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# Educational Consequences of a Sibling's Disability: Evidence from type 1 diabetes

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While there is a growing literature on family health spillovers, questions remain about how sibling disability status impacts educational outcomes. As disability is not randomly assigned this is an empirical challenge. In this paper we use Danish administrative data and variation in the onset of type 1 diabetes to compare education outcomes of focal children with a disabled sibling to outcomes of focal children without a disabled sibling (matched on date of birth of the focal child, sibling spacing and family size). We find that having a disabled sibling significantly decreases 9th grade exit exam GPAs, while having no impact on on-time completion of 9th grade. However, educational trajectories are impacted, as we find significant decreases in high school enrollment and significant increases in vocational school enrollment by age 18. Our results indicate that sibling disability status can generate economically meaningful inequality in educational outcomes.

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# Educational Consequences of a Sibling's Disability: Evidence from type 1 diabetes[1]

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**Abstract**

While there is a growing literature on family health spillovers, questions remain about how sibling disability status impacts educational outcomes. As disability is not randomly assigned this is an empirical challenge. In this paper we use Danish administrative data and variation in the onset of type 1 diabetes to compare education outcomes of focal children with a disabled sibling to outcomes of focal children without a disabled sibling (matched on date of birth of the focal child, sibling spacing and family size). We find that having a disabled sibling significantly decreases 9th grade exit exam GPAs, while having no impact on on-time completion of 9th grade. However, educational trajectories are impacted, as we find significant decreases in high school enrollment and significant increases in vocational school enrollment by age 18. Our results indicate that sibling disability status can generate economically meaningful inequality in educational outcomes.

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## 1. Introduction

When someone experiences a health shock, his or her family is also impacted. For example, Fadlon and Nielsen (2019) find health spillovers onto spouses and children while Fadlon and Nielsen (2021) find spousal labor supply spillovers. Also, child health impacts parental labor supply and mental health (for some recent examples, see Eriksen, Gaulke, Skipper and Svensson, 2021, Steingrimsdottir and Gunnsteinsson, 2019, Breivik and Costa-Ramón, 2022, and Adhvaryu, Daysal, Gunnsteinsson, Molina, and Steingrimsdottir, 2022).

There is a growing literature measuring sibling educational spillovers in the context of a health or disability shock, but those papers have largely focused on sibling spillovers in only one direction (older to younger only or younger to older only). For example, the empirical strategy in Daysal, Ding, Rossin-Slater, and Schwandt (2021) only allows them to document negative impacts of infectious disease on younger siblings while the empirical strategy in Black, Breining, Figlio, Guryan, Karbownik, Nielsen, Roth, and Simonsen (2021) means they can only document spillovers from the third born child onto older siblings. Breining (2014) only looks at spillovers from ADHD onto older siblings.[7] One key exception that includes both older and younger siblings in the analysis is Daysal, Simonsen, Trandafir, and Breining (2020) which finds that early life medical interventions for children with low birthweight led to positive educational spillovers. However, differences in effects by birth order are not focused on in that paper.

This paper adds to the literature on whether educational outcomes are impacted by sibling disability status by using type 1 diabetes (T1D) as a disability shock, which allows us to test for differences in impacts by birth order and age at sibling's diagnosis. This source of variation

[7] The education literature more generally has also focused on only one direction of spillovers. For example, Nicoletti and Rabe (2018), Qureshi (2018), Joensen and Nielsen (2018), Hyunkuk (2021), and Karbownik and Özek (2021) all focus solely on education spillovers in general from older to younger siblings while Landersø, Nielsen, and Simonsen (2020) solely focuses on education spillovers in general from younger to older siblings.

follows Eriksen et al. (2021), which uses variation in T1D onset to estimate spillovers onto parental labor supply and parental mental health, and Lóven (2017), which uses variation in T1D onset to estimate sibling spillovers in labor market outcomes in Sweden. Lovén (2017) only tests whether the labor market estimates are robust to controls for education and thus does not test for educational spillovers directly. This matters because she concludes that educational spillovers are not important, while we find evidence of economically meaningful educational spillovers.

