Are Some Birthdays Better than Others?

An analysis on the persistence of relative age effects

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Abstract: A cut-off date for school eligibility creates a continuum of ages when students start attending primary school. This means that in one class, some students are younger and some students are older. This is called “relative age” in literature. Relatively older students are more mature, and some studies show that this creates an advantage for the relatively older students. The results in this study show an insignificant effect of relative age on test scores of about 0.10-0.15 standard deviations in the eighth grade. Furthermore, the results show that relative age has an insignificant effect on education years of approximately 0.25 years, a significant higher income of approximately 15% for males, and also an insignificant higher skill level. Lastly, the effect of relative age on health is analysed. Since education attainment affects health, it may be the case that relative age has an indirect effect on health. The effect of relative age on self-reported health is statistically and economically insignificant, but the effect of relative age on dead shows that relative older students are less likely to die before the age of approximately 70 years. This result, however, is not significant.

“On average, the typical adult human being has one breast and one testicle”

SuperFreakonomics, Steven D. Levitt & Stephen J. Dubner

Preface

This master’s thesis is the last project I finish at the Erasmus University Rotterdam. I have enjoyed my time at this university. However, all good things must come to an end and I am excited that a new chapter in my book will start very soon. I would like to thank the university in general for providing and spreading knowledge.

Furthermore, I would like to thank my supervisor, Prof. Dr. Webbink for supervising my thesis, but more importantly for helping me with the struggles and difficulties I faced in the empirical study. I can safely state that I learned more practical applications in empirical research from him than I did in the years during my studies. For that I am very grateful. I would also like to thank the supervisor of my Bachelor’s thesis, Dr. Van Kippersluis, in retrospect. He also helped me with some issues in my Bachelor’s thesis and I believe he is an example to all young (assistant) professors.

I would like to thank my father for providing the financial support for my Bachelor’s degree. Furthermore, I would like to thank my best mate Sjors (alias “Hansie Hansie”) for reading and correcting my papers and theses throughout the years. Lastly, I would like to thank my girlfriend for supporting me and motivating me.

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Key words: Relative age, school entry age, health economics, socioeconomic status, instrumental variables, reduced form, Brabant-survey

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I. Introduction

Most developed countries use a cut-off date to decide which children are obliged to start attending primary school. Students born just before the cut-off date are obliged to start attending primary school after the cut-off date. On the other hand, students born just after the cut-off date have to wait a year. This cut-off date thus generates different school year cohorts. However, students within one school year cohort are not exactly the same age. This difference in age is called "relative age". Relative age is analysed in many different fields. For example, it has been analysed extensively in sports (see Alger (2004), Cobley *et al.* (2009) and Raschner *et al.* (2012)) and short and long-term socioeconomic outcomes (see Bedard & Dhuey, (2006), and Black *et al.* (2008). Several studies also analyse the effect of relative age on educational attainment.

Human capital (e.g. education attainment) is an important variable in economics, since it is a determinant of how well individuals in an economy can perform. Human capital may affect long-term characteristics in a society, such as the socioeconomic status of individuals. Several studies show that relative age may affect human capital[1]. However, the results are ambiguous. For example, Elder and Lubotsky (2008) show that the effect of relative age exists in the short term, but the effect dies out very quickly. On the other hand, Fredriksson and Öckert (2005) find that relative age has a long-lasting effect on performance; McEwan and Shapiro (2008) also state that relative age affects outcomes on both the short and long term. Lastly, Bedard and Dhuey (2006) show that relatively older students are more likely to follow a university's programme.

If the effect of relative age dissipates over time, it is not particularly interesting for an economy to take the effect of relative age into account. If, on the other hand, the relative age effect does propagate in the long term via human capital, there may be serious (dis)advantages for students who are born (before) after the cut-off date.

Other studies have examined the effect of these relative age differences on short and long-term performance.

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[1] It is likely that relative age does not affect the total amount of human capital, but rather the distribution of human capital across individuals.

Bedard and Dhuey (2006) investigate the relative age effect in several countries. The authors show that the youngest students in the fourth and eighth grade score substantially lower on tests. The relatively oldest students have higher grades for mathematics and science courses. The authors also measure the effect of relative age on academic results when students are approximately 18 years old. Their results imply that relatively older students are better represented in (pre)university programs.

A study by Dhuey and Lipscomb (2006) finds that the relatively oldest students develop more leadership skills. Firms tend to require students to have developed soft skills (e.g. leadership), since these skills are of great value to these firms. The study by Dhuey and Lipscomb indicates that the students who are relatively older develop more leadership skills and, *ceteris paribus*, will have a greater chance of being hired by a firm and/or getting more senior positions. This means that the oldest students are likely to have a higher wage than the youngest students, since senior positions generally pay more.

In this paper, the effect of relative age on long-term performance is also analysed. However, the time horizon of this period study is much longer than that of other studies. The first important contribution to the existing literature is that I have access to a unique dataset, which tracks students for over 60 years. The dataset consists of approximately 3000 students in the Netherlands from 1952 until 1993, with mortality dates later added to the database. Some studies show that the effect of relative age is decreasing over time; this study is one of the first that provides more insight into the effect of relative age in the long term. Furthermore, the effect of relative age in the Netherlands has not been analysed in other studies. This paper fills this gap by analysing the effect of relative age on long-term performance.

The channel through which relative age propagates in the long term is likely to be educational attainment. Educational attainment may also cause better health for an individual. A paper by Cutler and Lleras-Muney (2005) identifies several different channels through which education may affect health. The conclusion in their paper is that education has a causal effect on health, but that the effect propagates through various channels. Several other studies show that more highly educated people tend to have, on average, better health compared to people with a lower education level (see for example Van Kippersluis and Van Doorslaer (2011) and Van Kippersluis *et al.* (2010)). This result is rather robust and one of the most stable results in the field of health economics. Translating these findings to the essence of this study, it means that if a relatively older person has a higher level of education, he also has better health. However, since there is a channel between relative age and health, it may be the case that the effect of relative age on health leaks away through the channel. This would mean that relative age and health are not related to each other. The question whether relative age also affects health has not been addressed in the current literature. This is another important contribution that this study will make to the existing literature. This study will hopefully be a forerunner for future papers that will address the question more extensively.

Three different estimation techniques are used to analyse the effect of relative age on performance. The first technique is an OLS design. However, the variable "age in class" is likely to be endogenous since there are many students who are not "on track" (shown in Sections III, IV and V). The causes the point estimates to be downwardly biased (shown in Section V). Therefore, a reduced form with *assigned* relative age model is used as exogenous variation in the "observed age" variable. Assigned relative age is defined as the month of birth relative to the cut-off date for school eligibility. In the Netherlands, the cut-off date is the first of October of a certain year. Students born in October are thus the oldest, and students born in September are the youngest. Furthermore, an IV estimation technique is used, with *assigned* relative age as an instrument for observed age.

The main finding in this paper is that the data suggests that there is a positive, but insignificant, relationship between relative age and long-term performance. The RF and IV models always point in the same direction and, in most cases, the sign of the variable of interest is positive. This indicates that relative age[2] has long-term consequences. The point estimate of relative age on educational attainment is positive, indicating that a relatively older person has a long-term advantage. The same counts for a person's income and skill levels. Furthermore, the relative age effect on health is also positive, but not economically significant. Lastly, the probability that a respondent died before 2009 is lower for relatively older individuals. Furthermore, the results are robust if they are compared with only the most extreme observations, namely students who are born in the first and last quarter relative to the cut-off date.

[2] In this study, relative age is measured as the combined effect of "absolute age" and "relative age" (Black *et al*., 2008).

The remainder of this paper is as follows: Section II will present an overview of the results of other studies. This is split in two parts, the first concerning the effect of school entry age[3] on (long) term outcomes in other studies, and the second on the effect of education on health and the ways in which education affects health. Section III gives more information about the empirical strategy and also discusses the advantages and disadvantages of the methods. Furthermore, the differences between the estimation techniques are discussed extensively. Section IV discusses the dataset and variables of interest, and gives an overview of the variables in two different tables. The first table presents the descriptive statistics and the second table shows the variables and measurements in a structured way. Section V shows the results of the statistical models and discusses the implications of these results. These results are compared with the outcomes of the other studies mentioned in Section II. To compare the results in Section V, the test scores are standardised to a mean of zero and a standard deviation of one. The standardised results are shown in the appendix (A13). At the end of Section V, a robustness check is shown for only the most extreme observations, and the results are presented in the appendix (A14). Finally, Section VI gives a summary of the results. Furthermore, the implications of the results are discussed. This paper ends with the limitations of the empirical analysis and suggestions for further research.

II. Literature review

In this section, I will discuss the results of other empirical studies. Many other researchers have analysed the effect of school starting age on performance. These studies generally measure the combined effect of relative age and absolute age, as it is hard to disentangle the two effects. In this section, I will therefore refer to "school entry age" or "the combined effect of absolute age and relative age" in this section. The second part of the literature review discusses the effect of educational attainment on health, and the ways in which education affects health. Since there are no studies which analyse the effect of relative age on health, I can only discuss the relationship between educational levels and health.

[3] School entry age is the combined effect of relative age and absolute age in most studies.

II.I

The cut-off date for school eligibility is useful in a quasi-experimental design and many authors exploit this date to explore the effects of school entry age. Most studies measure the combined effect of relative age and absolute age. The terms “school entry age” and “combined effect of relative and absolute age” are therefore used analogously in this section. From Section III and onwards, I will refer to “relative age” only. The reader must keep in mind that this is the combined effect of absolute age and relative age. The results of these studies can be compared to the results shown in Section V. Furthermore, some studies analyse the effect of delayed school entry. These studies are discussed in this section, but the results are not compared with the outcomes in this study.

Several papers have shown that (relatively) older students tend to perform better in the short and long term compared to younger students. Students who are born just after the cut-off date for school eligibility have to wait a year before entering primary school and therefore these individuals are (relatively) older in class. This also means that their cognitive capabilities are better developed than their younger counterparts (Cook & Kang, 2013). This implies that students who are older at the time they start attending primary school should perform better, *ceteris paribus*. However, there are also several studies which do not find that age has an effect on performance.

Elder and Lubotsky (2009) use a Two Stage Least Squares (2LSLS) approach to investigate the effect of kindergarten entry age. The authors state that there are two different views on the effect of entry age. The first view is that children who are (relatively) older are more mature and perform better in both the short and long-term. The second view is that age-related differences are only based on pre-kindergarten learning, but older and younger students tend to have the same learning rate. Therefore, in this view, the age-related differences fade away over time. The authors show that the effect of school entry age exists at the start of kindergarten, but this effect is rapidly decreasing over time. In fact, the entry age effect has already vanished by the time the students are in the eighth grade. The authors state that the initial differences between performances are driven by the skills children acquired before entering kindergarten, and thus the second view is considered superior to the first view. The authors also state that it is likely that relative age has less effect than absolute age on the short term results.

Bedard and Dhuey (2006) estimate the effect of relative age in primary school. They use an IV approach to estimate the relative age effect in the short-term (Grade 4 and Grade 8) and the long-term ((pre)university programs). They use *assigned* relative age as an instrument for observed age. The authors find that in some countries, the average grade for mathematics increases by 0.3 points for each month of additional relative age. In Grade 8, test scores are also positively influenced by relative age, with coefficient estimates ranging from 0.13 to 0.38 per month of additional relative age. Overall, the conclusion is that relative age has a significant and positive impact on the short term. The effect, however, decreases over years, since the coefficient estimates in Grade 4 are genuinely larger than the coefficient estimates in Grade 8. This contradicts the study of Elder and Lubotsky (2009), which find that the relative age effect has already disappeared in Grade 8.

Puhani and Weber (2005) analyse the effect of school entry age on test scores in Germany. The authors use an IV estimation procedure, with the month of school start used as an instrument. At the end of primary school, the effect of school entry age on test scores may be as large as 0.4 standard deviations. This effect is, however, not solely based on relative age. The authors measure absolute age as well, as it is not possible to discriminate between relative and absolute age in their design. The authors also state that German school principals tend to not value the effect of relative age. The principals indicate that absolute age is the more important determinant of maturity and, hence, performance.

