The effect of sibship density on children's educational outcomes in Germany

Erasmus University of Rotterdam

Erasmus School of Economics

Student: Bram van Diepenbeek

Supervisor: Aart Gerritsen

Second Assessor: Laura Hering

Abstract

In this paper the effect of sibship density on educational outcomes in Germany is studied. Sibship density is one of the characteristics of a sibship and describes how closely the siblings are to one another in age. The sample consists of children born between 1970 and 1996. As outcome variables both years of education and highest educational level completed are used. Through performing Ordinary Least Squared Regressions and Ordered Logistic Regression a small but significant positive association is found between sibship density and the educational outcome. This is surprising, since negative relations have previously been found by other papers. Whether the results are different because the German educational system is different from the US or because the time setting of this study is different, remains unknown and offers possibilities for further research.

1. Introduction

Education is one of the more researched topics in policy economics, as almost every government in the world provides an educational framework for its civilians. It is seen as one of the more important factors of one's later income (Sullivan and Wolla, 2017). This also means that education is a stage in which inequality can find its origin or diverge even more. The factors that determine educational achievement are therefore of much importance and interest. There are quite a few components which are generally seen as the more important ones. In a renowned paper by Hanushek (1992), he identifies family inputs, school inputs and other exogenous inputs as the most defining components of the education production function.

In this paper I will zoom in on the family input aspect of this function. There have been numerous studies into the effects of family. One more specific element is the family composition. Most studies on family composition study the effects of sibship on educational outcomes, but there are also studies where parental composition or household resources are the main variables of interest. The number of siblings, also known as sibship size, and birth order in relation to educational outcome are the more broadly researched. In this paper, I will study the effects of sibship density thoroughly. Sibship density is a characteristic of the sibship composition and is defined as the difference in age in between siblings.

From a theoretical perspective, the general hypothesis is that size of a sibship is inversely related to educational outcomes. The main theory is the Resource Dilution Theory (RDT). Another common theory is about the Confluence Model (CM). The RDT implies that larger families can lead to decreased investment in each child's development and education. Parents will have to divide their time, energy and money over more siblings, resulting in less resources per child. This theory has naturally been tested empirically and, generally, this inverse relation is found. The CM builds upon the idea that the intellectual environment at home is connected to the average age of sibship. If a sibling is much older than the average age of the sibship, the intellectual development will be less developed. For younger siblings, this expected relation is the opposite.

Although there has been quite some research into the effects of sibship size on educational outcomes, relatively little research has been done into the role of sibship density. As the RDT is seen as the main theory behind the empirical findings, questions about the density of sibships emerge. The reasoning of the RDT is being further built upon. The idea is that when children are more have less age difference, parents cannot give their undivided time, attention and energy to any one child, leading to lesser resources per child. Therefore, the next question will be studied in this paper:

What is the effect of sibship density on the educational outcome of children in Germany born between 1970 and 1996?

Besides the fact that most studies on this topic are relatively old, and a lot has changed since, the German educational system is very different to the American education system, where most studies on this topic find their setting. It is reasonable to expect that children form larger and/or poorer families are a less of a disadvantage in Germany than in the US, since (financial) barriers to higher education are higher in the US (Powell and Solga, 2011). Studying this relation in a German setting is therefore relevant. Results could be relevant for policy makers too. There are of obviously policies in place to provide financial resources to help (relatively poorer) parents with raising their children, but they might not be enough and do not per se benefit the educational performances of children in large families with high density directly. For example, the money transferred towards household could also be spent on purposes that do not contribute to the educational development of children. Suppose that higher density negatively affects educational outcomes, additional policies within school could be helpful to support those children. Extra tutoring or more contact hours for children with closer siblings could be possibilities.

The datasets used for the empirical findings are from the German Socio-Economic Panel (SOEP) database and the sample consists out of children from two- and three-children's families. I study the effects of the sibship density between siblings on both the years of education and highest level of education completed by individuals. The chosen treatment variables represent the total age difference in years between siblings and the difference in years to the average age of the sibship. The latter shows the number of years between an individual's age and the average age of the sibship. I use a cross-sectional analysis in which I perform several Ordinary Least Squares (OLS) regressions and Ordered Logistic Regressions (OLR). Surprisingly, I find a positive association between the sibship density and educational outcome. Although the coefficients are relatively small and they are not all significant, they do consistently indicate a positive relationship between the sibship density and their educational outcomes. This is interesting, since previous research on this topic find results that indicate a negative relation between sibship density and educational outcomes. Several potential explanations are possible. They could be different because the German setting is different than the American, where most research on this topic has been done. The time setting of this study is also different. Perhaps the previously founded negative relationships between sibship density and educational outcomes is less prevailing in more recent time settings. However, without further research into this, these explanations remain hypothetical.

The paper consists of the following sections. Firstly, I will discuss the theoretical framework surrounding this topic. After understanding this, I will study and review the important literature connected to the theories. I will also analyze the relevant institutional details. After having done so, the chosen data and methodology for this study will be defined and explained. The results of my empirical analysis will be presented and interpreted. Lastly, I will conclude and discuss the limitations, possibilities for further research and potential policy implications of this study.

2. Theoretical framework

To understand the mechanisms behind sibship density, we first need to focus on family composition and mainly sibship composition and its effects on educational development. In this theoretical framework I will first briefly review the factors that impact educational outcome. Then we will dive deeper into existing theories on the relations between sibship size & density and educational outcomes of children.

2.1 The education production function

Education is one of the oldest public goods in the developed world and has thus gained a lot of interest in the field of policy economics. In a renowned paper by Hanushek (1992) he constructs the next education production function:

$$A_{it} = \Phi\left(F_i^{(t)}, S_i^{(t)}, X_i^{(t)}\right)$$

The three most important components are respectively denoted as family inputs, school inputs and other exogenous factors. Because of the rich dataset, he can empirically analyze both family inputs and school inputs and tries to show that the *importance of* school inputs should not be underestimated. He also notes that the two are not totally separated from each other, since middle- and high-income parents search for good schools specifically. Now I will zoom in on the family input component of the education production function.

2.2 Family input and theories

Family inputs are obviously crucial in the transmission of human capital, and it still is a very broad concept. There are a lot of factors within a household that affect a child's intellectual development. On the one hand there is the nature part of family input, which seems evident. As part of your intelligence, or at least part of your potential intelligence, is genetic and thus inherited. On the other hand, there is the nurture part of the family input, which covers multiple facets. Environment at home, parental involvement, type of neighborhood, accessible resources and family composition are all examples of factors that have an impact on the development of a child (Boyd and Bee, 2014).

There have been diverse studies on the effects of family composition on educational outcomes. Family composition is a term which defines the number of siblings you have, what their gender is, the sibship density, but also if your parents are together or divorced for example. The consensus is that family composition has a significant effect on the development of children and therefore on the educational outcomes of children.

