EARNINGS BY INITIAL STANDARDIZED EXIT EXAM SCORES.
Notes. Net earnings are calculated per hour in the year immediately after students finished their last exit exam. Dots represent the mean earnings by initial standardized exit exam scores. The full range of scores is depicted on the x-axis. This bin size was suggested to be the "optimal" bin size (Calonico, Cattaneo and Titiunik 2014).

The estimates in **Table 3** (Panel B) confirm this conclusion. We find that the effect of passing the initial standardized exit exams on log earnings (*reduced form*) is insignificant, regardless of the specification. These results are consistent with other similar studies (Clark and Martorell 2014, Jepsen, Mueser and Troske 2016) who also found no discontinuity effects at the passing threshold for earnings, but large effects in the first stage.

6.2. The Effect of a High School Diploma on Earnings

The instrumental variables estimates of the effect of a high school diploma on net earnings are presented in **Table 4**. It appears from Panel A that a high school diploma does not have a causal effect on net earnings immediately after leaving school. Regardless of the specification, the estimates are small and not significantly different from zero.

TABLE 4 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON EARNINGS

Panel A: Full sample	(1)	(2)	(3)	(4)
Diploma (1=yes, 0=no)	0.029	0.013	0.009	0.008
	(0.053)	(0.010)	(0.009)	(0.021)
Polynomial order	linear	linear interaction	quadratic	quadratic interaction
Number of students	435,768	435,768	435,768	435,768
Panel B: Not in Post-Secondary Education	(5)	(6)	(7)	(8)
Diploma (1=yes, 0=no)	0.559***	0.340***	0.297***	0.223***
	(0.046)	(0.049)	(0.052)	(0.085)
Polynomial order	Linear	linear interaction	quadratic	quadratic interaction
Number of students	118,446	118,446	118,446	118,446

Notes. Robust standard errors are in parentheses. Outcome in both panels is net earnings per hour in the year immediately after students finished their last exit exam. All specifications include an indicator for the track (1=pre-university track, 0=general track) as well as additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income).
*** Significance at the 1% level.

A possible concern, however, is that students who obtained a diploma are more likely to invest in skill acquisition and therefore, more likely to enrol into post-secondary education. This is indeed the case in our sample as high school dropouts cannot, by law, enrol into higher education.[9] We observe that about 73% of the students enrolled into post-secondary education immediately after either obtaining a diploma (students went to higher education) or after dropping out (students went to adult education). Therefore, we present the results with these students excluded in Panel B, consistent with Jepsen et al. (2016). We find that, once we exclude students who enrolled into post-secondary education, the earnings effect of a diploma is likely to be positive. In particular, students with a high school diploma who did not enrol into post-secondary education are likely to earn a wage premium of 0.2 euros to 0.5 euros per hour immediately after leaving school. In **Table A1** in the Appendix, we consider several other coding schemes of earnings. We observe that the effect of a high school diploma on earnings is about 4% or about 800 euros per year.[10]

[9] In **Table A3** in the Appendix, we also estimate our models using an indicator for post-secondary education as an outcome. Unsurprisingly, we observe a positive effect of a high school diploma on post-secondary education enrolment of about 12%.

[10] It should be noted that the effect of a high school diploma on earnings is significantly positive at the 10% level even in the full sample when we consider the log of earnings. As using the log of earnings removes students with zero

In **Figure A1**, we repeat the analyses for earnings two and three years after leaving secondary education. Due to data restrictions, we can only conduct this analysis for earlier cohorts. In particular, we consider outcomes two years after leaving school for cohorts who took their initial standardized exit exams until school year 2011-2012, and three years after leaving school for cohorts who took their initial standardized exit exams until school year 2010-2011. The results indicate that the positive effect of a high school diploma on earnings is persistent over time.

In **Table A2** and **Figure A2** in the Appendix, we repeat the analysis for employment as an outcome and observe similar results as for earnings. The results in **Table A2** indicate that a high school diploma does not affect employment one year after leaving secondary education in the full sample. However, if we exclude students who enrolled into post-secondary education, a high school diploma significantly increases earnings by 2 to 4 percentage points from a mean employment rate of about 85% depending on the specification. Further, **Figure A2** suggests that these effects are stable over time.