A study by McEwan and Shapiro (2008) show that the effect of delaying school entry by one year is persisting (or even increasing) over time. These authors exploit discontinuity in enrolment dates with a regression discontinuity design. They show that delaying school entry is beneficial in the long term. Delaying entry decreases the probability that a student has to repeat one or more years in primary school. Furthermore, test scores in the fourth and eighth grade are significantly higher for older students (about 0.3 standard deviations). The authors also find that the age effect is constant or even increasing over time. This contrasts other studies, since it is generally the case that the relative age effect decreases over time. An important note in this design is that the exploitation of enrolment age in fact measures more than only relative age. It does measure relative age, but also the absolute age at enrolment, and the absolute age during the tests. The authors conclude that they *suspect* that relative age is also of importance in their results, but it cannot be proven in their design.

A Swedish study also finds that school entry age has an effect on primary school grades (Fredriksson & Öckert, 2005). The study shows that children born just after the cut-off date score better on tests (approximately 0.2 standard deviations). This is in accordance with most other literature. Fredriksson and Öckert also find that this effect persists over time, even into late adulthood, which will be discussed later in this section. The authors also state that relative age alone is not of great importance. Lastly, Black *et al.* (2008) estimate the combined effect of absolute age and relative age on performance in Norway. Using a 2SLS approach, they show that the combination of relative and absolute age has a positive effect on test scores. The authors find an increase of approximately 0.08 standard deviations on test scores based on school entry age.

Even though evidence on the effect of school entry age in primary school is mixed, several studies have attempted to measure the persistence of (relative) age in (pre)university programs. The previously mentioned study by Bedard and Dhuey (2006) estimates the persistence of the relative age effect in (pre)university programs. The authors use RF and IV models, combined with school fixed effects and find that relatively older students are more likely to participate in (pre)university academic programs. Furthermore, the relatively older students have a higher probability of entering a flagship university in the U.S. (Bedard & Dhuey, 2006). A British study shows that enrolment rates for relatively younger students are significantly smaller than enrolment rates for relatively older students (Rosenbaum, 2013). Black *et al.* (2008), however, find that there is little evidence that the combined effect of relative age and absolute age has an influence on educational attainment. They also show that wages are not significantly affected by relative age either.

The earlier mentioned study by Fredriksson and Öckert (2005) finds that educational attainment is also significantly affected by school entry age. Those who start school at a later stadium are expected to have a higher educational attainment of approximately 0.05 standard deviations. The effect of relative age on earnings is mixed. In the short run, late school starters have a disadvantage since they are less experienced (because they attend school for a longer period and start school later). However, in the long run these students are fully compensated, with an earnings advantage of about 0.03 standard deviations. The authors also note that the differences are most likely driven by absolute maturity rather than relative age.

The aforementioned study by Puhani and Weber also examine the relationship between school entry age and educational attainment. The authors show that the average years of education is prolonged by approximately a half year for the oldest students. However, the authors are not able to discriminate between relative age and absolute age. Therefore, it is unknown whether relative age is really of importance.

Dhuey and Lipscomb (2006) use *assigned* relative age to measure the effect of relative age on long-term outcomes. They analyse the effect of relative age on the probability of having more leadership skills. The result is that the oldest students in one group develop more soft skills, such as leadership. These students are more active in sports teams and are more likely to be president of a club. The authors also show that leadership qualities are not dependent on genetics or family background. Soft skills are of great importance to companies. It is genuinely the case that individuals who possess better leadership skills have a higher probability of holding a high position in a company. This result is confirmed by a study of Du *et al.* (2012). They find that the share of CEOs is disproportionally small for the relatively youngest students. This confirms that the development of leadership skills, a necessary trait for a CEO, is dependent on relative age.

The studies show that (relative) age has a positive impact on educational attainment and the development of several psychological skills. Therefore, it is expected that (relatively) older students will usually have a higher wage and a more demanding job. A study by Fredriksson and Öckert (2005) confirms this. Furthermore, the fact that the share of CEOs is disproportionally large for the relatively oldest students indicates that these individuals have a higher wage. On the other hand, several studies show that the effect of school entry age does not have long-term implications (Black *et al.*, 2008) (Elder & Lubotsky, 2008).

However, an important note must be added to the findings of the other studies. Angrist and Krueger (1991) estimate the effect of compulsory schooling laws. This law obliges students to attend school until they reach certain age[4]. The authors use this law as a natural experiment in

[4] In the Netherlands, this is 18 years.

their design. The relatively older students reach this age at an earlier date, and therefore the chance of dropping out is larger for this group. Angrist and Krueger estimate the impact of compulsory education attainment on earnings using an IV approach where education is instrumented by the quarter of the year in which students are born. The authors find that students who attended school longer have a higher wage on average as a result of extra schooling. The authors also recognize the relative age effect, but they state that relative age is not important. The study shows that relative age may also be negative for the oldest students, since they are allowed to drop out earlier. However, it is unlikely that the best performing students drop out of school. Therefore, it is expected that relative age has a positive impact on long-term performance. This is borne out in the studies previously discussed.

The effect of (relative) age on performance is somewhat ambiguous on the short term. One study reports a positive, but declining, effect of school entry age on grades in primary school; whereas other studies find no effect at the end of primary school. However, most other studies show that students who started attending primary school at a higher age tend to perform better in terms of socioeconomic outcomes. Older students are likely to develop more soft skills and generally have a higher education level. Also, wages are higher for these individuals. However, most results are not in terms of relative age since the designs of the studies do not allow researchers to discriminate between absolute age and relative age, but they did express their thoughts about which effect would be dominant.

Fredriksson and Öckert state that relative age is of minor importance, and that absolute age is the most important determinant. The study by Puhani and Weber also points in this direction, whereas McEwan and Shapiro, and Bedard and Dhuey state that relative age is of importance. In Sections III, IV and V, I will show that this study also estimates the *combined* effect of relative age and absolute age. In Section V, the results are compared to the outcomes obtained by Bedard and Dhuey (2006), Puhani and Weber (2005), Fredriksson and Öckert (2005), Black *et al.* (2008), and Elder and Lubotsky (2008). The reader must keep in mind that from here onwards I will refer to “relative age.”

II.II

In this section, the literature on the relationship between education and health is discussed. First, the different channels through which the causality mechanism runs are explained. Thereafter, I turn to several papers that analyse the relationship between education and health.

Several studies have examined the relationship between education and health. A study by Cutler and Lleras-Muney (2006) explain that the causal relationship of education and health can be propagated in various ways. The first way is education. Education improves health because more highly educated people generally have a higher income, and, thus, better access to health care. This statement finds support in a study by Autor, Katz and Kearney (2005). However, it is unlikely that this aspect alone explains the total causality mechanism. The second way is the labour market. Better educated people are also likely to hold better positions in better companies. These companies generally provide more safe work environments. However, this aspect does not explain the total causal mechanism either (Lahelma *et al.*, 2004). The third way is the value of future (e.g. personal discount rate). More educated people have invested a lot in themselves and have a bright future ahead of them. They may value the future more highly than other people and invest more in health. However, this is hard to measure. A fourth way is information and cognitive skills. More educated people tend to have better information about health and are better informed about how they can obtain better health. However, this gap is decreasing, as information about health is not limited to highly educated people today (Meara, 2001). Another way is preferences. Education may have an impact on the preferences of an individual and thereby increase one's preference for health (Becker & Mulligan, 1997). The next way is rank in society. This is based on the position of an individual in society. People at the lower end of the hierarchy tend to have less control over their lives, and therefore have more stress-related diseases. The last way in which the education effect is spread is through one's social network. More educated people have a larger network and they may find support in this network. This is supported by a study conducted by Berkman (1995). Lastly, people may get more feedback from their own network, and accordingly adjust their habits. The general conclusion in the paper is that education affects health, but that this effect is splintered across several areas.

A study by Van Kippersluis and Van Doorslaer (2011) finds that people who have a higher level of education are expected to live longer. This result is very robust for adding several control variables, such as the background of an individual and their intelligence. The authors show that people who completed an HBO or WO program in the Netherlands live longer than students who completed only primary school. The authors state that the channel of the labour market is likely to be a reason why this causal effect exists. In the study by Cutler and Lleras-Muney (2006), this is also one of the described channels. More educated people tend to have better health, as they generally work in a field that offers safe work environments. This is in accordance with a paper by Cutler and Lleras-Muney (2006), since they find that the effect of education on health runs through several channels. However, evidence on death is mixed and is not a topic which has been analysed very much yet (Van Kippersluis *et al.*, 2011). Cutler and Lleras-Muney (2006), for example, show that education lowers the five-year mortality rate by about 1.8 percentage points, but several other papers do not find this effect. Another study by Van Kippersluis *et al.* (2013) analyses education's effect on health. The authors use the Brabant-survey to analyse the effect, and they find that education is an important determinant for health.

The last study which is discussed in this section examines the risk for cardiovascular diseases. It uses several socioeconomic status variables to analyse the risk of the disease (Winkleby *et al.*, 1992). From that study, it can be obtained that people with less education have a higher risk of getting a disease. Cutler and Lleras-Muney (2006) also find that more educated people have a lower probability of having (chronic) diseases. This study thus confirms one of the channels discussed at the beginning of this section.

III. Empirical strategy

In this section, I will provide the empirical strategy. As is stated earlier, I cannot disentangle the combined effect of relative age and absolute age. However, I will refer to "relative age" in the remainder of this paper; this is in line with the study by Bedard and Dhuey (2006). I first discuss the methodology and statistical models. I also explain how the RF and IV estimator are related to each other. Thereafter, I explain why I prefer some models over others. In section III.II I give more details about the conditions of the IV model. Section IV Data is complementary to this section, as it extensively discusses the variables of interest in this study.

III.I

Three different estimation techniques are used to analyse the effect of relative age on performance; the first technique is based on OLS, the second technique is based on the reduced form of an IV model, and the third is the IV model itself. I follow the approach laid out by Bedard and Dhuey (2006).

The OLS models use observed age as independent variable and controls for eleven different variables, which are presented in Section IV. The following equation represents the OLS model:

$$y_{i,j} = \alpha + \beta Age_{i,j} + X\gamma + \varepsilon_{i,j},$$

β measures the causal effect of relative age of student i in year j, given that the assumptions of OLS are satisfied. X is a vector of control variables, which remain constant over time. Observed age is measured in months, meaning that (relatively) older students have a higher value for this variable.

The coefficient of the variable "observed age," however, is likely to violate at least one of the assumptions of OLS, namely exogeneity. An example is that students who had to repeat one or more years are older in absolute terms (i.e. "observed age" is higher), while they are relatively younger (e.g. born one month before the cut-off date). This means that "observed age" is correlated with the error term, and it is likely that "ability" is the omitted variable.

The coefficient β is therefore likely to be biased and inconsistent, as observed age suffers from severe endogeneity problems. In this case, the coefficient β does not measure the causal effect of relative age. Since the group also contains students who had to repeat one or more years, it is likely that the estimate is downwardly biased. The students who had to repeat grades are likely to have a low ability level. This ability level is unobservable, and, hence, not included in the models. The oldest students have a high value on "observed age," but they have a low ability level. Therefore, a high value on observed age is related to a low level of ability, and thus it is likely that a high value on age leads to low test scores. This indicates that relative age has a negative effect on performance. OLS is therefore considered as an inferior estimator in this design.

In formula form, the OLS coefficient is estimated by $b = \beta + (x'x)^{-1}x'\varepsilon$, where β is the true causal impact and b is the point estimate of OLS. However, $E[b] \neq \beta$, since the second term is non-zero. The second term is most likely to be negative, since there are a large number of students who repeated one or more grades and have a low ability level. Thus, the variable "observed age" cannot be interpreted as the causal effect of relative age.