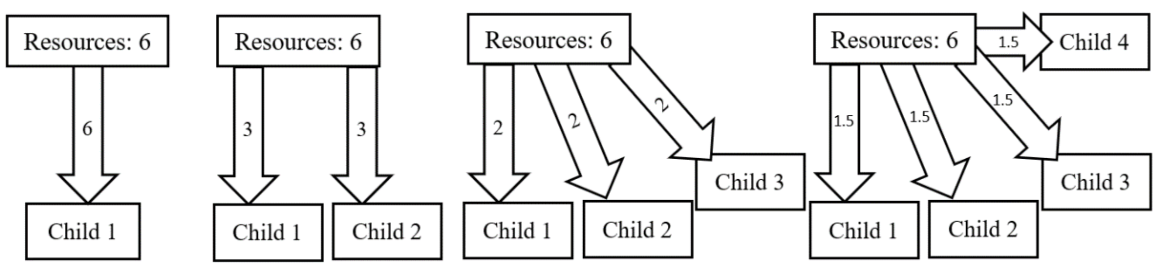
2.2.1 Utility function and budget constraints.

This is one of the older economic theories that has extensions to the fields of family composition theories. It was first introduced by Becker (1960) and later expanded by him and others in papers that discuss fertility patterns and choices more abstractly (Becker and Barro, 1988). The theory is a more formal framework in which parents experience a budget (time, energy and money) constraint and thus face a quantity-quality trade-off when making decisions about the nurturing of their children. The theory argues that parents have a parental utility function and allocate their resources to maximize the utility. Depending on the convexity or concavity of their function, they will spend their resources differently. If they prefer equal outcomes for their children, they will spend more time with their least able children. But if they prioritize an achievement maximization strategy, they will spend more resources on their most able child. The theory also focusses on the public and private time spent by parents with their children. Spending public time, where all children are present, increases the chances of spillover effects. If parents tend to spend more private time with some children due to the choices caused by their utility function, spillover effects are not possible. Since testing this theory requires micro-level data about allocation choices, like ‘time spent helping homework’ and ‘time spent playing with children’ for instance, it is hard to test empirically and is out of the scope of this study. Because other theories on this subject built further upon this theory, it is important to describe.

2.2.2 The Resource Dilution Theory

The Resource Dilution Theory is the most widely accepted theory about the effects of family composition on educational outcomes in the existing literature. This theory argues that larger families will automatically decrease the resources allocated to each child. Resources are here also defined as time, energy and financial resources. All these resources benefit the development of a child and if they receive less resources per child, their development suffers. This theory also encompasses birth order effects. Analyzing the argumentation of this theory should lead to suggesting that children further up the birth order receive less resources than children who were born earlier. Figure 1 depicts this idea. As a result, the development of younger siblings would be subordinate to that of older siblings.

Figure 1: Resource Dilution and birth order



There are also counter arguments to be made against resource dilution. Parents could make important decisions about working or housing with the expectation that they will have more children and anticipate this. Furthermore, some scientists argue that siblings stimulate each other’s development. Through communication within the household spillover effects emerge and this provides the possibility to learn from each other. However, it is very difficult to understand and find evidence about the relationships between siblings and its spillover effects. It would also require more micro-level data to test the possible spillover effects empirically. The confluence model tries to disentangle those effects from the perspective of average intellectual age of the household (Simonsen et al, 2017)

2.2.3 The Confluence Model

The Confluence Model has been developed in the psychological field and is about the intellectual environment at home (Zajonc and Markus, 1975). Both the position in the birth order and the density of the sibship are determinants in this theory. The impact of the sibship will be discussed in the next section. If a sibling is older than the average age of the sibship, he is expected to be negatively impacted by this. This is because the average age is correlated to the average intellectual age of the sibship. If this intellectual age is younger than a siblings own age, he will experience less intellectual stimulation. Due to lower intellectual stimulation experienced by siblings, their intellectual development is less encouraged. For siblings who are younger than the average age, this effect is the opposite. This model follows a different argumentation than the resource dilution theory with regards to birth order effects. On the one hand could a larger sibship size lead to lower average age, but the effects are different for younger and older siblings and are dependent on density (Zajonc, 1983).

2.4 Theories and extensions to sibship density

The Resource Dilution Theory and the Confluence Model also offer insights regarding the impact of sibship density on educational outcomes but do not necessarily implicate similar outcomes. The line of reasoning behind the Resource Dilution Theory is being further built upon. The idea is that when children have a higher sibship density, parents cannot give their undivided time, attention and energy to any one child, leading to lesser resources per child. If there was more age difference between children, parents could spend more time and energy resources per child. This is because the intensity of raising a child is at the beginning of their lifespan. Furthermore, early childhood is a critical period in terms of (intellectual) development for children (Boyd & Bee, 2014). Besides these time and energy resources, financial resources, like savings for example, could also be depleted more quickly when the density is higher. Costs rise more quickly if children are born closer to each other. Besides that, the costs rise more rapidly, parents can generally work less if their children are born more quickly after one another and thus build savings less quickly.

Considering the effects of sibship density on educational outcomes with regards to the theoretical framework of the Confluence Model is more difficult. This is because the impact of sibship density is considered to be partly dependent on birth order in this framework. The oldest siblings are generally considered to be at a disadvantage, since they are always older than the average intellectual age. If the density is higher, this is relatively less negative for them than if the siblings are much younger. For the youngest siblings, it is the other way around. The average intellectual at home is always higher than their own age and this difference increases more if the density is lower. However, if the distance to their older siblings is too high, the potential spillover effects might be at risk since they will not be stimulated intellectually. Once again, the fundamental assumption of this theory is that there are intellectual spillover effects within households and this assumption is hard to find and prove.

3. Literature review

As we have now discussed the most important theories about the subject, we can analyze empirical studies that aim to verify these theories with data. First, I will discuss studies that research the effects of sibship size and birth order effects on educational outcomes. After this, I will analyze the studies on sibship density.

3.1 Family size and birth order

Various papers have studied the effects of family size on educational outcomes and attainment. Iacovou (2001) studies family composition and educational outcome in the UK and finds that children with relatively more siblings perform worse at school, even when controlling for a lot of variables like social class, micro-level information about the parents' involvement in childhood and social environments of children. She also finds evidence sibship size is a more important determinant of educational attainment for families with higher financial difficulties. Downey (1995) conducts an extensive empirical study on the effects of family size and parental resources in the US. A significant negative relation is found between family size and educational outcome, supported with the indication that the resource dilution causes this. He substantiates this indication by including several variables which represent time and financial resources. For example, he uses the frequency of talk, having a computer, having educational objects and going to cultural activities. Chen et al. (2019) study the differences in educational outcomes between children from two-parent families and single-parent families and find evidence that children from the latter families have lower educational attainment. Black et al. (2005) perform a very interesting and extensive study. Firstly, they find a significant negative effect between family size and educational performance. However, when they add birth order variables to their models, those effects disappear and are shifted to the birth order variables. This indicates, that for their sample, birth order causes negative effects on educational outcomes and not necessarily family size.