6.3. Heterogeneity by Students' Gender, Ethnicity and Educational Track

It is possible that the earnings effect of a high school diploma varies across different types of students. Therefore, in **Table 5**, we present the results by several observed characteristics that are included in our data, and have been found to exert a heterogeneous effect on the returns to schooling. These are gender (Harmon, Oosterbeek and Walker 2003, Psacharopoulos and Patrinos 2018), ethnicity (Chiswick and Miller 2008, Henderson, Polachek and Wang 2011), and track (Balestra and Backes-Gellner 2017, Mazrekaj, De Witte and Vansteenkiste 2019). The table includes the full sample in Panel A and excludes students who enrolled into post-secondary education immediately after the last exit exam in Panel B. To conserve space, we only present the results with standardized exit exam scores modelled as a linear interaction, as this specification yielded best performance based on goodness-of-fit statistics. Nonetheless, as for the main effects, alternative specifications yield very similar results.[11] Our results suggest that a high school diploma does not affect earnings for any of the subgroups for the full sample. By contrast, once we exclude students in post-secondary education, we observe a positive effect for all subgroups. We find no

earnings (who mostly entered post-secondary education), this result is consistent with the finding that many students enrol into post-secondary education, driving the effects downward.

[11] The results are available upon request.

heterogeneous effects by ethnicity. On the other hand, we find heterogeneous effects by gender and by track. The effect appears to be higher for girls than for boys and higher for students in the pre-university track than students in the general track.

TABLE 5 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON EARNINGS, BY GENDER, ETHNICITY, AND TRACK

	Boys	Girls	Foreign	Dutch	Pre-university track	General secondary track
Panel A: Full Sample						
Diploma (1=yes, 0=no)	0.008	-0.012	0.004	0.005	0.008	0.009
	(0.010)	(0.017)	(0.018)	(0.014)	(0.013)	(0.023)
Number of students	195,660	240,108	51,856	383,912	226,599	209,169
Panel B: Not in Post-Secondary Education						
Diploma (1=yes, 0=no)	0.176***	0.564***	0.364***	0.326***	0.429***	0.290***
	(0.070)	(0.067)	(0.115)	(0.056)	(0.090)	(0.053)
Number of students	63,132	55,314	26,887	91,559	46,673	71,773

Notes. Robust standard errors are in parentheses. Outcome in both panels is the net earnings per hour in the year immediately after students finished their last exit exam. Standardized exit exam scores are modelled as a linear interaction. Specifications by gender and by origin include an indicator for the track (1=pre-university track, 0=general track). All specifications include additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income).
*** Significance at the 1% level.

6.4. Alternative Specifications

Until now, the current study used an approach based on global polynomial methods to estimate the causal effect of a high school diploma on earnings. Nonetheless, as suggested by Lee and Lemieux (2010), both global as local polynomial methods should be used when conducting an RD analysis. Therefore, a local linear and a local quadratic regression with a triangular kernel is performed in this section. However, the choice of bandwidth is crucial in these specifications. Consistent with prior studies (Clark and Martorell 2014, Jepsen, Mueser and Troske 2016), we use the "optimal" bandwidth by Imbens and Kalyanaraman (2012), but also explore the robustness of our results to a variety of other bandwidths. Each specification includes the full set of covariates. Nonetheless, our results are robust to the exclusion of covariates. **Table 6** presents the results. In Panel A, we observe the results for the full sample and in Panel B, we observe the results for students who did not enrol in post-secondary education. The results are very similar to the results using global polynomial methods regardless of the specification with no effect in the full sample and a positive effect of about 0.35 euros to 0.43 euros per hour.

TABLE 6 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON EARNINGS USING LOCAL POLYNOMIAL METHODS

	IK bandwidth (± 0.497)	± 0.25	± 0.75	± 1.00	± 1.25
Panel A: Full Sample					
Local linear regression					
Diploma (1=yes, 0=no)	0.001	0.001	0.004	0.009	0.010
	(0.011)	(0.012)	(0.014)	(0.025)	(0.031)
Local quadratic regression					
Diploma (1=yes, 0=no)	0.002	0.002	0.003	0.009	0.009
	(0.010)	(0.009)	(0.009)	(0.015)	(0.016)
Number of students	435,768	435,768	435,768	435,768	435,768
Panel B: Not in Post-Secondary Education					
Local linear regression					
Diploma (1=yes, 0=no)	0.351***	0.348***	0.370***	0.381***	0.399***
	(0.008)	(0.011)	(0.013)	(0.015)	(0.019)
Local quadratic regression					
Diploma (1=yes, 0=no)	0.355***	0.350***	0.385***	0.401***	0.429***
	(0.013)	(0.015)	(0.018)	(0.020)	(0.025)
Number of students	118,446	118,446	118,446	118,446	118,446

Notes. Robust standard errors are in parentheses. Outcome in both panels is the net earnings per hour in the year immediately after students finished their last exit exam. Specifications by gender and by origin include an indicator for the track (1=pre-university track, 0=general track). All specifications include additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income).
*** Significance at the 1% level.