It is necessary to use an alternative estimation technique. In this case, an instrument is a possible solution. A good instrument means that the following condition holds: $E\{(y_i - x'_{1i}\beta_1 - x_{2i}\beta_2)z_{2i}\} = 0$, where *z* is the instrument. The instrument is exogenous if it is not correlated with the error term (Verbeek, 2012).

Instruments are generally used in a quasi-experimental design. An instrument uses exogenous variation in the variable of interest ("observed age"). In the study by Bedard and Dhuey (2006), the cut-off date for school eligibility is used as an instrument. Based on this cut-off date, a variable "relative age" is constructed. This is the month of birth relative to the school cut-off date. This date is arbitrarily chosen and not related to any specific characteristics. This is an indicator that relative age is exogenous. Furthermore, month of birth of a student is also likely to be random (exogenous). This is shown later in this section.

The relatively oldest students have a value of "12" assigned for the instrument. Accordingly, relative age takes the value of "1" in case the student is born one month before the cut-off date, making them the relatively youngest students in a school year cohort. This variable is then used as an instrument for observed age. The instrument relative age itself is also used in reduced form models. The RF and IV models should always point towards the same direction. The instrument itself measures the effect of relative age on performance, and is often called the "intention to treat". The RF model estimates the causal effect of the *offer* of the treatment (i.e. relative age). The offer of the treatment, however, does not incorporate the fact that in the eighth grade the original school year cohort has changed. Since students may repeat a grade, the RF models estimate a lower effect of relative age, since not all students who are offered the treatment accepted it. In this context, this means that students who had to repeat a grade did not accept the offer of treatment. The IV estimator corrects for those students, and thus shows the true treatment on the treated (TOT) effect (Khandker *et al.*, 2010). However, the RF and IV models are related to each other, since they incorporate the same instrument in the model.

Formally, the relationship between the RF and IV model can be presented by the following formula:

$$IV = \frac{RF}{FS},$$

where IV stands for the IV estimator, RF for the reduced form, and FS for the first stage. The RF model estimates the treatment effect for those who are *offered* a treatment. However, since not all individuals accept the offer of treatment (i.e. the students who are not on track), the TOT effect must be corrected for this. The first stage is used as a correction for the individuals who turned down the offer of the treatment. The first stage in this case is likely to be smaller than one, as there are more students who have to repeat a grade and are thus one school year cohort later than originally placed. Students who may skip a grade are thus one school year cohort earlier than originally placed.[5]

To clarify the relationship between IV, RF and FS, consider the following example: an instrument, z, affects the dependent variable, y, only through the independent variable x. If z grows by one unit and x accordingly grows by 0.5 unit, and the 0.5 unit increase in x in turn causes y to grow by two units, then the RF model estimates an impact of the instrument on y of $\frac{\Delta y}{\Delta z} = \frac{2}{1} = 2$. However, not all individuals accept the treatment since the effect of z on x is not a one-to-one relationship. In this case, the first stage is: $\frac{\Delta x}{\Delta z} = \frac{0.5}{1} = 0.5$, since a unit increase in z leads to a 0.5 unit increase in x. The IV model corrects for the individuals who are offered a treatment, but do not accept the treatment (first stage). The IV estimator thus estimates a TOT effect of : $\frac{\Delta y}{\frac{\Delta x}{\Delta z}} = \frac{2}{0.5} = 4$.

The RF and IV models are superior to a multiple OLS design, since the instrument is likely to solve the endogeneity issue. It is likely that the instrument is exogenous, and therefore the point estimates of the RF and IV models can be interpreted as the causal effect of relative age on performance.

The RF model is given by the following equation:

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[5] Students who have skipped a grade received treatment, but are not offered a treatment.

$$y_{i,j} = \theta + \varphi Relage_i + X\delta + \varepsilon_{i,j} \ ,$$

where φ estimates the effect of *assigned* relative age on the different outcomes in both the short and long run. The other terms are the same as the ones in the OLS design.

The IV models are based on two stages. The first stage of the model is given by the following equation:

$$Age_{i,j} = \omega + \mu Relage_i + X\gamma + v_{i,j}$$

The first stage is not interesting for the relationship between relative age and performance. However, it is very interesting to check the discrepancy between those who are offered the treatment and those who accepted the treatment (i.e. gives insight in the students who had to repeat a grade). In this case, it is necessary that the F-statistic of the instrument is significant, meaning that the instrument is not weak.[6] This indicates that the first stage condition is satisfied in the IV approach.

The IV estimator crucially depends on two assumptions. The first assumption is already shown in this paper, namely the first stage. Assigned relative age must be correlated with observed age. The two are naturally correlated in this case. The second crucial assumption is, however, more treacherous. Bedard and Dhuey (2006) also recognize this problem. In their paper, they state that assigned relative age may be correlated with an unobservable variable; ability. They try to analyse whether parents in different socioeconomic classes planned out the month their children would be born. This may due to the mother pursuing a career and preferring to give birth during summer, when most people are on vacation. Therefore, it is necessary to determine whether the quarter of birth is correlated with the educational level of the mother and other covariates. Table A2 in the appendix gives more insight into this problem. Nevertheless, it is impossible to formally test for the exogeneity of the instrument.

The IV model is given by the following equation:

$$y_{i,j} = \pi + \rho \widehat{Age_{\iota,t}} + X\tau + \varepsilon_{i,j} \ ,$$

[6] A weak instrument (F<10) causes the standard errors to be high. If this is the case, then the point estimates are likely to be insignificant.

with ρ measuring the causal effect of relative age on the dependent variable, and, again, X as a vector of control variables. Since the variable "observed age" is likely to be endogenous, the instrument "relative age" is used as exogenous variation in the "observed age" variable.

An important note is that the relative age variable measures the combined effect of both *relative* age and *absolute* age (Black *et al.*, 2008). This problem, however, is not possible to circumvent.

A last note is that the OLS and IV models are exactly the same in the case that the composition of the original school year cohort does not change over time. If this were the case, the variables "observed age" and "relative age" would be perfectly collinear. This is obviously not the case in the sample, which will be discussed in the next chapter. The following expression shows the estimator of the IV model:

$$\widehat{\beta_{IV}} = \left(\sum_{i=1}^{N} z_i x_i'\right)^{-1} \sum_{i=1}^{N} z_i y_i$$

If all rules are strictly followed and the composition of the original school year cohort is constant, then $z_{2i}=x_{2i}$, and the IV estimator is the same as the OLS estimator.

III.II

In Section V, Results, I show the results of the models that are mentioned in this section. However, I prefer the RF and IV models over the OLS models. This is because the OLS estimator is likely to be biased and inconsistent and therefore does not measure the causal effect of relative age on performance. The group of students who had to repeat one or more grades is rather large and therefore the OLS models are likely to estimate a *negative* relationship between observed age and performance. A negative relationship is counterintuitive, but it can easily be explained by students who had to repeat grades. The RF and IV models are likely to be more trustworthy. The IV model, however, will generally produce higher standard errors than the RF model. This may cause the effect in the IV models to be less significant than in the RF models. This is not necessarily true since IV generally estimates a larger coefficient. The first stages in the Appendix also show that the F-statistic of the instrument is very high; indicating that the first stage condition is satisfied.

The endogeneity issue causes the OLS estimate to be inconsistent. The Durbin-Wu-Hausman test can be used to test whether the variable "observed age" has endogeneity issues. This test is based on the first stage of IV estimation. The residuals of the first stage are saved and added to the OLS model[7]. If the coefficient of the residuals in the OLS model significantly differs from zero, then it is safe to assume that the variable "observed age" is endogenous. In almost all cases, the Durbin-Wu-Hausman test rejects the null. This means that there are issues concerning endogeneity in the OLS estimator. In Appendix A1, the results are shown per model. These results imply that the IV estimator is superior to the OLS estimator.[8] The Durbin-Wu-Hausman test also shows a negative sign for the residuals in the OLS models. This accords with the earlier statement that OLS underestimates the causal effect.

IV. Data

In this section, I provide more details about the dataset. I first mention the source and how the data is collected. Furthermore, I check whether a formal cut-off date for school eligibility exists in the Netherlands. Thereafter, I discuss the variables individually. The descriptive statistics corresponding to the variables are presented in the last page of this section. This section concludes with an analysis on the nature of non-response in the surveys.

IV.I

The Dutch science institute, KNAW, owns an online database "DANS". In this database, the data is stored. The dataset can be found under the name "Brabant-data". The database is freely accessible to everyone registered at DANS. The dataset contains three surveys; one in 1952, one in 1983, and one in 1993.

In 1952, approximately 3000 eighth graders in the province of Brabant participated in a comprehensive survey. The survey dealt with questions on the socioeconomic environment in which the student lived. The school principal filled in the surveys for the students in 1952, together with details about the school. Furthermore, the students made several standardized tests

[7] Adding the residuals to the OLS model reproduces the IV estimator, albeit with inappropriate standard errors.
[8] Even if age is not endogenous, the IV estimator can be applied. This comes at the cost of higher standard errors.

in Grade 8. The survey from 1952 provides information on the early performance of students, as well as social background indicators and school variables.

Professor Joop Hartog rediscovered the dataset three decades later. He tracked down 2998 students in the original dataset, and asked the individuals to fill in a survey about their socioeconomic status. In 1983, 2528 students answered the survey. At that time, they were about 45 years old. The respondents provide information about their own socioeconomic status, with questions regarding their educational attainment, earnings and skill level. In 1993, the survey was repeated and 1956 individuals answered the survey. Again, they answered questions on their socioeconomic status. In 1993, the researchers also asked questions about health.

The panel in 1983 and 1993 differ from each other. In total, 1486 individuals responded to both surveys. This means that 1042 respondents in 1983 did not answer the survey in 1993 and that 470 respondents in 1993 did not respond to the survey in 1983. Since the panel differs substantially, it is counterintuitive to compare the results of 1983 with 1993. The last update of the data was in 2010. In that year, all 2998 individuals were tracked to see whether they were still alive in the year 2009. There was no formal survey in 2010.

Not every respondent filled in the entire survey. This means that the number of observations may vary for different variables. I assign values to missing observations in the control variables, so there are no observations lost for no response on control variables. The exact procedure is explained in more detail in the next section.

IV.II

In the Netherlands, a cut-off date for school eligibility exists. This is not different than in other countries. In most countries, students have to wait a whole year if they are born just after the cut-off date. In the Netherlands, however, the school system has rolling admissions. This rolling admissions policy states that children are obliged to attend school as soon as they turn 5. A child thus must attend primary school on his fifth birthday, regardless of cut-off dates. However, in practice, almost all students start attending primary school at the age of four (Leuven *et al.*, 2004). Those children are placed in the first grade (according to Dutch standards). [9]

Nevertheless, the Netherlands has a formal cut-off date for school eligibility. This cut-off date for school eligibility determines whether a student moves to the second grade. It is important to note that there is a conceptual difference between the terms “school year” and “school year cohort.” In the Netherlands, one school year cohort consists of students born between October 1 in year t until September 30 in year $t+1$. The school year cohort follows the formal rule of October 1, whereas a school year is based on the summer holidays. Children are only allowed to go to the second grade if they are a certain age, which is based on the cut-off date for school eligibility.