3.2 Sibship density

Powell and Steelman (1990) study the effects of sibship density on school performance in the US. Their data comes from two dataset created in 1972 in the United States. They use data on verbal and math test scores to measure school performance and use parental education, race and sex as control variables. Two different sets of treatments variables are used. Firstly, they create five variables which show how many siblings there are x-years older or younger. The categories are 3 years older, 1-3 years older, within 1 year of the individual, 1-3 years younger and more than three years younger. Secondly, two variables are created which show how many siblings there are inside and outside a three-year age difference. The first approach takes the degree and direction of the density into account, while the second approach only takes the degree of the density into account. Strong significant negative coefficients are found for siblings which are have little age difference. The coefficients for siblings with a age difference within a year all around –3. And siblings which are 1-2 years older or 1-2 years younger all within –1 and –3. The coefficients for the variables which show the effects of siblings which are more than three years older vary between –0.4 and 0. This shows that having siblings which are closer spaced is more harmful to school performance than having siblings who are much older. It is notable that the values for the variables which show the effects of siblings which are more than three years younger vary between –0.3 and 0.5. If the Confluence Model was dominant over the Resource Dilution Theory, having younger siblings would be more harmful than having older siblings. The results found by this paper do not support this and thus indicate that the Resource Dilution Theory is dominant over the Confluence model. Furthermore, the variable which shows how many siblings there are within a three-year age difference are all between –1 and –3, while the variable which shows how many siblings there are outside a three-year are between –0.3 and 0.1. This also shows that having more closely spaced siblings is more detrimental for educational outcomes than having siblings who are much older or younger.

In another study by Powel and Steelman (1993) they try to analyze the relationship between sibship density and educational attainment. Their sample covers 58,000 individuals from the US and the data is from 1980-1984. Here the outcome variables used are post-secondary school attendance and high school attrition. The latter variable shows if an individual dropped out of high school. For sibship density, they create two variables showing how many siblings there are within and outside two years of the age of the individual. They also use the proportion of the sibship that are within two years of the age of the individual. Measures that show the total number of siblings, the respondent's ordinal position in the sibship and if they are the oldest or youngest are also included. Besides OLS, they also perform multivariate logistic regressions. A positive relation is found between sibship density and high school attrition. A high density is also negatively impacting post-secondary school attendance, even when controlling for a wide set of variables. What is remarkable is that in all the models the coefficient which shows the effect of the proportion of closely spaced siblings is far more negative than the coefficients which represent the number of siblings. This indicates that for their sample, sibship density is perhaps more important than family size. It is concluded that when comparing the multiple models with different controlling variables and corresponding coefficients, that the resource dilution is the best fitting theory.

Jaeger (2009) tries to determine if the CM or RDT is the most explanatory factor sibship density behind the negative relationship between sibship size and density and educational outcome, since most studies do not make an empirical distinction between the two theories when studying this topic. He argues that in the CM affects educational attainment solely through the cognitive ability in the household, while it follows from the RDT that there is an additional effect of sibship size on educational attainment because of the diluted parental resources which is unrelated to cognitive ability. By using an extensive dataset which include measures for cognitive ability, he finds an indication that the RDT is the more dominant factor in causing the negative relationship.

Having analyzed all the theories and reviewed the theories above, I formulated the next hypothesis:

Hypothesis 1: A lower sibship density is beneficial for educational outcomes

I also expected different results for older and younger children. According to both the Resource Dilution Theory and the Confluence Model, a lower density between siblings is more beneficial for the youngest siblings. However, a lower density is not beneficial for the oldest siblings according to the Confluence Model, but it is beneficial according to the Resource Dilution Theory. Since the latter is expected to be more important, I formulate the following hypothesis.

Hypothesis 2: A lower sibship density is relatively more beneficial for youngest siblings than for the oldest siblings

4. Institutional details

Education itself is a form of institution and it is organized differently in every country. Therefore, it is important to discuss and analyze those differences if we want to interpret the results correctly. The relation between sibship structure and educational outcome is probable to be different between countries. It is only logical to assume that the financial aspect of the RDT is of greater influence in countries where post-secondary education is relatively expensive, like the US, than in countries where it is heavily subsidized by the government like the Netherlands. In this section I will provide an overview of important details of the German education system and relevant policies.

Tanskanen et al. (2016) and Park (2008) studies the differences in the relation between parental resources, sibship size and educational performance between twenty developed countries. First, they establish the negative relation between sibship size and educational performance and find that this negative association is smaller when parents have more resources. They also show that the relation between sibship size and educational outcome is much less negative in countries with stronger public support for childcare, universal child benefits and larger public expenditures on education and family. Although Germany is included in both papers, but the results per country are not very expressive. They only show some key figures about public expenditures on education and family per country, but these are not remarkably different than for other developed European countries.

4.1 Educational setting in Germany

Children in Germany start their education on average at the age of six years old in primary education, known as Grundschule, and lasts for four years. Then they go to their secondary education which is already divided into different levels. This stage lasts for five to nine years, depending on the level of education. The children that take secondary schooling for five to six years typically go to vocational school or technical college afterwards and have the possibility to follow a university of applied sciences for three years afterwards but can also apply to university later via different ways. Children who follow secondary schooling for nine years have the possibility to attend university subsequently, which takes at least three years for a bachelor's degree and at least one year for a master’s degree. If someone completes a bachelor’s and master’s degree their educational careers can last for 18 years on average (Germany, 2022). The German education system is also known for its vocational and training (VET) system. It offers apprenticeship programs and practical training alongside general theoretical education. The system covers a wide spectrum of professions like more technical and industrial jobs, but also healthcare workers or commercial jobs. The VET system cannot be classified as a certain educational level in Germany, since it offers a lot of different levels and lengths of education (Cedefop, 2020; Amt, z.d.)

4.2 Higher Education and financial aspects

Like the Netherlands, secondary schooling is totally free in Germany. Moving to higher education, we see almost 400 public higher education systems and roughly 95% of the students enroll at those public institutions. Looking back in history, the tuition fees of higher education have not seen a stable trend. In 1969, the Framework Act for Higher Education was implemented. This act abolished all tuition fees. However, the constitutional court decided that a nationwide ban on tuition fees was unconstitutional in 2005. As a result, some states and their universities introduced them back between 2006 and 2007, at on average 500 euros per semester. Between 2011 and 2013 those universities removed their tuition fees again. In general, German tuition fees have always been quite low or non-existent (Hüther and Krücken, 2014; Powell and Solga, 2011). This is an important difference in comparison to the educational system in the US, where tuition fees for higher education are generally quite high and therefore create barriers for lower income students to enter higher education (Page and Clayton, 2016; Dill, 2022). The fact that the financial barrier to pursue higher education is low in Germany, causes the financial aspect of the RDT to decrease. It does not disappear completely, since richer parents can obviously financially support their children to a higher extent in a lot of different ways throughout their childhood and educational careers.