7. Discussion

The paper involved the comparison between the students who barely passed and barely failed the standardized exit exams in the final year of secondary education using a fuzzy regression discontinuity design. Both for the full sample as for different subgroups, we found no earnings effect of a high school diploma at first. However, it was observed from the results that most of the students who passed the exams actually enrolled in post-secondary education. Once the study focused on students who immediately entered the labour market after secondary education, we found a positive effect of a high school diploma on earnings of about 0.34 euros per hour or an increase of about 4% in the first year after leaving high school. Moreover, the results also indicated students with a diploma are 2 to 4 percentage points more likely to find a job. These positive effects persisted two and three years after leaving secondary education. Although the effects remained positive regardless of the gender, ethnicity, or track, we found larger positive effects for girls and students who have completed a program in the pre-university track. Therefore, it is argued that a high school diploma increases earnings and the probability of being employed.

This finding is in line with previous correlational studies that estimated sheepskin effects (Belman and Heywood 1991, Hungerford and Solon 1987, Jaeger and Page 1996). However, the current study is in contrast with Clark and Martorell (2014), which is the only study that estimated the sorting effect of a high school diploma quasi-experimentally. Clark and Martorell (2014) found no sorting effects in Texas. The difference in findings lies likely in the different samples of individuals under study. Whereas Clark and Martorell (2014) focused on students who already failed exit exams at least once, we focused on all students in non-vocational education who did not enrol into post-secondary education, but immediately entered the labour market.

To interpret our findings as sorting effects instead of human capital effects, several conditions under which sorting effects can occur are worth mentioning. As noted by Clark and Martorell (2014), diplomas will have a sorting effect if three conditions apply. First, diplomas should contain information about relevant productivity differences in a competitive labour market. We found a positive association between having a high school diploma and earnings of about 24%.[12] Therefore, employers are likely to use this information when screening the workers. Second, employers should observe diplomas and be able to verify them if necessary. This is especially likely in the Netherlands where a high school diploma is often asked upon job application and where diploma attainment can easily be verified through an online diploma register maintained by the Dutch Ministry of Education, Culture and Science (Government of the Netherlands 2019). This register includes all the obtained diplomas and can only be accessed by the student who obtained the diploma. Thus, employers just have to ask workers to contact the register and provide a confirmation that they have indeed obtained a diploma. Lastly, firms should not obtain the information about productivity differences from other sources. In the Netherlands, students do not obtain a certificate if they fail standardized exit exams. Although employers can ask workers for their individual grades or test workers themselves, this is unlikely to happen in practice due to cost

[12] We regressed hourly net earnings on high school diploma attainment (coefficient: 0.241, standard error: 0.001).

concerns, especially in occupations that solely require a high school diploma and not a higher education degree. Most companies request the high school diploma status and the secondary education track.

In sum, we interpret the positive earnings and employment effect of a high school diploma as a diploma sorting effect. From a policy perspective, this can be both beneficial as detrimental for the society. On the one hand, a high school diploma may help to place the right man or woman in the right job (Stiglitz 1975). On the other hand, private returns to education may exceed the social returns to education and it is likely that too much education is sought by students (Layard and Psacharopoulos 1974). Further research should aim to estimate which of these consequences of sorting prevails.

Although our research design could address most of the issues in the literature, this study is not without limitations. To mention few of our limitations, our study did not include students in vocational education as they took the standardized exit exams several years before graduation. It is unclear whether our results also hold for the vocational students who typically stem from a disadvantaged socioeconomic background and are especially likely to be high school dropouts. Moreover, as mentioned by Clark and Martorell (2014), a high school diploma can signal both high school completion (i.e. perseverance) and passing the exit exams (i.e. cognitive skills). In the current study, we are unable to distinguish between the two signals. The other limitation to mention includes that the study could only research on the short-run effects of a high school diploma. It would further be interesting to study whether sorting effects disappear after several years as employers learn more about the workers. Finally, our results solely apply for the population of compliers at the threshold as any study using a fuzzy regression discontinuity design. Addressing these limitations can thereby provide new potential avenues for further research.