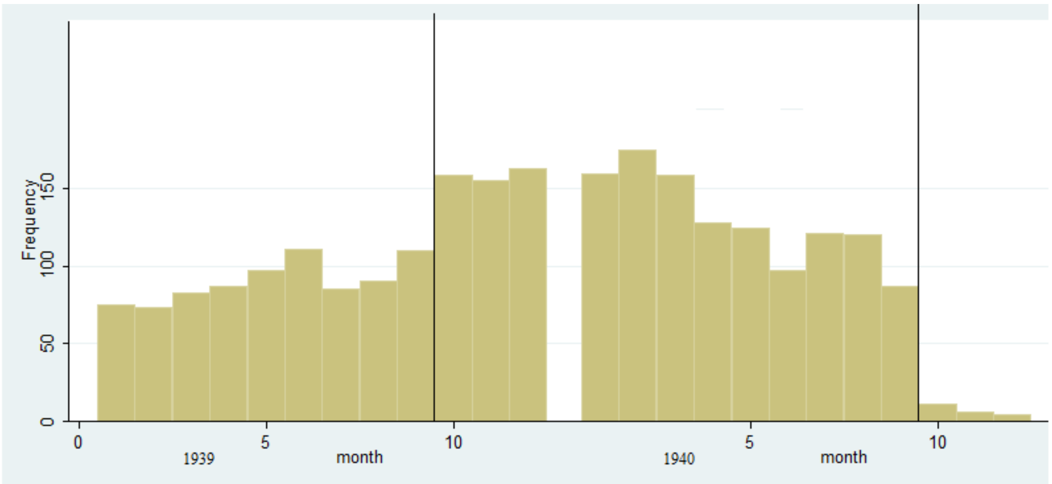
The following example gives more insight about the conceptual differences: A student who turns 4 before the first of October will go to the first grade until October 1. After October 1, the student will visit Grade 1 until the next summer holidays and start the second grade after the summer holidays end (Leuven *et al.*, 2004). In other words, the October 1 rule is used to generate different school year cohorts. The term “cut-off date for school eligibility” is used in the rest of this study. This refers to the formal October 1 rule.

This formal October 1 rule will be used as a quasi-experimental design, since the rule creates an exogenous variable, “month of birth relative to the cut-off date,” which is discussed in the previous section. Students who are born in October are generally the oldest students in the second grade and onwards. On the other hand, students born in September are relatively the youngest.

The analysis crucially depends on the cut-off date for school eligibility. It is, however, uncertain whether the formal October 1 rule already existed in 1952. Therefore, the number of observations per month in the years 1939 and 1940 are presented.

[9] In the Netherlands, the first two grades are more like kindergarten.

Figure 4.1: # Observations per month



The black lines indicate the relevant school year cohort. The white space between the bars indicates the transition from 1939 to 1940.

In this figure, the number of observations rises in the tenth month (October) in 1939. This indicates that the rule already existed in 1952. The large number of observations in the months before October 1939 can be explained by students who had to repeat a grade. Since those students were the youngest in their school year cohort, it is likely that they had to repeat a grade and are thus in a school year cohort one year later. This is also obvious in the few months before October 1940. The students who are originally in the same school year cohort are the youngest in class, and are therefore more likely to repeat a grade. This may explain why the months before September 1940 do not have many observations.

If the observations of September 1939 are added to the number of observations in September 1940, the number of observations would also be more or less equal to the number of observations in the first few months after the cut-off date for school eligibility. In this setting, it would mean that the students who are born in September 1939 (i.e. who had to repeat a year) are an indicator for the number of students who are born in September 1940 and had to repeat a year (and are thus not observed).

The decline in the number of observations in October 1940 is substantial. This indicates that the formal October 1 rule already existed in 1952. The reason why the number of observations is not zero after September 1939 may be because the rules are not strictly followed. Another possibility is that excellent students may have skipped a grade.

IV.III

This section gives an overview of the variables of interest. I first discuss which variables are presented in which survey and after that I turn to the variables individually. I start with the short-term variables, followed by socioeconomic outcomes and health variables. Table 4.2 at the end of this section shows the descriptive statistics of all mentioned variables. It first shows the endogenous variable “observed age” which is age in months in 1952.[10] After that, it shows the instrument “Relative age” which takes a value of 12 for students born in October and a value of 1 for students born in September. A higher value indicates that a student is (relatively) older. Furthermore, Table 4.3 at the end of this section gives a short overview of the measurement of the variables. Lastly, I describe how the results in the next section can be compared to results of other studies.

The dataset contains the exact birth dates of the students and test scores for six different courses. The test scores are based on a standardised test at that time, with a maximum score of 10. The short-term effect of relative age on performance investigates the relationship between relative age and test scores.

The first important socioeconomic variable is educational attainment. This variable is measured on an ordinal 6-point scale, where a higher value indicates a higher level of education. The maximum values of the 1983 and 1993 survey are used in the analysis. This is done to generate more observations, and I assume that the education level of individuals in 1983 and 1993 are in all cases equal to each other. Since the statistical models I use are not generally suited for factor variables, I transform the variable. This variable is “years of education” and this is the first variable that is analysed.[11]

The second variable is income. This variable is observed in both 1983 and 1993. There are, however, individuals who are self-employed. Therefore, the variables wages and income from self-employment are added to each other and this variable is called “gross income in Dutch guilders in year x.” Thereafter, I take the natural logarithm of the variable and use it in the

[10] Age in 1983 and 1993 are not reported, since these values are a linear function of the 1952 variable.
[11] This variable takes a value of 15 if a person has finished a WO (i.e. university) program. It takes a value of 14 if the person finished an HBO program. A value of 11.5 is given to individuals who finished a VWO or HAVO secondary school. A value of 10 is given to individuals who finished a MAVO program.

analysis. Since income tends to differ substantially over time, it is not applicable to construct a maximum value variable. Furthermore, the number of observations in 1993 is not really large. Therefore I do not discuss the results of the relative age effect on income in 1993 extensively, since the power of the tests is likely to be low.

The last socioeconomic variable is skill level. This variable is observed in 1983 and 1993, and it is measured on an ordinal 7-point scale. The analysis uses the maximum value of the reported skill levels in 1983 and 1993. However, this procedure is not as straightforward as the educational attainment variable and therefore I also present the results of both surveys individually.

The effect of relative age on health exploits two different variables. The first variable is self-reported health in 1993. This variable is measured on a 5-point scale, where a value of "1" indicates that a person is very healthy, and a value of "5" indicates that the person has severe health issues. This variable is thus measured reversely. Therefore, I construct a new variable which is: "6-health93" and this variable is used in the analysis. This makes the interpretation more straightforward and easier.

The second health variable is "dead." This variable is, for obvious reasons, not asked in a survey. However, the researchers tracked down all individuals in the 1952, 1983 and 1993 surveys and updated the database with mortality dates. The variable "dead" is a binary variable, where a value of 1 indicates that a person died before 2009. In this case, the point estimate should be negative.

In the models, I will also control for several other variables. In total, eleven control variables are used. The control variables are social background indicators and schooling indicators, based on the survey in 1952. Also, a lot of observations are missing in the control variables. To overcome this problem, there are values given to missing observations. The models are corrected for the individuals who have an assigned value for a certain indicator.

Social background variables are added to the models since children may inherit their parents' skills and parents' higher socioeconomic status indicate better skills. The social background control variables contain eight different indicators. The first two are the educational attainment of the mother and father. These are measured on a 6-point scale, and are *not* redefined to assigned years of education in the statistical models. The next variable is the social class of the student's family. This is measured on a 3-point scale and is mainly based on the occupation of the father. These three variables have an assigned value of “0” in the case of no response. The next variable is a dummy variable indicating whether the family is considered antisocial or not. Also, the marital status of the parents is added. In this case, the value “2” is used for missing observations. The total number of siblings in 1952 is also used in the model. In case of no response, the average of the respondents is taken. In the model, I will also create a dummy to indicate individuals with assigned numbers for this variable. The last two variables are: a variable which indicate whether a person has to work in the family’s business and the expectations the parents have about what their child would reach in their lives.

The other control group contains three indicators which give more information about the school. The first variable is the number of teachers. Again, a lot of missing values are present. The average number of teachers is assigned to the missing observations. The other two are factor variables, and give more information about the type of school; namely the official religion of a school and a variable indicating whether the school is girls only/boys only/mixed. The value “0” is assigned to missing observations.

In all control variables, it is necessary to assign values. As explained earlier, the individuals that have an assigned value for a certain variable are identified by a dummy. It is necessary to fill the gaps, since there are too many individuals lost in the analysis otherwise.

The next two tables present the descriptive statistics of the variables and the last table summarizes the variables which are discussed in this section.

Table 4.2: Descriptive statistics

Variable	No. of Obs	Mean	Std. Dev.	Min	Max
Dependent variables					
Grade math	2784	5.22	1.86	1.00	10.00
Grade physics	2760	5.27	1.86	1.00	10.00
Grade history	2754	5.29	1.88	1.00	10.00
Grade fill in ex.	2756	5.27	1.95	1.00	10.00
Grade express	2748	5.27	1.86	1.00	10.00
Grade reading	2751	5.23	1.94	1.00	10.00
Years of education	2645	10.80	1.54	10.00	15.00
Ln Income 1983	1668	10.43	0.94	3.40	13.12
Skill level	2522	4.41	1.77	1.00	7.00
Health	1923	3.73	1.01	1.00	5.00
Dead	2998	0.12	0.32	0.00	1.00
Social background variables					
Educ. Lvl. Father	2998	1.58	1.34	0.00	6.00
Educ. Lvl. Mother	2998	1.45	1.18	0.00	6.00
SES status family	2998	1.37	0.70	0.00	3.00
Anti-social	2998	0.26	0.62	0.00	2.00
Marital status parents	2998	0.07	0.31	0.00	2.00
No. of siblings	2998	5.95	2.68	1.00	19.00
Family business	2998	1.30	0.95	0.00	5.00
Wish	2998	3.21	1.84	0.00	5.00
School variables					
No. of Teachers	2998	6.92	2.41	1.00	12.00
Religion	2998	1.30	0.66	0.00	5.00
Type	2998	1.81	0.71	0.00	3.00
Endogenous variable					
Age in months	2998	151.70	8.63	130.62	178.09
Instrument					
Relative age	2998	6.48	3.40	1.00	12.00

Table 4.3: Overview of variables

Variable	Definition	Survey
	Dependent variables	
Grades	The grades obtained in the sixth grade for six different courses	1952
Years of education	The assigned years of education	1983/1993
Income	The natural logarithm of income (wages + income from self-employment)	1983/1993
Skill level	Skill level required for the job, measured on a 7-point scale	1983/1993
Health	Self-reported health, measured on a 5-point scale	1993
Dead	Dummy variable indicating whether a person died before 2009	Updated
	Social background variables	
Education level father	Educational level of the father, measured on a 7-point scale	1952
Education level mother	Educational level of the mother, measured on a 7-point scale	1952
Social class family	Social class of the family, measured on a 3-point scale	1952
Marital status parents	Dummy variable indicating whether the parent is single or not	1952
Antisocial	Dummy variable indicating whether a family is considered antisocial	1952
No. of siblings	The total number of siblings in the family	1952
Family business	Student's activity in the family business, measured on a 5-point scale	1952
Wish	The wish of the parents about what the student should achieve in life	1952
	Schooling variables	
Teachers	The number of teachers of the school an individual attended	1952
Type of school	The type of school, males only/females only/mixed	1952
Religion	Dominant religion of the school	1952
	Endogenous variable	
Age	Age measured in months	1952/1983/1993
	Instrument	
Relative age	Assigned relative age	Self-constructed

Several other studies measure the effect of relative age in standard deviations. Therefore, I standardize the grades for the courses to be able to compare the results. The other studies standardised the dependent variables to a mean of zero and a standard deviation of one.[12] The "egen, standard errors" function in Stata is used to generate the standardised dependent variable.

[12] This can be done by using the following formula: $\frac{Y_i-\mu}{\sigma}$, where Y_i stands for the observed grade of an individual, μ for the mean of that grade and σ for the standard error of the grade.

In the appendix (Table A3), the mean and standard deviations of the standardised dependent variables are shown. These results are compared to other studies.