4.3 Relevant public policies for parents

There are several policies in place to support parents in different ways in Germany. Similar to the Netherlands, policies like Parental Leave, Child Benefits, Childcare Support or Housing Support all exist in Germany too. Some of those policies are also income related and support parents with a lower income to a higher extent. As the development of those policies over the last decennia are very miscellaneous and the dataset does not provide enough appropriate and relevant information to include these, I will not analyze them more thoroughly (Martin, 2018; Family Policies, 2014)

5. Data & methodology

5.1 Dataset

The data used in this paper were obtained from the German Socio-Economic Panel (SOEP), which is conducted by the German Institute for Economic Research. This institute started the survey in 1984 and has been conducting the surveys on an annual basis. It is a longitudinal household survey that contains a wide set of economical and sociological topics like socioeconomic status, employment, education, demographic information, and family background. The targeted population consists of all individuals living in Germany, regardless of citizenship or nationality. They use a multi-stage stratified sampling design and samples are refreshed annually. For representative purposes, some groups are over-selected. The data is collected with face-to-face interviews (DIW Berlin, n.d.).

5.3 Sample selection

To answer the research question, it is important to critically select the sample. The data I use is derived from three different datasets. Two datasets include demographic and sociological data about the individual and the individual's parents, separately. The third data set contains demographics about the individual's siblings. This last data set is the smallest and contains roughly

23,000 individuals. After the individual's IDs are matched there are 9,000 observations left, since the datasets do not necessarily contain exactly the same individuals every year.

I drop certain observation to protect the validity of the results. First, I drop individuals without siblings. I also drop individuals if none of their siblings is within an age difference of ten years, since I assume that the impact of the RDT and CM will almost be secluded. For example, if the individual has two brothers and one is five years younger but the other one is 12 years younger, I keep them in the sample. I only drop the individuals if none of their siblings is within a ten year age difference. The last survey was done in 2020 and people in Germany are on average 24 years old when they complete their master's degree. Since the highest educational level is ‘upper secondary’ which also includes bachelor’s degrees and Fachhochschule (hbo), the minimum of 24 years seems like a reliable boundary and thus all people born after 1996 were dropped. It appeared that not all the respondents who were born between 1970 and 1996 finished their chosen education when they last participated in the survey. For example, someone born in 1990 last participated in the survey in 2008. I cannot know if this individual already finished his or her education, so I drop individuals if the period between their birth and last participation is less than 24 years. By dropping all observations with the same person ID except the most recent observation, I ensure that I do not have duplicate individuals in my sample. The minimum birth age of the sample is set at 1970, to increase the sample size to a sufficient level. The data did not contain variables about the marital status of the individual's parent. It did contain a variable which showed how many years the individual lived with both parents which had a maximum value of 15. If an individual did not live with both parents during the childhood, it could be because of divorce, death of a parent, or something else. Those individuals experienced different dynamics at home. They generally have fewer financial resources, could receive less attention and the intellectual age is lower. If I do not know the reason for each individual, I cannot control for this separately. Therefore, I dropped all observations with values below 15. If the parental age upon birth is lower than 18, the individual is dropped because teenage parenthood affects educational outcomes negatively (Brooks and Furstenberg, 1986). Because of the droppings described above, the number individuals from families with a sibship size bigger than three are below a hundred. Since these family dynamics are likely to be different to be different to the dynamics of two and three children’s families and the observations are very little, I decided to drop those too. This leaves me with a sample of 1,299 individuals.

5.2 Variable selection

The variables used in this paper are shown in table 1 The goal of this paper is to measure the effect of sibship density on educational outcomes. There are multiple options to measure educational outcomes. It is possible to use years of education, highest degree attained, test scores or grade point averages. The dataset does not include information about grades received during the education, but it does include data about the first two options. As described in the institutional details section, the German educational system consists of various stages and levels and offers multiple ways to obtain certain degrees. Because of this, years of education or the highest degree attained are not necessarily interchangeably when evaluating the educational outcome of an individual. To increase the reliability of my conclusion, I choose to use both options as outcome variables. I will elaborate more on these two outcome variables in the descriptive statistics section.

As mentioned in the literature review section, different ways of measuring sibship density are possible. Multiple papers use the number or proportion of siblings within or outside x-number of years, since their data contains allows to have enough variation in those measures. As stated, my sample size is limited. Therefore, I unfortunately cannot use these measures since the variation would not be sufficient. I measure the density of a sibship in two different ways. Firstly, I use the total age difference in a sibship as a measure. This is the age difference between the siblings in two children's families and the age difference between the oldest and the youngest child in three children's families. To be able to include individuals from two and three children's families in one regression, I normalize the variables by dividing the total age difference by two for individuals from three children's families. Although this still does not create perfect uniformity, it does increase the validity. Secondly, I measure the difference in years to the average age of the sibship. To do so, I first calculate the average age of an individual's sibship and then measure the difference between their own age and this age. For both variables, I transformed all the values to absolute numbers. Because of this, interpreting the results will not be different when analyzing the models for the oldest or youngest siblings. A benefit of these variables is that they offer more concrete interpretation possibilities, since I measure the density in difference in years instead of e.g. proportion that is within an x-year age difference.

Controlling variables should represent factors that impact both the educational outcome and sibship density or solely the educational outcome. As noted in the theoretical framework section, family inputs, school inputs and exogenous factors are seen as the determinants of educational outcomes. The data does not provide possibilities to control school inputs. Family input consists of genetic input and a lot of factors during the nurturing and childhood of a child. I control for genetic inputs using the highest educational level of both parents. Not only does the educational level of parents impact the level of their children, but it might also impact the number of children they have and thus the density. In Germany, as in more developed countries, women with higher educational levels tend to have less children (Westphal & Kamhöfer, 2019; Local, 2023). The RDT also considers financial resources of influence on the educational outcome. Unfortunately, the data does not allow me to create representative variables which describe the financial resources within a household during childhood. However, educational level and income are correlated in Germany (OECD, 2014). It is therefore reasonable to say that educational level partially controls for the income of parents. Furthermore, I add the age of the parents upon birth and the nationality of the parents. The age of the parents upon birth is also likely to be impacting the number of children and thus the density. If parents have children at a later stage in their life, the probability of having a lot of children is likely to be lower. I choose to use the nationality of the parents as a control variable instead of the individual's nationality since most individuals are classified as German in the dataset. This control variable thus moderately represents the migration background of the individual. Lastly, the individual's gender is included as a control variable.

Table 1: Description of the variables

Symbol	**Name**	**Description**
Y	Years of Education	The discrete outcome variable which shows the number of years that an individual has been in school. It has a minimum value of 7 and a maximum value of 18.
γ	Highest Level of Education	The categorical outcome variable which shows the highest level of education completed by an individual. It has the values 0 for ‘no school degree’, 1 for ‘secondary degree’, 2 for intermediate school degree, 3 for ‘technical school degree’ and 4 for ‘upper secondary degree’.
AV	Age to Average	The discrete treatment variable which shows the difference in years to the average age of the sibship.

TOT	Total Age Difference	The discrete treatment variable which shows the difference in years between the siblings.
X_1	Highest Education father	The categorical control variable which shows the highest level of education completed by the father of an individual. It has the same classification as the outcome variable Highest Education.
X_2	Highest Education mother	The categorical control variable which shows the highest level of education completed by the mother of an individual. It has the same classification as the outcome variable Highest Education.
F	Father's age	The discrete control variable which shows the age of the father upon birth of the individual. Has a minimum value of 18 and a maximum value of 64.
M	Mother's age	The discrete control variable which shows the age of the mother upon birth of the individual. Has a minimum value of 18 and a maximum value of 44.
G	Gender	The binary control variable sex, which is (1) for male and (0) for female.
D_1	Father's nationality	The dummy control variables of the father's nationality. The dummy categories are German, Western-European, Eastern European, Middle East, South America and Africa.
D_2	Mother's nationality	The dummy control variables of the mother's nationality. The dummy categories are the same as the father's nationality dummy categories.