Appendix

TABLE A1 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON EARNINGS (DIFFERENT CODING OF EARNINGS)

Outcome:	log hourly net earnings	log hourly gross earnings	annual net earnings	log annual net earnings	log annual gross earnings
Panel A: Full Sample					
Diploma (1=yes, 0=no)	0.099 (0.181)	0.022* (0.012)	20.124 (29.833)	0.021* (0.010)	0.024* 0.012)
Number of students	341,642	341,642	435,768	341,642	341,642
Panel B: Not in Post-Secondary Education					
Diploma (1=yes, 0=no)	0.041*** (0.002)	0.047*** (0.004)	779.912*** (40.008)	0.038*** (0.003)	0.044*** (0.004)
Number of students	100,561	100,561	118,446	100,561	100,561

Notes. Robust standard errors are in parentheses. Outcomes in both panels are measured in the year immediately after students finished their last exit exam. Standardized exit exam scores are modelled as a linear interaction. Specifications by gender and by origin include an indicator for the track (1=pre-university track, 0=general track). All specifications include additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income).
*** Significance at the 1% level.
* Significance at the 10% level.

TABLE A2 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON EMPLOYMENT

Panel A: Full sample	(1)	(2)	(3)	(4)
Diploma (1=yes, 0=no)	0.004	0.016	0.011	0.012
	(0.028)	(0.033)	(0.019)	(0.019)
Polynomial order	linear	linear interaction	quadratic	quadratic interaction
Number of students	435,768	435,768	435,768	435,768
Panel B: Not in Post-Secondary Education	(5)	(6)	(7)	(8)
Diploma (1=yes, 0=no)	0.031***	0.039***	0.021***	0.022***
	(0.007)	(0.008)	(0.007)	(0.007)
Polynomial order	Linear	linear interaction	quadratic	quadratic interaction
Number of students	118,446	118,446	118,446	118,446

Notes. Robust standard errors are in parentheses. Outcome in both panels is an indicator for employment (1 is employed, 0 is not employed) in the year immediately after students finished their last exit exam. Standardized exit exam scores are modelled as a linear interaction. All specifications include an indicator for the track (1=pre-university track, 0=general track) as well as additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income).
*** Significance at the 1% level.

TABLE A3 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON ENROLMENT IN POST-SECONDARY EDUCATION

	(1)	(2)	(3)	(4)
Diploma (1=yes, 0=no)	0.121***	0.122***	0.147***	0.161***
	(0.002)	(0.003)	(0.003)	(0.005)
Polynomial order	linear	linear interaction	quadratic	quadratic interaction
Number of students	435,768	435,768	435,768	435,768

Notes. Robust standard errors are in parentheses. Outcome in both panels is an indicator for enrolment in post-secondary education (1 is enrolled, 0 is not enrolled) in the year immediately after students finished their last exit exam. Standardized exit exam scores are modelled as a linear interaction. All specifications include an indicator for the track (1=pre-university track, 0=general track) as well as additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income).
*** Significance at the 1% level.

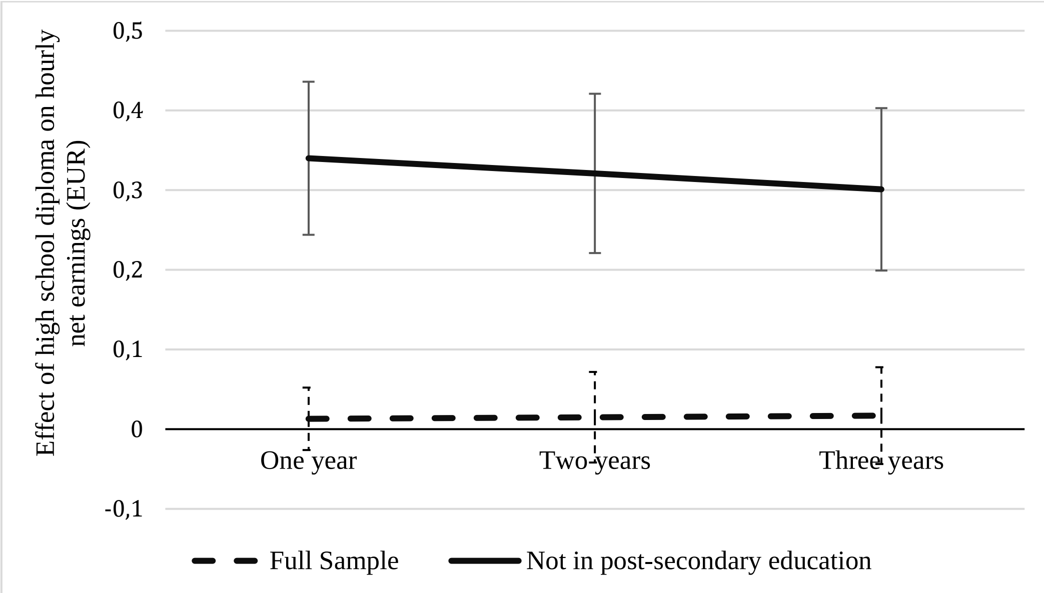

FIGURE A1 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON EARNINGS OVER TIME