A last point of concern is selective non-response. If, for example, students born in different months are selectively not responding to surveys, this may bias the results. It is necessary to check whether the probability that a person responds to the survey in 1983 and/or 1993 depends on the month of birth. The variables which are used for month of birth are “month of birth” and “month of birth relative to the cut-off date (i.e. relative age)”. Furthermore, it may be the case that the worst-performing students in primary school do not answer to later surveys. Therefore, the test scores for the different courses are also used to analyse whether there is selective non-response. A4 shows the estimates for the mentioned variables on the probability of participating in the survey of 1983, 1993 or both. The results show no selective non-response depending on month of birth. However, the better-performing students in Grade 8 are more likely to participate in all surveys. The point estimates indicate a positive relationship between test scores and participating in a survey. The worst-performing students are thus not represented in later surveys. This is not necessarily a problem if these worst-performing students are distributed randomly over the months.

V. Results

In this section, I will show the results of the statistical models. I first establish the relationship between relative age and performance on the short term. Thereafter, the effect of relative age on socioeconomic outcomes is discussed. The effect of relative age on health is scrutinised in section V.III. All obtained results are compared individually with results of other studies. This section concludes with a robustness check. In this robustness check, the analysis is repeated for individuals who are born in the first and last quarter relative to the cut-off date for school eligibility, and the effect of relative age in quarters is also discussed. A last point of concern is that all results are referred to as relative age, but the estimations contain both relative age and absolute age. The statistical software package “Stata” is used to generate the results.

V.I

This section provides insight in the short-term effect of relative age on performance. The six different courses are mathematics, science, history, fill-in exercises, expressing, and reading. The short term has many observations, namely approximately 90% of the total panel. The first stages of the IV models are presented in tables A5 and A6 in the appendix. The tables show that the instrument is highly significant (F>>10).

The table below presents the point estimates of the variables "observed age" in the OLS models, "assigned relative age" in the RF models, and "predicted age" in the IV models.

Table 5.1: Short term effects of relative age on performance

Course	OLS	OLS	RF	RF	IV	IV	No. Of Obs.
Mathematics	-.042***	-.0192***	.011	.011	.023	.022	2784
	(.004)	(.004)	(.010)	(.009)	(.022)	(.019)	
Physics	-.026***	-.0048	-.002	-.003	-.005	-.006	2760
	(.004)	(.004)	(.010)	(.009)	(.019)	(.017)	
History	-.039***	-.0119***	.011	.010	.022	.020	2754
	(.004)	(.004)	(.010)	(.009)	(.022)	(.018)	
Fill-in exercises	-.052***	-.0265***	.004	.003	.008	.006	2756
	(.004)	(.004)	(.011)	(.010)	(.023)	(.020)	
Expressing	-.0259***	.0006	.007	.006	.015	.013	2748
	(.004)	(.004)	(.010)	(.009)	(.022)	(.019)	
Reading	-.0322***	-.005	.009	.009	.0178	.019	2751
	(.004)	(.004)	(.011)	(.010)	(.023)	(.019)	
Controlled	No	Yes	No	Yes	No	Yes	

Test scores are based on a 1-10 scale. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level and *** at the 1% level. OLS is the model with "observed age" as independent variable and RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), antisocial, number of siblings in family, family business, wish, number of teachers, type of school and official religion of the school. Standard errors are reported in parentheses.

The OLS models indicate a negative relationship between age and test scores. The coefficients are in almost all cases negative and significant. This means that if the student is older, he or she will have a lower grade for a certain course. However, this result is likely to be caused by students who had to repeat one or more grades. Those students are expected to be the worst-performing students. These students are the oldest in a group and have thus a high value for the variable "observed age". This causes the OLS estimates to be biased and inconsistent.

The IV models estimate a larger coefficient for the relative age effect than the reduced form. This is expected; the first stage is smaller than one. Also, the relative age effect is robust for adding the eleven control variables.

The RF and IV models do not show a significant impact of relative age on performance. The signs, however, are in almost all cases positive. The fact that relative age is not significant in the models does not necessarily imply that the effect does not exist. The power of the tests in this study is likely to be lower than in other studies, since the number of observations is much lower.

The next table (Table 5.1.1) shows the results if the sample is separated by gender. In the female case, all models show a positive sign in the RF and IV models. The positive sign implies that relatively older students have higher grades. Again, almost all cases are insignificant. However, the grade for mathematics in the female case is significant at the 10% level. This means that the relatively oldest students have, on average, a grade that is 0.5 higher compared to their younger counterparts. In the male case, the sign is mostly negative. This sign is not different from zero and is genuinely small. Also, the 95% confidence interval mostly indicates that the coefficient could be positive and large (thus indicating that the standard error is large). Nevertheless, the results in Table 5.1.1 are disregarded in further analysis. The results in Table 5.1 are superior because they contain both groups and thus more observations.

The study by Bedard and Dhuey (2006) find an effect of relative age on grades for mathematics and science. The grades grow by approximately 0.12-0.25 per additional month of relative age. The authors show that in several OECD countries, the relative age effect is 0.08-0.26 standard deviations for different courses in the eighth grade. In this study, the effect is approximately 0.10-0.15 standard deviations. This is more or less equal to the results of Bedard and Dhuey. However, Fredriksson and Öckert (2005) find a larger effect (approximately 0.2 standard deviations). Puhani and Weber (2005) also estimate a larger effect (approximately 0.4 standard deviations). The study by Elder and Lubotsky (2008), on the other hand, argue that the effect of relative age has already vanished by the time the students are in the eighth grade. The authors find an insignificant effect ranging from 0.07-0.10 standard deviations. This study shows that the effect of relative age is somewhat larger than the results in the study by Elder and Lubotsky.

Nevertheless, one conclusion can be drawn from the OLS case. The OLS point estimate is downwardly biased, since the signs are in all cases negative. The OLS models indicate (in most cases) a negative relationship between age and performance. The students who repeated a grade are likely to cause this counterintuitive result, because they have a lower ability level compared to the students who are on track. Therefore, the RF and IV models are considered superior to the OLS models, as they do not suffer from the endogeneity problem. The IV estimates in all models a larger effect of relative age on performance compared to the RF models. This, however, comes at the cost of larger standard errors.

Taking all these results into consideration, it is not perfectly clear whether relative age does exist in the eighth grade. The point estimates are in almost all cases positive, but insignificant. This, however, can be explained by the fact that this study has fewer observations than other similar studies.

Table 5.1.1: Short-term effects of relative age on performance

Course	OLS	OLS	RF	RF	IV	IV	No. Of Obs.	Gender
Mathematics	-.047***	-.024***	.031**	.024*	.060*	.046*	1144	Female
	(.006)	(.006)	(.015)	(.013)	(.033)	(.027)		
Physics	-.030***	-.006	.015	.007	.028	.012	1140	Female
	(.006)	(.005)	(.0142)	(.012)	(.027)	(.022)		
History	-.035***	-.005	.017	.013	.032	.024	1127	Female
	(.006)	(.005)	(.015)	(.012)	(.030)	(.023)		
Fill-in exercises	-.052***	-.022***	.028*	.020	.054	.039	1133	Female
	(.007)	(.006)	(.017)	(.014)	(.035)	(.027)		
Expressing	-.031***	-.002	.021	.013	.039	.023	1136	Female
	(.007)	(.006)	(.016)	(.013)	(.031)	(.024)		
Reading	-.040***	-.012**	.005	-.005	.010	-.008	1139	Female
	(0.007)	(.006)	(.017)	(.014)	(.031)	(.025)		
Mathematics	-.038***	-.017***	-.002	0	-.006	0	1640	Male
	(.005)	(.005)	(.013)	(.0125)	(.029)	(.027)		
Physics	-.024***	-.004	-.014	-.014	-.031	-.029	1620	Male
	(.005)	(.005)	(.013)	(.0120)	(.028)	(.025)		
History	-.041***	-.015***	.007	.004	.015	.010	1627	Male
	(.005)	(.005)	(.014)	(.012)	(.031)	(.027)		
Fill-in exercises	-.053***	-.030***	-.013	-.014	-.029	-.030	1623	Male
	(.005)	(.005)	(.014)	(.013)	(.032)	(.028)		
Expressing	-.023***	.002	-.002	-.002	-.005	-.005	1612	Male
	(.005)	(.005)	(.014)	(.013)	(.031)	(.028)		
Reading	-.028***	-.001	.011	.013	.024	.027	1612	Male
	(.005)	(.005)	(.014)	(.013)	(.033)	(.029)		
Controlled	No	Yes	No	Yes	No	Yes		

Test scores are based on a 1-10 scale. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level and *** at the 1% level. The results are sorted by gender. OLS is the model with "observed age" as independent variable, RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school and official religion of the school. Standard errors are reported in parentheses.

V.II

This section investigates the relationship between relative age and long-term socioeconomic status. Socioeconomic status is divided into three parts, namely income, education level and skill level. I first establish the relationship between relative age and educational attainment, since this is likely to be the main channel through which relative age propagates in the long term. Thereafter, I turn to the income, and finally the skill level is analysed. A7 shows the first stages of the IV models, and A8 shows the gender-specific results.

The variables “years of education” and “skill level” are constructed by taking the maximum value of 1983 and 1993 for the corresponding variable. This is done because those levels are robust over the period. The separate analysis for the skill levels in 1983 and 1993 are presented in A10. In case of the income variable, this is not possible. Incomes are not robust over the years, and the number of observations does not increase that much by doing this (a mere 300). Therefore, only the 1983 income is analysed in this section. The effect of relative age on incomes in 1993 is presented in the appendix (A9).

Table 5.2: Relative age effect on socioeconomic outcomes

Socioeconomic outcome	**OLS**	**OLS**	**RF**	**RF**	**IV**	**IV**	**No. Of Obs.**
Years of education	-.044***	-.030***	.013	.010	.027	.021	2645
	(.004)	(.003)	(.009)	(.008)	(.019)	(.016)	
LN income 1983	-.011***	-.005**	.007	.007	.016	.015	1668
	(.002)	(.002)	(.006)	(.005)	(.013)	(.013)	
Skill level	-.050***	-.033***	.004	.005	.009	.011	2522
	(.004)	(.004)	(.010)	(.009)	(.024)	(.022)	
Controlled	No	Yes	No	Yes	No	Yes	

Years of education are redefined from the ordinal variable education level. LN income 1983 is the natural logarithm of gross earnings in 1983 in Dutch guilders. Skill level is an ordinal variable, with 7 categories. The stars indicate the significance level: * indicates that the variable is significant at the 10% level, ** at the 5% level and *** at the 1% level. OLS is the model with “observed age” as independent variable and RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), antisocial, number of siblings in family, family business, wish, number of teachers, type of school and official religion of the school. Standard errors are reported in parentheses.

The number of observations is quite large for the years of education and skill level variables. Income has fewer observations than the other two variables. It is likely that not all individuals have a job (especially females), and this may cause the number of observations to be low. In the appendix (A9), the results for income in 1993 are shown, but there is no emphasis on it in this section.

The OLS model indicates that older students have a lower level of education than the younger students, since the sign is negative in all OLS models. This is because the oldest students are students who had to repeat a grade and are the worst-performing students, and thus it is not surprising that OLS estimates a negative relation between observed age and years of education. The RF and IV models estimate a positive sign for relative age on years of education. This effect is not significantly different from zero, but this might be explained by the low power of the tests. The point estimates indicate that the relatively oldest students have received more education (approximately 0.23 years). The study by Puhani and Weber (2005) estimates a larger effect, namely approximately 0.5 years of education. The point estimates in my study are thus somewhat lower than the Puhani and Weber study. The results also correspond to the results by Bedard and Dhuey (2006). They find that relatively older students are more likely to be enrolled in postsecondary education, and these results also point in that direction. Lastly, Fredriksson and Öckert (2005) also show a positive effect of relative age leads on educational attainment. These results contrast the findings by Black *et al.* (2008), since the authors find little evidence on the effect of relative age on education attainment.

Table 5.2 also shows that income is negatively influenced by age in 1983. This means that the worst-performing students in primary school (the ones who had to repeat one or more grades) also perform poorly in the long term. The RF and IV models estimate a positive sign in all cases, meaning that income is positively influenced by relative age. The relative age point estimates vary between 0.006 and 0.015. The point estimate is also called semi-elasticity, and indicates the relative change in LN income due to an absolute one unit increase in relative age.[13] This result implies that income for the relatively oldest students is approximately 15% higher than wages for the relatively youngest students.