5.4 Descriptive statistics

In table two the descriptive statistics of discrete variables are shown. Since children in Germany generally start their education when they are six years old, the average graduation age in my sample is 19 years. The minimal and maximum options in the survey for Years of Education were 7 and 18 years long. I also added the average Years of Education for the oldest and youngest siblings. Here we see that the oldest siblings on average study a little bit longer than the youngest siblings. During the period of my sample, the average age upon birth were almost 30 and 27 for fathers and mothers respectively.

Table 2: Descriptive statistics of discrete variables

Variable	Mean	Standard Dev.	Min	Max	Obs.
Years of Education	13.23	2.82	7	18	1,299
Oldest	13.47	2.87	7	18	673
Youngest	13.13	2.77	7	18	501
Father's age	29.51	5.43	18	64	1,299
Mother's age	26.64	4.73	18	44	1,299

In table three the descriptive statistics of categorical variables are shown. Because the SOEP data has been annually surveyed since 1984 and degrees and levels in an educational system evolve over time, they have chosen to categorize the variable level of education as shown. Since they only provide these categories, it is not possible to link to them to certain degrees in the current educational system. For example, a bachelor's degree and a master's degree both classify as upper secondary school. In table four we can see how many years it has taken the individuals in my sample to complete their educational level. This way, I try to show how the levels of education are connected to the years of education. I will discuss the potential bias of the indistinctness of this variable in the discussion section. From table three we can also see that the number of individuals in technical school are lower than Intermediate School or Upper Secondary School. This is because it represents schooling in a more practical and technical way and falls in between those levels. Lastly, we see that the educational level of the children is on average higher than that of their parents. This is probably since the newer generation are more educated than older ones.

Table 3: Descriptive statistics of categorical variables

	Individual		Father		Mother	
	Freq.	Percentage	Freq.	Percentage	Freq.	Percentage
No school	22	1.62	39	2.87	33	2.43
Secondary school	195	14.34	529	38.90	437	32.13
Intermediate school	422	31.03	415	30.51	594	43.68
Technical School	129	9.49	66	4.85	43	3.16
Upper secondary school	592	43.53	311	22.87	253	18.60
Total	1,299	100	1,299	100	1,299	100

Table 4: Education outcome comparison

Educational Level	Years of Education 7	8	9	10	11	12	13	14	15	16	17	18
No Diploma	o——	————	——o									
Secondary School			o——	————	——o							
Intermediate School				o——	————	————	——o					
Technical School						o——	————	————	————	————	——o	
Upper Secondary School							o——	————	————	————	————	——o

Table five shows the distribution of the children over the two and three children's families. We see that most of the individuals are from two children's families. The table also shows how many oldest and youngest siblings the sample has. We see that the sizes of those groups do not differ largely. These two groups will be used for separate models.

In appendix A, the distribution of the variables Years of Education, Age to Average, Total Age Difference and birth years of the sample are shown. For Years of Education, it is remarkable that there is a high a spike at 18 years. As stated, this was the maximum option in the survey. Everyone who studied 18 years or longer is compiled in this value. Why this could be a problem will be described in the discussion section. The histograms for the Total Age Difference and the

Age to Average do not show surprising distributions. The Total Age Difference shows little outliers. The histogram of the Age to Average might initially seem a little bit unusual at first. Throughout creating this value, it has been divided. Because of this it gives fractional numbers. The distribution itself is similar to the distribution of the Total Age difference.

Table 5: Distribution of the samples

	Two Children Families		Three Children Families		
	1	2	1	2	3
Freq.	526	421	147	125	80
Percentage	55.56	44.44	41.76	35.51	22.73
	Oldest	Youngest			
Freq.	673	501			
Percentage	57.73	42.27			

5.5 Methodology

To test my hypothesis, I perform several analyses. As mentioned before, I use two outcome variables and multiple treatment variables to test my hypothesis. I also use two different types of regressions. Since I check if the results alter after different model choices, these different regressions should simultaneously be seen as different sensitivity and robustness checks. For the models with Years of Education as an outcome variable, I use Ordinary Least Squares (OLS) regressions. Previous literature has not found a specific, for example exponential, relation between the sibship density and the educational outcome. The Years of Education variable is a discrete variable. The differences between 12 and 13 years and 15 and 16 is both one year. Therefore, OLS seems like an appropriate method. For the models with the Level of Education as an outcome variable, I cannot say the same. The difference between no school diploma and a secondary school diploma is not the same difference as the difference between a technical school diploma and a upper secondary school diploma. As a result, I use Ordered Logistic Regression (OLR) as a method for the Level of Education variable. This is possible because the categories are ordered from lower to higher levels of education. However, when using OLR as a method, two assumptions need to be tested. Firstly, we need to test if there is no perfect multicollinearity. In Appendix B table 5 the correlations between the independent variables of the models are shown. The correlation between the age of the parents is the highest, which is quite logical. But with a value of 0.705 it does cross the rule-of-thumb value of 0.8. The education between the education of parents is also notable with a value of 0.584. However, this is also within acceptable limits. The second assumption for the OLR is the proportional odds assumption. According to this assumption, the relation between the independent variable and the ordered outcome variable should be constant and proportional across all categories. In other words, the relation between the sibship density and the level of education should be proportional for all the different education levels. To test this assumption, I performed a likelihood ratio test on different samples that are used for the models. The values of these tests can be found in Appendix B table six. The results of these tests are not significant, which indicates that the assumption is not violated.

To test my hypothesis, I estimate different models. Firstly, I take the whole sample and regress Years of Education and Highest Level of Education on both Total Age Difference and Age to Average of the sibshi. I do this using the next regression formulas:

$$\gamma_i \ = \beta_1 AV_i + \ \beta_2 S_i \ + \beta_3 X_{1i} + \beta_3 X_{2i} + \beta_4 F_i + \beta_5 M_i + \beta_6 G_i + \beta_7 D_{1i} + \beta_8 D_{2i} \ + \varepsilon_i$$

$$\gamma_i \ = \beta_1 TOT_i + \ \beta_2 S_i \ + \beta_3 X_{1i} + \beta_3 X_{2i} + \beta_4 F_i + \beta_5 M_i + \beta_6 G_i + \beta_7 D_{1i} + \beta_8 D_{2i} \ + \varepsilon_i$$

$$Y_i \ = \beta_0 \ + \ \beta_1 AV_i + \ \beta_2 S_i \ + \beta_3 X_{1i} + \beta_3 X_{2i} + \beta_4 F_i + \beta_5 M_i + \beta_6 G_i + \beta_7 D_{1i} + \beta_8 D_{2i} \ + \varepsilon_i$$

$$Y_i \ = \beta_0 \ + \ \beta_1 TOT_i + \ \beta_2 S_i \ + \beta_3 X_{1i} + \beta_3 X_{2i} + \beta_4 F_i + \beta_5 M_i + \beta_6 G_i + \beta_7 D_{1i} + \beta_8 D_{2i} \ + \varepsilon_i$$

The variables shown in the formulas are described in table 1. Since the data I analyze is obtained from one specific moment in time, I perform a cross section analysis. To test hypotheses 2a and 2b, I create two subsamples. The subsamples consist of the oldest sibling and the youngest sibling in the sibships. I do this to test if the relation between the density and educational outcome is different for the oldest and the youngest siblings.