Notes. The figure reports fuzzy regression discontinuity design estimates. Vertical bands represent +/- 1.96 times the standard error of each point estimate. Outcome in both panels is an indicator for employment (1 is employed, 0 is not employed) one, two, and three years after students finished their last exit exam. We consider employment one year after leaving school for cohorts who took their initial standardized exit exams from school year 2007-2008 until school year 2012-2013, two years after leaving school for cohorts who took their initial standardized exit exams until school year 2011-2012, and three years after leaving school for cohorts who took their initial standardized exit exams until school year 2010-2011. All specifications include an indicator for the track (1=pre-university track, 0=general track) as well as additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income.

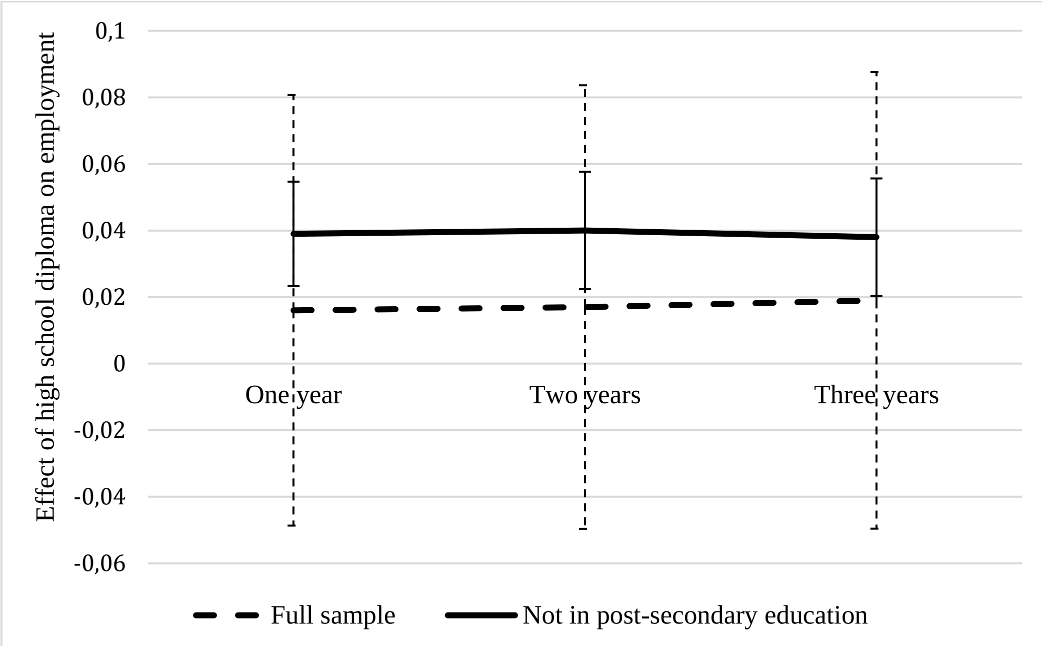

FIGURE A2 – THE EFFECT OF A HIGH SCHOOL DIPLOMA ON EMPLOYMENT OVER TIME

Notes. The figure reports fuzzy regression discontinuity design estimates. Vertical bands represent +/- 1.96 times the standard error of each point estimate. Outcome is net earnings per hour one, two, and three years after students finished their last exit exam. We consider earnings one year after leaving school for cohorts who took their initial standardized exit exams from school year 2007-2008 until school year 2012-2013, two years after leaving school for cohorts who took their initial standardized exit exams until school year 2011-2012, and three years after leaving school for cohorts who took their initial standardized exit exams until school year 2010-2011. All specifications include an indicator for the track (1=pre-university track, 0=general track) as well as additional covariates (gender, ethnicity, age at initial standardized exit exams, age at initial standardized exit exams squared, year of initial standardized exit exam, age of the father, age of the mother, neighbourhood of residence, and parental income.

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