However, males are more likely to participate in the labour market. Therefore, the effect of relative age on incomes presented in A8 is considered more appropriate, since the analysis is split for men and women. In 1983, income is significantly influenced by relative age in the male case (shown in A8 in the appendix). The RF and IV models indicate that the difference between the natural logarithms incomes is 0.242 for the relatively older students (thus 24.2% higher). The

[13] This is only possible if the dependent variable is a logarithm with base *e* instead of base 10.

female case shows no significant relative age effect on the long term. This may be the result of a low amount of observations in the female case (a mere 438 observations). It may be the case that women are more likely to be unemployed, and this causes the amount of observations to be low. Taking all this in consideration, the estimate for women alone is not reliable, as the amount of observations is rather low. There is also a possibility that females' participation on the labour market may depend on other characteristics than relative age.

This result corresponds to the findings by Fredriksson and Öckert (2005). They show a positive impact of relative age on earnings. The point estimate in this study is, however, not significantly different from zero. Again, it is likely that the amount of observations is the reason for the low significance level. However, Black *et al.* (2008) also do not find a positive effect of relative age on earnings.

At first glance, it seems strange that the amount of education years is not significantly influenced by relative age, but in the male case incomes are significantly influenced by relative age. This may imply that there may be channels other than education through which relative age propagates in the long term. An explanation why income in 1983 is significantly influenced by relative age may be that students who are relatively older are more confident and have a psychological advantage over their relative younger counterparts. Alternatively, relatively older students may decide to enrol in a higher education program earlier than their younger counterparts. This means that these individuals enter the labour market at a younger age and have more time to build up a reputation, and, thus, have a higher income. This is also discussed in the paper by Fredriksson and Öckert (2005). In their paper, the authors show a positive long-term effect of relative age on earnings, but in the short run it is negative. This is explained by the fact that older students generally spend more time being educated and therefore have a lower income at a young age. This, however, is offset in the long term, as higher education has a positive return on income.

A9 shows the effect of relative age on income in 1993. The point estimate indicates that relative age has no significant impact on income, and the sign is negative. This, however, does not imply that the relative age gap has disappeared somewhere in the period 1983-1993, since the panel in 1993 is different than the panel in 1983. For example, there are many cases of individuals who answered the 1993 survey and did not answer the 1983 survey. The opposite is also observed. If the analysis for LN income 1993 is repeated for the group who responded to both 1983 and 1993 surveys, the coefficient estimate for 1983 and 1993 are both not significant (not shown). Also, the number of observations is substantially lower in 1993. Therefore, the results of relative age on income in 1993 are not scrutinised further.

The last item for socioeconomic status is the skill level. Table 5.2 shows that the OLS model estimates a negative relationship between age and skill level. This is as expected, for reasons which have been explained earlier. The RF and IV models show a positive sign for the effect of relative age on skill level, indicating that students who are relatively older are expected to have a higher skill level. The relatively oldest students are, on average, more highly skilled compared to their younger counterparts. The signs, however, are not significant. This is mainly due to the low point estimates, since the standard errors are rather low. Also, if the analysis is split for gender, there is no significant relationship.

Since it is less obvious that the skill level has remained constant for 10 years, it is necessary to analyse the results for 1983 and 1993 apart from each other. A10 shows the results. The point estimates suggest that relative age has a positive influence on skill level in 1983. This means that older students are expected to have a higher skill level for a job. However, the point estimates are very low, and this is also the reason why the effect is not significant. In 1993, the sign is negative, but the amount of observations in 1983 is twice as large as in 1993. Therefore, it is not possible to compare the results with each other, since the panel is different. The point estimates in 1993 are also very low and not significant. The overall conclusion is therefore based on the results of the maximum value of 1983 and 1993, as this has the highest number of observations. In this case, it is necessary to assume that the skill level is constant in the period 1983-1993. Also, the 1983 variable can be used, as it still has over 2000 observations. Both results imply that relative age has an effect on skill level, albeit very small and not significant.

The three dimensions of socioeconomic status – educational attainment, income, and skill – indicate that the relationship between relative age and performance in the long term is positive. The results are, however, not significant. The point estimates are somewhat low in comparison to other studies and therefore it may be the case that in the Netherlands the relative age effect is smaller than in other countries.

V.III

This section investigates the relationship between relative age and health. The first variable considered is self-reported health. This variable is based on questions in the 1993 survey. The second variable is a binary variable, indicating whether a person died before 2009. Since the level of education is not significantly affected by relative age, it is expected that there is limited evidence for a significant result of relative age on health. However, the sign should be positive, since the sign of education is positive. In the case of the dead variable, the point estimate should be *negative* since a negative sign indicates that the probability that a person died is *smaller*.

The health variable is obtained from the 1993 survey. Participants of the 1993 survey were asked to rate their health. In 2009, the researchers added mortality dates to the database for all 2998 people. The individuals who were still alive are approximately 70 years old in 2009. Furthermore, nearly 12 per cent of the panel has died, or, in absolute terms, 348 individuals. 245 of those individuals are male. Table 5.3 below shows the point estimates of relative age on the health outcomes. Table A11 shows the first stages of the IV models.

Table 5.3: Relative age effect on health

Health	OLS	OLS	RF	RF	IV	IV	No. Of Obs.
Self-reported health	-.015***	-.0129***	.004	.003	.008	.006	1923
	(.003)	(.003)	(.007)	(.007)	(.014)	(.013)	
Dead	.002**	.001**	-.001	-.001	-.002	-.001	2998
	(.001)	(.001)	(.002)	(.002)	(.004)	(.004)	
Controlled	No	Yes	No	Yes	No	Yes	

Self-reported health is measured on a 5-point scale. Dead is a binary variable, where "1" stands for a deceased individual. The stars indicate the significance level: * indicates that the variable is significant at the 10% level, ** at the 5% level and *** at the 1% level. OLS is the model with "observed age" as independent variable, RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), antisocial, number of siblings in family, family business, wish, number of teachers, type of school and official religion of the school. Standard errors are reported in parentheses.

The OLS estimate shows that the age in months negatively affects health. This, however, is not surprising, as older individuals tend to have worse health than younger people.

The RF and IV models do not show a significant relationship between relative age and health. This is not a surprising result, since the expectation was that health is affected through the level of education. From that observation, it is not hard to draw the conclusion that health and relative age are not significantly related to each other. Nevertheless, the sign is positive. This indicates that if it were significant, relatively older students would have, on average, better health. This is in accordance with the expectations, since the sign for years of education is positive and education by itself has a positive effect on health. The amount of observations is rather low, and this may cause the statistical tests to have a low power.

Table 5.3 shows that death is not significantly influenced by relative age. The coefficients are not significant in the models. The sign in this case is negative. This may seem odd, but the dead variable takes a value of “1” if an individual has died in the period 1994-2009. A negative sign this indicates a higher chance of being alive in 2009.

The coefficient also measures the effect of absolute age. Therefore, it is unknown what the sign should be beforehand. This is because absolutely older people tend to have a higher death probability, and relatively older people may live longer because they have received more education. In this case, the point estimate is negative; indicating that the second channel – relative age – dominates the first.

The respondents are approximately 70 years old in the last update. However, the life expectancy in the Netherlands is greater than 70 years (WHO, 2013). This means that the average person in the panel has not died yet, and the fact that only 15% of the respondents are dead confirms this. It would be interesting to track these individuals even longer, in order to get more insights about the relationship between relative age and deaths. For example, in 2025 the results could be completely different.

Taking all the results into consideration, the results imply that relatively older individuals have better health and live longer. This effect is, however, not significantly different from zero, but this does not necessarily imply that there is no effect. The effect of relative age on self-reported health is negligible. However, for the dead variable, relative age seems to have a rather large effect. In total, approximately 12% of the panel has died. The relatively oldest people have on average a lower death probability of approximately 1.6%, which is rather large given the fact that there are not many people who died before 2009.

V.IV

In this section, I check the robustness of the results presented in Tables 5.1, 5.2 and 5.3. This is done in three parts. The first robustness check consists of the family background variables and schooling variables. These results are already shown in Table 5.1, 5.2 and 5.3. From these tables, it can be obtained that the point estimates of relative age in the RF and IV case do not change significantly if the control variables are added to the models. The second robustness check is a re-estimation with students born in the first quarter after the cut-off date and students who are born in the quarter before the cut-off date. Since these are the most extreme results, it may be the case that the coefficient estimates become larger. Table A14 shows the results for the robustness check. The last robustness check is the relative age effect in quarterly data. The results are not shown in this paper, but are shortly discussed at the end of this section.

In Table A14, the OLS point estimates in the first two columns show that the variable is still negative and significant in almost all cases. This is an indication that the variable is endogenous, because the students who had to repeat a grade are likely the reason why the point estimate is negative. The coefficients are, however, somewhat larger (i.e. less negative) in the robustness case. However, most coefficients do not differ substantially and therefore the OLS results are robust.

The RF models are shown in the third and fourth column. An interesting result is that the point estimates are smaller in each model. This is somewhat unexpected, since it was expected to be larger. However, the differences between the estimated coefficients are approximately 0.005 in the grades for different courses. This is economically not significant, and thus the RF models are robust.

The IV models are shown in the fifth and sixth column and also do not indicate severe robustness problems. The point estimates are, again, somewhat smaller, but this difference is negligible. The conclusion is thus that all results are robust for comparing the models with the individuals born in the first and last quarter relative to the cut-off date.

Lastly, the model is robust for assigned relative age in quarters. The coefficients become somewhat larger, but the changes are not significant. A larger coefficient is expected, since it discriminates less between birthdays. Therefore, there is a larger group who are the relatively oldest students, and a larger group who are the relatively youngest students. This causes the coefficient of relative age to increase a bit. The results are not shown in the appendix.

VI. Conclusion

In this section, I will first summarise the outcomes of this study and its implications. Thereafter, the limitations of the empirical analysis are discussed together with suggestions for further research.

VI.I

In this paper, the relative age effect on the short and long term is tested. The cut-off date for school eligibility is used as a quasi-experimental design. In the Netherlands, the formal rule is that this cut-off date is the first of October of a certain year. At that date, a school year cohort starts (Leuven *et al.*, 2004). It is uncertain whether the formal rule already existed in 1952. However, the number of observations increase significantly in October 1939, and drops significantly in October 1940. This indicates that the formal rule already existed in 1952, as is discussed in Sections III and IV. The instrument, *assigned* relative age, is then constructed as month of birth relative to the formal October 1 rule. The variable also includes absolute age, and therefore the results are based on the combined effect of relative age and absolute age. The results are referred to as relative age, but they measure absolute age as well.

The studies discussed in section II show that the evidence on the effect of relative age on short-term and long-term performance is mixed. However, most papers did not analyse the relative age effect in the Netherlands. In this paper, I only discuss the case of the Netherlands, and this is a contribution to existing literature. Furthermore, it is one of the first studies to analyse the effect of relative age on health. Also, the length of the period study is much longer in my case than that of many other papers. The empirical design laid out by Bedard and Dhuey (2006) is applied to this paper.

The dataset is provided by the KNAW and is freely accessible at their online database, DANS. This is a unique dataset, which tracks approximately 3000 students in the Dutch province of Brabant. The length of the period study (about 60 years) far exceeds the length of other studies.

This gives more insight in the effect of relative age on the long term. Furthermore, the data allows for the discovery of an exciting new topic, namely the relationship between relative age and health.

In Section V, the effect of relative age on the short and long term is presented. The OLS case is disregarded in this section, since the Durbin-Wu-Hausman test indicates that there are issues concerning endogeneity. The OLS results are only shown for pedagogical purposes. The signs in the RF and IV models are in most cases positive, but not significant. The relative age effect is initially rather low, as the test scores in the eighth grade are not much affected by relative age. Several studies show that relative age has an effect of approximately 0.25-0.5 standard deviations on the short term, while in this study the effect is not larger than 0.15 standard deviations in the eighth grade (see Bedard and Dhuey (2006), Black *et al* (2008)., Elder and Lubotsky (2008), and Fredriksson and Öckert (2005)).