The first hypothesis says that if the sibship density is lower, this is more beneficial for the educational outcomes of children. It is important to remember that the variables show the difference in years and all have absolute values. So, if the density is lower, the difference in years increases. This is why I expect the coefficients to be positive. Hypothesis 2 predicts that the effects of a lower density will be relatively more beneficial for the youngest siblings and relatively less beneficial for the oldest siblings, because of the Confluence Model. This is why I expect the coefficients for the youngest siblings to be more positive than the coefficients for the oldest siblings.

6. Results

6.1 Total sample

In table six the regressions to test the first hypothesis are shown. Surprisingly, all the treatment variables indicate that there is a negative relationship between the difference in years between siblings and educational outcomes. In other words, a higher sibship density is associated with higher educational outcomes. Looking at the models with Years of Education as an outcome variable, we see that all treatment variables have negative and significant coefficients, but that these values turn less negative when controlling variables are added. A one-year increase in the total age difference between siblings is associated with a decrease of 0.021 years of education holding all other variables equal. A one-year increase in the Age to Average is associated with a decrease of 0.30 years of education. These number of years are respectively equivalent to approximately 1 and 1.5 weeks. So, if we compare an individual which has a total age difference of 52 years in his sibship to an individual who has a total age difference of 1, the first individual is expected to have one year less of education, according to the model. Since a Total Age Difference of 52 years is unrealistically big, the magnitude of the association is really small. Although the coefficient of the Age to Average coefficient is 1.5 times bigger, the magnitude of this association is still not substantial. So although the treatment variables have negative values, they are of little magnitude.

If we look at the models with OLR methods and Highest Level of Education as an outcome variable, interpretation of the coefficients is different and more difficult. Normally, the OLR methods gives logistic odds as output coefficients. The coefficients in these models are already transformed from logistic odds to normal proportional odds ratios. When interpreting these coefficients, values under one should be seen as a negative impact, and above one as a positive impact. If the coefficient moves further from one, the magnitude of the association is higher. In terms of my variables, a negative value further from one indicates that the chances of attaining a relatively higher education level are lower. When comparing the coefficients for the methods with the two outcome variables roughly indicate the same results. The concrete interpretation of the Total Age Difference coefficient in the model with control variables is as follows: for an increase of one year in the total age difference, the odds of completing a higher educational level are approximately 0.96 times the odds of being in a lower category. So, I again find a slightly negative relation between Total Age Difference and Highest Level of Education as well. As in the OLS models, the coefficients of the Age to Average variable are more negative. However, the coefficients turn insignificant after adding the control variables. Moreover, the OLR coefficients decrease in magnitude when I add controlling variables, just like in the OLS model.

When looking at the controlling variables, logical coefficients appear. The educational background of the parents are clearly the most important factors when predicting a child's educational outcome. This is not surprising, since intelligence is mainly dependent on genetics and is the most impacting factor for educational outcome (Deary et al, 2007). If parents have higher educational levels, it is also more likely that they will have higher income and place more importance on schooling for example. These factors are also very probable to impact educational outcome positively. The coefficients show that if both parents have finished 'upper secondary schooling' instead of 'secondary schooling', the child's years of education is predicted to be 3.645 years longer, holding all other variables constant. For the ordered logistic model, significant and substantial positive coefficients are found for the educational level of the parents too. Some of the coefficients for the ages of the parents are significant and the values are relatively small. On the contrary, gender does is significant and shows that the men in our sample have higher educational outcomes than women. It is remarkable that for the two different methodologies the significance of the coefficients for the age of the parents differs. Lastly, some of the dummy variables that represent the nationality of the parents were significant and had high values. Individuals whose fathers were from the Middle East had one year less of schooling, on average. Furthermore, we do not see remarkable differences in the coefficients of the Total Age Difference and the Age to Average variables. For the models without control variables, the values of the treatment variables differ somewhat but are all negative or indicate a negative relation (for the OLR regressions). When adding the control variables to the model those differences diminish.

Table 6: Regressions of the total sample

	Years of Education				Highest Level of Education			
Total	-.117***	-.021*			.918***	.964***		
Age	(.039)	(.035)			(.023)	(.017)		
Difference								
Age to			-.170**	-.030**			.871***	.938
Average			(.067)	(.059)			(.038)	(.045)
Father’s		.744***		.750***		1.842***		1.810***
Education		(.079)		(.078)		(.129)		(.121)
Mother’s		.473***		.475***		1.592***		1.634***
Education		(.088)		(.086)		(.109)		(.112)
Agedad		.035*		.036*		1.021		1.020
		(.018)		(.019)		(.016)		(.016)
Agemom		.032		.032		1.048***		1.049***
		(.023)		(.023)		(.018)		(.019)
Sex		.425***		.423***		1.337***		1.357***
		(.137)		(.139)		(.131)		(.151)
Cons	13,754	9,428	13,635	9,405				
(Pseudo)R2	.007	.249	.005	.255	.004	.132	.008	.132
N	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299

Note: standard error in parentheses. * Includes p-value <0.1, ** includes p-value<0.05 and *** includes p-value<0.01

6.1 Youngest and oldest siblings sample

In table seven and eight the regressions for the subsamples with all the youngest and all the oldest siblings are shown. According to the hypothesis we would have expected that a lower density is more beneficial for younger siblings than for older siblings and thus that we expect relatively more positive coefficients for the youngest siblings. For this hypothesis, we find contradictory results as well. For the youngest siblings I have found more negative coefficients instead of more positive ones. The coefficients of the models with the control variables for the whole sample were -.021, -.030, .964 and .938. For the youngest siblings I find the coefficients -.086, -.178, .909 and .798 and they are all significant. The coefficients of models with the Total Age Difference as treatment variable are still not very substantial in terms of magnitude, but the models with Age to Average have taken a substantially larger magnitude. A one-year increase in the Age to Average is associated with a decrease of 0.178 years of education. This. A value of 0.178 years is equal to more than 2 months. So, If we compare an individual whose age to average is a little more than five years to an individual whose age to average is one, the first individual is expected to have one year less of education, according to the model. The proportional odds ratios are also substantially lower than in the sample for all the siblings. This indicates once more again that more age difference between siblings is associated with lower educational outcome for younger siblings.