The number of years of education is not significantly affected by relative age, but more interesting is the positive sign of the coefficients. This is an indication that relative age has a positive impact on education level, albeit not a significant one. The effect is approximately 0.25 years for the relatively oldest students. Bedard and Dhuey (2006) find in their study that relatively older students are more likely to enrol in a (pre)university program. However, Puhani and Weber (2005) estimate a larger effect of relative age. These authors find an effect of approximately 0.5 years in Germany.

Furthermore, the incomes in 1983 are also positively affected by relative age, but the effect is not significant. Black *et al.* (2008) also show that incomes are not significantly affected by relative age. On the other hand, Fredriksson and Öckert (2005) find a significant positive effect of relative age on earnings. The same applies to skill level; it is shown that skill level is positively affected by relative age, albeit insignificantly. The number of observations is rather low, and this may cause the power of the outcomes to be low.

The other two variables are based on a person’s health. Self-reported health is not significantly affected by relative age, but this is expected since the effect of relative age on education is not significant. More important is the positive sign. This indicates that there may be a positive relationship between relative age and health. However, the effect is economically not significant and this may indicate that the relative age effect has been spilled somewhere in the education attainment channel. The variable “dead” is also not significantly affected by relative age, but again, this is due to the fact that relative age has no significant impact on the education level of an individual.

The overall conclusion that can be drawn is that it is unknown whether relative age affects long-term performance in the Netherlands. However, there are strong indications that students just born after the cut-off date perform better than students born just before the cut-off date. In all cases, the signs are as expected but not significant. If relative age does indeed have a significant positive effect, it may be beneficial for parents to plan births in order for their children to be the relatively oldest in the class.

The effect of relative age on self-reported health is not significant. The sign itself was also very small, indicating that the effect is negligible. Nevertheless, there is a weak indication that there is a relationship between the two. The effect of relative age on dead is also not significant, but the sign is rather large. If the relationship between relative age and health is more scrutinised in the future and it is found that there is a relationship between relative age and health, it may be interesting for insurance companies to adjust their insurance fees. These companies mostly use statistical discrimination (e.g. students’ health insurance fees are lower). However, it is likely that the Dutch government will not accept such a type of discrimination, as persons cannot control in which month they are born. Such discrimination would probably be viewed as unjust, and, hence will be forbidden.

VI.II

There are several issues with the empirical design in this study. The number of observations is rather low compared to other studies. This may cause power issues. It can be expected that the power of the statistical tests in this study is lower than the power in other papers.

Furthermore, the respondents were initially resident in only one province of the Netherlands, Brabant. Therefore, the results may not be generalizable for the Netherlands as a whole. For example, it could be the case that the type of students in Brabant differs from students in other provinces. However, the dataset is tested at the time for any differences between Brabant and the other provinces of the Netherlands. The conclusion is that there are no significant differences between Brabant and other provinces (van Praag, 1992). Therefore, the results are representative for the Netherlands.

Another problem is the dataset. It contained several issues regarding measurement errors in different surveys. In some cases, a respondent reported a lower level of education in 1993 than in 1983. However, the average years of education in 1983 and 1993 are approximately equal to each other. Also, excellent students could have skipped a grade and are thus placed one school year cohort ahead. However, it is not likely that these is a problem, as excellent students born one year later may have skipped a grade and thus “replace” the other excellent students in this survey. Lastly, it is not perfectly clear whether the formal October 1 rule already applied in 1952. However, the data indicates that the October 1 rule already existed in 1952.

Furthermore, the variable of interest does not measure relative age only. The coefficients also include the effect of absolute age. This problem is present in most other papers (see for example Fredriksson and Öckert (2005), Black *et al.* (2008), and Bedard and Dhuey (2006)). The conclusions regarding relative age are based on personal expectations and cannot be proven in these designs. Since most other studies find that absolute age has a positive effect on socioeconomic outcomes, it is likely that the point estimates in this study are upwardly biased. The true causal effect of relative age is thus likely to be lower the estimated point estimates in this study. However, in case of health it is likely that the effect of relative age is underestimated in the models, since it is likely that the part “absolute age” is negative.

Another point of concern is that the variable also measures the effect of season of birth. Since only one country is used with one cut-off date, it is not possible to correct for season of birth effects (Bedard & Dhuey, 2006). This problem, however, is also present in other studies that use only one country with one cut-off date (Fredriksson & Öckert, (2005), Puhani & Weber, (2005)).

Also, the time period may not be comparable to the situation today. For example, the study environment is different. Today, it is common to enrol in a university’s program, whereas around 1960 this was not the case (especially not for women). Therefore, a student’s decision to study longer may be dependent on other factors than relative age at that time. However, today the study environment is totally different than that of the 1950s. Therefore, the obtained results may not be valid for students today.

A last point of concern is that the RF and IV models are also used on binary and ordinal variables (skill level, self-reported health and death). However, a least squares technique does not perfectly fit these data types. On the other hand, estimation techniques which combine IV and multiresponse models are not user-friendly. Nevertheless, the RF and IV techniques are able to give an indication about what the relationship looks like. This study essentially tries to get an insight about the relationship and therefore the techniques used are appropriate. Angrist and Pischke (2009) also state that estimation techniques such as logit require additional assumptions. These assumptions may not be satisfied, and thus an estimator based on least squares could be superior.

Lastly, I try to explore a new topic – the relationship between health and relative age – and do not find much evidence on significant results. Future papers may use the design as a benchmark for their study. The dataset in this study is also interesting and useful to analyse this relationship, but it would be advisable to update the mortality dates every now and then. In about 15 years from now, the variable “dead” should substantially differ from the one used in this study, and it will contain more information about the relationship between relative age and death.

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Appendix

A1: Durbin-Wu-Hausman test

Dependent variable	DWH1	DWH2
Mathematics	-.068***	-.044**
	(.022)	(.019)
Physics	-.024	.001
	(.021)	(.019)
History	-.065***	-.034*
	(.022)	(.019)
Fill in exercises	-.064***	-.035*
	(.023)	(.021)
Expressing	-.044*	-.013
	(.023)	(.020)
Reading	-.054**	-.026
	(.024)	(.021)
Years of education	-.047***	-.054
	(.004)	(.017)
Log income	-.011***	-.019***
	(.002)	(.012)
Skill level	-.051***	-.041**
	(.004)	(.019)
Health	-.0164***	-.021
	(.003)	(.015)
Dead	.002**	.003
	(.001)	(.004)
Controlled	No	Yes

Durbin-Wu-Hausman tests for the models presented in table 5.1, 5.2 and 5.3. Coefficients are the saved residuals of the first stage models. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. Stars denote significance level, * is significant at the 10% level, ** at the 5% level, *** at the 1% level.

A2: Correlation matrix

	Quarter 1	Quarter 2	Quarter 3	Quarter 4
Years of education father	-0.0096 (0.5988)	0.0176 (0.3349)	-0.0195 (0.2854)	0.0118 (0.5188)
Years of education mother	-0.023 (0.2089)	0.0285 (0.1187)	-0.0310 (0.0899)	0.0262 (0.1520)
SES: Not reported	-0.0289 (0.1137)	-0.0112 (0.5395)	0.0239 (0.1902)	0.0173 (0.3438)
SES: Low	0.0054 (0.7694)	0.0067 (0.7137)	-0.0032 (0.8596)	-0.0091 (0.6171)
SES: Middle	0.0225 (0.2178)	-0.0006 (0.9734)	-0.0206 (0.2603)	-0.002 (0.912)
SES: High	-0.0336 (0.0662)	0.0024 (0.8968)	0.0301 (0.0993)	0.0021 (0.9097)
Marital status parents: Single	0.0369 (0.0435)	-0.0045 (0.8037)	-0.0534 (0.0034)	0.0202 (0.2679)
Marital status parents: Married	-0.0266 (0.1452)	0.0107 (0.5585)	0.0284 (0.1201)	-0.0119 (0.5148)
Marital status parents: Not reported	-0.0272 (0.1371)	-0.01 (0.5856)	0.0575 (0.0016)	-0.0198 (0.2796)
Not anti-social	0.0068 (0.7113)	-0.0026 (0.8885)	-0.0292 (0.1095)	0.0251 (0.169)
Anti-social	0.0012 (0.9476)	-0.0055 (0.7633)	0.0011 (0.9503)	0.0032 (0.8609)
Anti-social not reported	-0.0097 (0.5966)	0.0081 (0.6564)	0.0362 (0.0474)	-0.0348 (0.0566)
Work: Not reported	0.019 (0.2986)	-0.0166 (0.3641)	-0.0143 (0.4331)	0.0116 (0.5253)
Work: No	-0.0214 (0.2417)	0.0354 (0.0529)	-0.0017 (0.9243)	-0.012 (0.5113)
Work: Rarely	0.0077 (0.6754)	-0.0029 (0.8756)	-0.0056 (0.7574)	0.0007 (0.9712)
Work: Regularly	0.0038 (0.8341)	-0.0331 (0.0697)	0.0237 (0.1943)	0.0058 (0.7509)
Work: Seasonal	-0.0022 (0.9063)	-0.0002 (0.9914)	0.002 (0.911)	0.0004 (0.9837)
Work: Often	0.0109 (0.5518)	-0.0107 (0.5586)	-0.001 (0.955)	0.0006 (0.9732)
Wish parents not reported	0.0026 (0.8883)	0.0006 (0.9718)	0.0216 (0.2363)	-0.0252 (0.1677)

Wish parents: Own business	0.0265 (0.147)	-0.0207 (0.2566)	-0.0237 (0.1945)	0.0175 (0.3381)
Wish parents: Work, no education	-0.0086 (0.6387)	0.0016 (0.9318)	-0.0045 (0.8041)	0.0119 (0.5142)
Wish parents: Work and education	-0.0118 (0.5171)	-0.0114 (0.5341)	0.0143 (0.4347)	0.0095 (0.6045)
Wish parents: No work, education	-0.0013 (0.9432)	0.0025 (0.8903)	-0.001 (0.9552)	-0.0002 (0.9925)
Wish parents: ULO	-0.0067 (0.7152)	0.0157 (0.391)	-0.0037 (0.8383)	-0.0053 (0.7735)
Schooltype: Not reported	-0.0098 (0.5935)	0.0182 (0.3185)	-0.0214 (0.2407)	0.0133 (0.4682)
Schooltype: Girls only	-0.0148 (0.4186)	0.0159 (0.3835)	0.0089 (0.6257)	-0.0099 (0.5898)
Schooltype: Boys only	0.0127 (0.4873)	-0.01 (0.5845)	-0.0064 (0.7262)	0.0034 (0.8507)
Schooltype: Mixed	0.0041 (0.8204)	-0.0114 (0.5333)	0.0028 (0.8803)	0.0045 (0.8056)
Religion school: Not reported	-0.0171 (0.348)	0.0151 (0.4075)	0.0215 (0.239)	-0.0193 (0.2903)
Religion school: None	-0.0019 (0.9183)	0.0155 (0.3958)	-0.0395 (0.0305)	0.0261 (0.1531)
Religion school: Catholic	0.0179 (0.3273)	-0.0088 (0.6299)	-0.018 (0.3253)	0.0085 (0.6412)
Religion school: Protestantism	0.002 (0.9107)	-0.023 (0.208)	0.0159 (0.3848)	0.0053 (0.7738)
Religion school: Special school	-0.0025 (0.8901)	-0.0031 (0.8674)	-0.0013 (0.9438)	0.007 (0.7001)
Religion school: Public	0.0126 (0.4918)	-0.015 (0.4122)	0.0006 (0.9728)	0.0016 (0.9319)
# of siblings in family	-0.0023 (0.8983)	-0.0037 (0.8396)	-0.0043 (0.8126)	0.0106 (0.5626)
# Teachers in school	-0.0048 (0.7948)	0.0094 (0.6055)	-0.0053 (0.7699))	0.0007 (0.9678)

Correlation matrix of quarter of birth with mentioned covariates. Education levels of father and mother are redefined to a continuous scale. P-values are reported in parentheses.