Looking at the results of the oldest siblings, we see that the coefficients are all closer to zero than in the coefficients for the whole sample. The coefficient in the second model is even slightly positive. The coefficients for models without control variables are significant, but significance disappears when adding the control variables. So, I have not found strong evidence to support a relationship between sibship density and educational outcome for the oldest siblings. It is notable that the coefficients in the regressions for the whole sample fall in between the coefficients for the models with the youngest and oldest siblings. Moreover, it is remarkable that in the models for the youngest siblings the coefficient for the education is of the father have higher value compared to coefficients for the education of the mother, while these coefficients are roughly equal in the model for the oldest siblings. Furthermore, the coefficients for the age of the father have high values for the models of the youngest siblings, while the coefficients for the age of the mother have high values for the models with the oldest siblings. The (pseudo) R^2 values of the models of the different samples do not differ heavily.

Table 7: Total Youngest children

	Years of Education				Highest Level of Education			
Total	-.143**	-.086*			.902***	.909***		
Age	(.037)	(.053)			(.023)	(.028)		
Difference								
Age to			-.237***	-.178**			.821***	.798***
Average			(.090)	(.089)			(.049)	(.058)
Father's		.856***		.848***		1.922***		1.907***
Education		(.134)		(.125)		(.196)		(.191)
Mother's		.229*		.231*		1.370***		1.354***
Education		(.136)		(.138)		(.149)		(.147)
Agedad		.071**		.069**		1.059**		1.051**
		(.032)		(.030)		(.023)		(.028)
Agemom		.016		.018		1.037		1.038
		(.038)		(.039)		(.031)		(.031)
Sex		.501**		.513**		1.266		1.291
		(.030)		(.219)		(.222)		(.225)
Cons	13.689	6.614	13.618	6.999				
(Pseudo)R2	.009	.251	.013	.255	.004	.120	.008	.121
N	501	501	501	501	501	501	501	501

Note: standard error in parentheses. * Includes p-value <0.1, ** includes p-value<0.05 and *** includes p-value<0.01

Table 8: Total Oldest children

	Years of Education				Highest Level of Education			
Total	-.071**	.033			.944***	.972		
Age	(.056)	(.049)			(.017)	(.020)		
Difference								
Age to			-.184***	-.031			.867***	.961
Average			(.071)	(.064)			(.042)	(.052)
Father's		.594***		.593***		1.797***		1.742***
Education		(.107)		(.103)		(.151)		(.144)
Edumom		.622***		.614***		1.811***		1.804***
		(.119)		(.116)		(.173)		(.173)
Agedad		.035		.035		1.017		1.016
		(.028)		(.027)		(.022)		(.020)
Agemom		.059*		.059*		1.090***		1.088***
		(.034)		(.033)		(.029)		(.028)
Sex		.488**		.468**		1.638***		1.621***
		(.198)		(.194)		(.256)		(.261)
Cons	13.754	8.155	13.853	7.912				
(Pseudo)R2	.003	.246	.008	.252	.003	.148	.005	.152
N	673	673	673	673	673	673	673	673

Note: standard error in parentheses. * Includes p-value <0.1, ** includes p-value<0.05 and *** includes p-value<0.01

6.3 Robustness analysis

As stated, the models above should already be seen robustness checks, but I do provide additional robustness analysis in this section. In appendix C the regressions are shown. I divided the sample into the two and three children's families to see if either one of them heavily caused the found coefficients by having values of high magnitude. But, as seen in the appendix, those regressions have roughly the same output as the models shown above. In the three-children's families, I also included the middle sibling to see if interesting values would emerge. For these siblings, The Total Age Difference can be interpreted in the same way as above. This is because I first took the absolute value from the age difference between these individuals and their youngest sibling, and then added this value to the age difference with the oldest siblings. After this, I also divided them by two. However, the Age to Average cannot be interpreted in the same way since the middle sibling will always have a relatively low age difference to the average age of the sibship.

7. Discussion & Conclusion

7.1 Limitations & Discussion

This study is exposed to several limitations. First, it is very hard to estimate an unbiased estimator. There are a lot of variables which eventually influence the educational outcomes of an individual. Therefore, my models are suffering to omitted variable bias. As stated, the education production function exists out of family inputs, school inputs and exogenous inputs. With the used dataset, it was impossible to control for any school inputs. Moreover, I did not have access to micro-level data about childhood. For example, variables about actual time spent with children in early childhood, financial resources or if parents helped children with homework would have been useful and relevant. Data about such variables would have led to different estimators since they are also impacting educational outcomes. The sample size also limits this paper to study the difference between two-, three-, four- and five-children's families. It would have been interesting to research if the effect of sibship density on educational outcome is different per size of sibship.

Moreover, the available outcome variables create exposure to possible bias. They only show the years of education in total and a few general levels of education which are not very specific. The Years of Education do not show if an individual did a certain class two times and studied longer, or followed a different educational path which took longer than average to attain a certain degree. The Highest Level of Education only shows a couple of educational levels without any specifics. The survey did not clarify to what extent one level is higher than another and did not connect the options to the stages of the German Education system. Furthermore, it does not make distinctions within those levels. For example, it is not shown if an individual only attained a bachelor's degree or master’s degree. If more specific information about educational outcomes would have been available, this could have led to more precise results and conclusions.

7.2 Conclusion, further research and policy implications

I study the effects of the sibship density on both the years of education and highest level of education completed by individuals. For this I use a cross-sectional analysis in which I perform several Ordinary Least Squares (OLS) regressions and Ordered Logistic Regressions (OLR). Surprisingly, I find a positive association between the sibship density and educational outcome. Although the coefficients are relatively small and they are not all significant, they do consistently indicate a positive relation between the sibship density and the educational outcomes. Since most theories and studies show a negative relationship between the sibship density and educational outcomes, these findings were surprising. They do offer interesting options for further research. Since most studies were performed in the US and used older data, the German higher educational system, which is very different to the American one, or the time setting of this study could have caused the results to be different. Therefore, it would be interesting to study this relationship in other European countries and with a richer dataset. If found that with more social educational systems, lower sibship density negatively affects educational outcome, more attention could be given to those children within schools. Besides this, research into the effects and mechanism behind intellectual spillover effects within sibships and how they are different for different sibship densities could be relevant, but more specific data is necessary for this. If more age difference would negatively impact educational outcomes, like in this paper, and this is caused by the lack of spillover effects, this should be made known to families and schools in order to provide equal chances to those children. Finally, the relations and consequences of different family compositions remains an interesting and complicated subject, while it is often crucial to a child’s development