A3: Summary statistics standardized dependent variables

Variable	Mean	Std. Dev.
Grade math	-1.11E-08	1
Grade physics	7.77E-10	1
Grade history	-7.56E-09	1
Grade fill in ex.	7.59E-09	1
Grade express	6.43E-09	1
Grade reading	-2.66E-09	1

Table A4: Check on selective non-response

Variable	1983	1993	Both
Relative age	-.005	-.006	-.008
	(.015)	(.012)	(.011)
Month of Birth	-.005	-.006	-.008
	(.015)	(.012)	(.011)
Mathematics	.074**	.129***	.156***
	(.029)	(.022)	(.021)
Physics	.157***	.093***	.165***
	(.030)	(.022)	(.021)
History	.070**	.122***	.147***
	(.029)	(.022)	(.021)
Fill in exercises	.075***	.129***	.155***
	(.028)	(.021)	(.020)
Expressing	.025	.104***	.107***
	(.029)	(.22)	(.021)
Reading	.032	.118***	.124***
	(.028)	(.021)	(.020)

Coefficients indicate the odds ratios for the mentioned independent variables in the logit models. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are reported in parentheses.

A5: First stages for the short term models

Course	FS1	F-statistic	FS2	F-statistic
Mathematics	.470***	102.006	.485***	117.057
	(.047)		(.044)	
Physics	.493***	109.44	.503***	123.591
	(.047)		(.045)	
History	.474***	101.566	.488***	113.336
	(.047)		(.045)	
Fill in exercises	.472***	102.263	.484***	116.524
	(.047)		(.045)	
Expressing	.479***	103.641	.495***	118.905
	(.047)		(.045)	
Reading	.481***	105.15	.491***	118.283
	(.046)		(.045)	
Controlled	No		Yes	

The table present the first stages corresponding to the models in section V.I (short term). It reports the coefficients estimates for assigned relative age on observed age. The F-statistic is obtained after using the "estat firststage" function in Stata. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. All coefficients are significant at the 1% level.

A6: First stages for the short term models, sorted by gender

Course	FS1	F-statistic	FS2	F-statistic	Gender
Mathematics	.507***	55.584	.521***	59.848	Female
	(.068)		(.067)		
Physics	.544***	62.496	.552***	66.454	Female
	(.069)		(.068)		
History	.522***	57.738	.532***	61.549	Female
	(.069)		(.068)		
Fill in exercises	.518***	58.699	.524***	61.438	Female
	(.068)		(.067)		
Expressing	.542***	61.881	.552***	65.532	Female
	(.069)		(.068)		
Reading	.531***	60.4396	.538***	63.589	Female
	(.068)		(.068)		
Mathematics	.445***	49.719	.459***	56.729	Male
	(.063)		(.061)		
Physics	.458***	51.307	.472***	58.708	Male
	(.064)		(.061)		
History	.441***	47.975	.457***	55.251	Male
	(.064)		(.061)		
Fill in exercises	.440***	47.962	.457***	55.334	Male
	(.064)		(.045)		
Expressing	.436***	46.791	.452***	53.963	Male
	(.064)		(.061)		
Reading	.447***	49.102	.456***	55.010	Male
	(.064)		(.061)		
Controlled	No		Yes		

The table present the first stages corresponding to the models in section V.I (short term) sorted by gender. It reports the coefficients estimates for assigned relative age on observed age. The F-statistic is obtained after using the “estat firststage” function in Stata. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. All coefficients are significant at the 1% level.

A7: First stages for the socioeconomic models

Socioeconomic result	FS1	F-statistic	FS2	F-statistic
Years of education	.483***	109.838	.489***	42.630
	(.046)		(.045)	
LN income	.424***	51.767	.425***	55.765
	(0.059)		(.057)	
Skill level	.424***	73.599	.426***	79.654
	(.049)		(.048)	
Controlled	No		Yes	

The table present the first stages corresponding to the models in section V.I I (socioeconomic outcomes). It reports the coefficients estimates for assigned relative age on observed age. The F-statistic is obtained after using the “estat firststage” function in Stata. The control variables are: gender. education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. All coefficients are significant at the 1% level.

A8: Relative age effect on socioeconomic outcomes

Socioeconomic outcome	OLS	OLS	RF	RF	IV	IV	No. Of Obs.	Gender
Years of education	-.038***	-.026***	0	.004	0	.007	1056	Female
	(.006)	(.005)	(.013)	(.012)	(.022)	(.020)		
LN income	-.004	.003	-.002	-.001	-.004	-.001	438	Female
	(.008)	(.008)	(.016)	(.017)	(.032)	(.037)		
Skill level	-.060***	-.039***	-.004	0	-.009	0	811	Female
	(.008)	(.007)	(.018)	(.017)	(.038)	(.036)		
Years of education	-.0472***	-.031***	.021*	.012	.052	.028	1589	Male
	(.005)	(.004)	(.012)	(.011)	(.032)	(.025)		
LN income	-.012***	-.007***	0.001**	.009**	. .025*	.022*	1230	Male
	(.002)	(.002)	(.005)	(.005)	(.014)	(.012)		
Skill level	-.046***	-.031***	.008	.006	.019	.015	1711	Male
	(.004)	(.004)	(.012)	(.011)	(.030)	(.027)		
Controlled	No	Yes	No	Yes	No	Yes		

Effect of relative age sorted by gender for the models in section V.II (socioeconomic outcomes). OLS is the model with “observed age” as independent variable; RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are reported in parentheses.

A9: Relative age effect on income 1993

Socioeconomic outcome	OLS	OLS	RF	RF	IV	IV	No. Of Obs.
LN income 1993	-.0145***	-.012***	-.001	-.002	-.003	-.003	1053
	(.003)	(.003)	(.006)	(.006)	(.013)	(.013)	
Controlled	No	Yes	No	Yes	No	Yes	

Effect of relative age on the natural logarithm of gross income in Dutch guilders in 1993. OLS is the model with "observed age" as independent variable; RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are reported in parentheses.

A10: Relative age effect skill level 1983 and 1993

Socioeconomic outcome	OLS	OLS	RF	RF	IV	IV	No. Of Obs.
Skill 1983	-.048***	-.034***	0	.004	-.0001	.008	2265
	(.004)	(.004)	(.010)	(.010)	(.023)	(.021)	
Skill 1993	-.043***	-.029***	-.006	-.007	-.013	-.015	1164
	(.006)	(.006)	(.015)	(.014)	(.032)	(.031)	
Controlled	No	Yes	No	Yes	No	Yes	

Effect of relative age on skill levels as observed in 1983 and 1993. OLS is the model with "observed age" as independent variable; RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are reported in parentheses.

A11: First stages for the Health models

Health	FS1	F-statistic	FS2	F-statistic
Self-reported health	.487***	80.247	.506***	90.190
	(.054)		(.053)	
Dead	.465***	104.699	.475***	117.778
	(.045)		(.044)	
Controlled	No		Yes	

The table present the first stages corresponding to the models in section V.I II (Health). It reports the coefficients estimates for assigned relative age on observed age. The F-statistic is obtained after using the "estat firststage" function in Stata. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. All coefficients are significant at the 1% level.

A12: Relative age effect on health

Health	OLS	OLS	RF	RF	IV	IV	No. Of Obs.	Gender
Self-reported health	-.005	-.003	.013	.013	.022	.021	772	Female
	(.005)	(.005)	(.011)	(.011)	(.018)	(.017)		
							1208	Female
Dead	.001	0	-.002	-.002	-.005	-.003		
	(.001)	(.001)	(.002)	(.002)	(.005)	(.004)		
Self-reported health	-.020***	-.016***	-.002	-.003	-.004	-.007	1151	Male
	(.003)	(.004)	(.009)	(.009)	(.021)	(.020)		
Dead	.002**	.002**	0	.001	.001	.001	1790	Male
	(.001)	(.001)	(.002)	(.002)	(.006)	(.005)		
Controlled	No	Yes	No	Yes	No	Yes		

Effect of relative age sorted by gender for the models in section V.III (health). OLS is the model with "observed age" as independent variable; RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are reported in parentheses.

A13: Relative age effect in standard deviations

Course	OLS	OLS	RF	RF	IV	IV	No. of Obs
Mathematics	-0.249	-0.114	0.065	0.064	0.137	0.133	2784
Physics	-0.155	-0.028	-0.014	-0.002	-0.029	-0.035	2760
History	-0.223	-0.069	0.062	0.056	0.131	0.114	2754
Fill in exercises	-0.297	-0.15	0.022	0.017	0.046	0.035	2756
Expressing	-0.153	0.034	0.043	0.037	0.089	0.075	2748
Controlled	No	Yes	No	Yes	No	Yes	

Effect of relative age in standard deviations for test scores in the eighth grade. Reported values are coefficients only. Significance levels correspond to the ones in Tables 5.1. All variables are standardized to a mean of 0 and a standard deviation of 1. OLS is the model with "observed age" as independent variable; RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. The stars indicate the significance level, * indicates that the variable is significant at the 10% level, ** at the 5% level, and *** at the 1% level. Standard errors are reported in parentheses.

A14: Robustness check

Dependent variable	OLS	OLS	RF	RF	IV	IV	No. of Obs	% of total Obs
Mathematics	-.040***	-.019***	.004	.008	.009	.017	1341	48.17%
	(.005)	(.005)	(.011)	(.010)	(.025)	(.022)		
Physics	-.018***	.003	-.007	-.002	-.015	-.005	1324	47.97%
	(.005)	(.005)	(.011)	(.010)	(.022)	(.020)		
History	-.042***	-.014***	.005	.008	.010	.016	1320	47.93%
	(.005)	(.005)	(.012)	(.010)	(.025)	(.021)		
Fill in exercises	-.044***	-.017***	-.007	-.004	-.014	-.009	1326	48.15%
	(.006)	(.006)	(.012)	(.011)	(.027)	(.023)		
Expressing	-.025***	.003	0	.002	0	.004	1321	47.93%
	(.006)	(.003)	(.012)	(.010)	(.026)	(.021)		
Reading	-.031***	-.003	.001	.007	.002	.015	1320	47.98%
	(.006)	(.005)	(.012)	(.011)	(.025)	(.022)		
Years of education	-.041***	-.026***	.012	.010	.026	.022	1268	47.94%
	(.005)	(.005)	(.010)	(.009)	(.023)	(.020)		
LN income	-.007***	.001	.013**	.013**	.033*	.032**	820	49.16%
	(.003)	(.003)	(.006)	(.006)	(.017)	(.016)		
Skill level	-.054***	-.035***	.004	.008	.010	.011	1224	48.52%
	(.005)	(.005)	(.012)	(.011)	(.028)	(.028)		
Self-reported Health	-.017***	-.013***	.004	.001	.009	.003	937	48.73%
	(.004)	(.004)	(.008)	(.008)	(.016)	(.016)		
Dead	.001	.001	0	0	0	0	1444	48.17%
	(.001)	(.001)	(.002)	(.002)	(.004)	(.004)		
Controlled	No	Yes	No	Yes	No	Yes		

The table present the results for the statistical models in table 5.1, 5.2 and 5.3 with only individuals born in the first and last quarter relative to the cut-off date. OLS is the model with "observed age" as independent variable, RF is the reduced form of the IV model and measures the effect of assigned relative age on test scores. The IV model uses assigned relative age as an instrument for observed age. The control variables are: gender, education levels of father and mother, social class of the family, marital status of the parent(s), anti-social, number of siblings in family, family business, wish, number of teachers, type of school, and official religion of the school. Stars denote significance level, * is significant at the 10% level, ** at the 5% level, *** at the 1% level.