8. References

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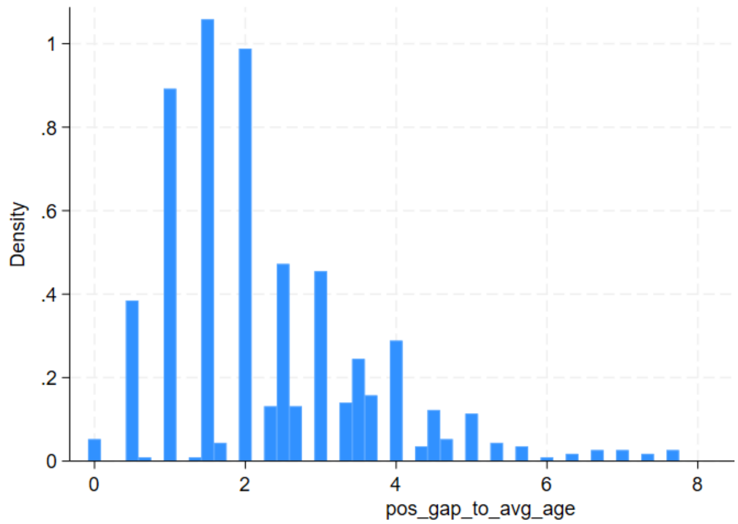
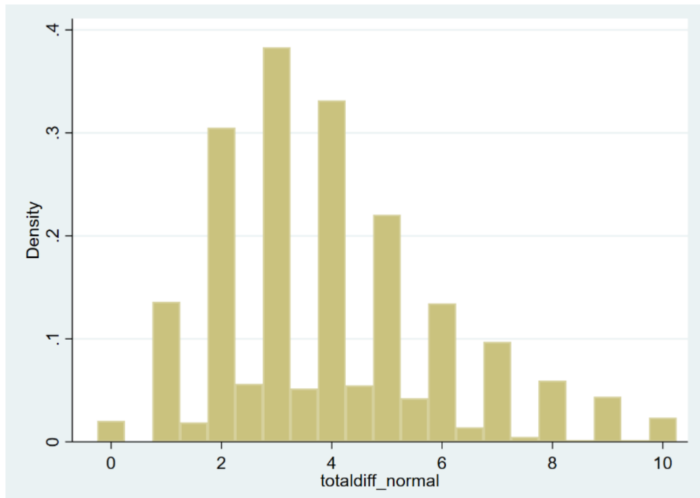
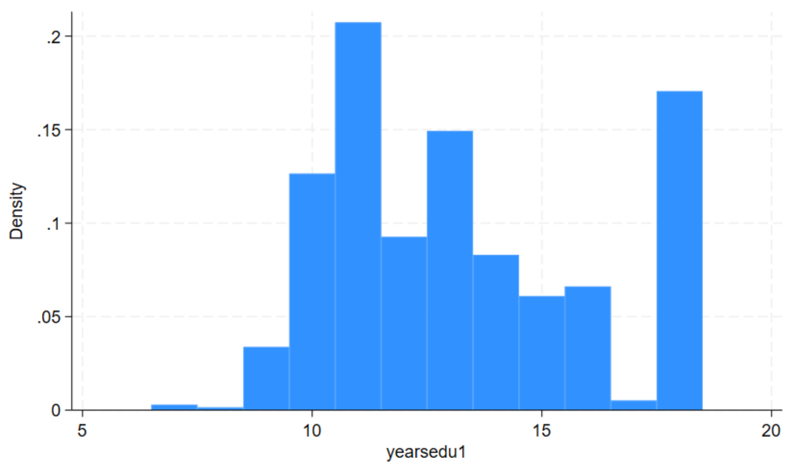
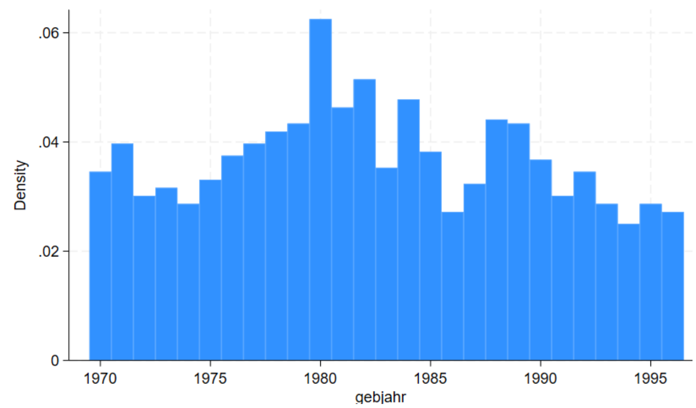
9. Appendix

Appendix A: Distribution of variables









Appendix B: Tests for Order Logistic Regressions

Table 9: correlation of independent variables

	Gap to Average	Total Space	Father's Education	Mother's Education	Father's Age	Mother's Age	Sex
Gap to Average	1.000						
Total Space	.776	1.000					
Father's Education	-.106	-.071	1.000				
Mothers's Education	-.136	-.105	.583	1.000			
Father's age	-.029	.006	.014	.094	1.000		
Mother's age	.045	.052	.180	.159	.709	1.000	
Sex	-.005	.029	.033	.023	-.032	-.029	1.000

Table 10: Likelihood ratio test

	Total	Oldest	Youngest
Chi2	2.59	4.34	1.22
Prob > Chi2	.459	.227	.748

Appendix C: Additional robustness analysis

Table 11: 2-children's families

	Oldest				Youngest			
	Years of Edu		Level of Edu		Years of Edu		Level of Edu	
Total Age Difference	-0.042	-.050	.968	.985	-.116*	-.057	.921*	.956
	(.061)	(.053)	(.015)	(.018)	(.061)	(.059)		
Father's Education		.603***		1.695***		.800***		1.879***
		(.121)		(.165)		(.138)		(.182)
Mother's Education		.585***		1.782***		.273*		1.243***
		(.140)		(.182)		(.154)		(.156)
Agedad		.026		1.012		.073**		1.025**
		(.030)		(.017)		(.032)		(.023)
Agemom		.045		1.059*		.020		1.033
		(.038)		(.022)		(.044)		(.027)
Sex		.498**		1.643***		.569**		1.483
		(.224)		(.281)		(.246)		(.249)
Cons	13.763	9.464			13.582	6.372		
(Pseudo)R2	.001	.206	.002	.141	.009	.228	.008	.119
N	526	526	526	526	421	421	421	421

Table 12: 3-children's families

	Old				Middle				Young			
	Years	Years	Level	Level	Years	Years	Level	Level	Years	Years	Level	Level
Total Age	-.123*	-.035	.915**	1.063	-.216***	-.129**	.891**	.932	-.121	-.092	.934	.945
Difference	(.065)	(.058)	(.037)	(.055)	(.062)	(.061)	(.043)	(.052)	(.078)	(.079)	(.049)	(.061)
Father's		.575***		1.403**		.928***		1.578**		1.199**		2.094***
Education		(.219)		(.252)		(.254)		(.318)		(.360)		(.586)
Mother's		.719***		1.937***		.263		1.550**		-.018		1.117
Education		(.071)		(.396)		(.237)		(.333)		(.400)		(.308)
Father's		.111		1.098		.094		1.085		-.079		0.925
Age		(.712)		(.066)		(.061)		(.055)		(.093)		(.071)
Mother's		.118		1.220***		.010		1.101		.091		1.142
Age		(.088)		(.093)		(.077)		(.067)		(.112)		(.101)
Sex		.376		1.450		-.188		1.216		.434		.662
		(.426)		(.530)		(.438)		(.454)		(.537)		(.317)
Cons	13.582	8.744			14.574	10.096			14.093	7.628		
(Pseudo)R2	.009	.466	.013	.318	0.062	.468	.014	.201	.028	.443	.008	.162
N	147	147	147	147	125	125	125	125	80	80	80	80