T1D is an ideal candidate for a disability shock for numerous reasons. First, T1D is an auto-immune disease in which the insulin producing beta cells in the pancreas are destroyed. This causes a substantial limitation to the endocrine system because the body cannot convert glucose to energy. It is impossible to survive without treatment if one has T1D (Hakim et al., 2010), meaning our control group will not include children with siblings who have undiagnosed T1D. Even with treatment, glucose levels are not as stable and are elevated compared with those without T1D, and this can lead to numerous other health problems which we discuss in more detail in the background section. Also, unlike the more common Type 2 Diabetes, it is not related to lifestyle; in fact, it is of unknown origin (Regnell and Lernmark, 2017). Research has tried to pinpoint the cause but has found a low degree of inheritability (Pociot and Lernmark, 2016), and no socio-economic gradient in diagnosis in Denmark (Prætorius, Urhoj, and Andersen, 2022). As the main threat to identification is that the unknown cause of T1D is related to educational outcomes (i.e., these children would perform worse even in the absence of sibling's diagnosis), the lack of a relationship between disease onset and both parent's income and education level is important.

Using full population administrative registry data from Denmark, we can identify siblings. Through administrative medical data we know whether each child was diagnosed with

T1D and through administrative education data we have access to educational outcomes and enrollment. Each child with an impacted sibling is matched with non-treated children based on their year of birth, sibling spacing, and family size. We rely on the quasi-randomness of T1D as a disability shock to estimate effects.

Our first contribution is that we estimate a different, but complementary, treatment effect than that estimated in Black et al. (2020). As Black et al. (2020) state, they estimate an effect of relative exposure to a disabled sibling and not the total exposure to a disabled sibling. This is because the effects are based on the relative effects on first-born versus second-born children and thus difference out the common effect impacting both first-born and second-born children. Using T1D allows us to estimate the effect of total exposure to a disabled sibling. Black et al. (2020) find that the relative exposure is a decline of 3.4% of a standard deviation on the 9th grade Exit Exam while we find that the total exposure is a decline of 3.8% of a standard deviation on the $9^{th}$ grade Exit Exam (with all controls included). Focusing on a specific, but relatively common health shock, has benefits since parental responses could vary by whether the disability impacts relative returns on investment (substitution effect of parental time investments across children) or how time intensive the treatment is (income effect on parental time investments in children); thus, averaging effects may mask economically important impacts on some siblings.

While both papers estimate impacts on $9^{th}$ grade Exit Exams, we contribute to the literature by documenting significant impacts on educational trajectories as well. Despite not finding a significant difference in the probability of enrolling in post-compulsory school education, when we instead focus on the intensive margin we find a significant 3.1 percentage point (pp) decrease in the probability of enrolling in high school compared with vocational school. This matters because attending academic high school is required if one wants to attend college, and thus labor market opportunities are likely impacted as well.

Since there is variation in age at sibling's diagnosis, we can investigate whether this is a source of heterogeneity. This is important because Black et al. (2020) compare effects on 9th grade exit exams when the sibling's disability occurs before age five and between age five and age ten to find larger effects if the disability is diagnosed earlier. They posit multiple hypotheses as to why this may be the case, including that having a disabled sibling is more detrimental at earlier ages given the literature on the importance of early childhood environments (for example, see Cuhna and Heckman, 2007). Therefore, we contribute to the literature by documenting that there appears to be periods in a child's life where investments matter more than others. Specifically, we observe 7.7% of a standard deviation decrease in Danish scores for the children aged 6-9 years of age at sibling's diagnosis, which is the age at which children enter school and acquire their basic reading skills.

Another statistical benefit to using T1D as our shock is that it allows us to test for differences in effects by birth order. Birth order could potentially be important because several papers show that birth order matters for a range of child outcomes. For example, children of higher birth order have better health endowments at birth, are more likely to be delinquent and involved with the criminal justice system, and have worse test scores and behavioral development (Pruckner, Schneeweis, Schober and Zweimüller, 2021, Breining, Doyle, Figlio, Karbownik, and Roth, 2020, and Silles, 2010). Also, according to Cunha and Heckman (2007) the returns to child investments will be larger the earlier the investment. Consistent with our hypothesis of larger penalties for younger siblings, we find no significantly negative impacts among children who are older siblings.

The rest of the paper is organized as follows. Section 2 provides background information on T1D and the Danish setting of this study. Section 3 describes the Danish administrative registry data, the matching of treated and non-treated focal children, and the matched regression used to estimate the effects. Section 4 discusses the impact of having a sibling diagnosed with T1D on our education outcomes of interest, a falsification test that uses focal children too old to be impacted by sibling's onset, and heterogeneous treatment effects. Section 5 discusses impacts on numerous measures of school well-being. Section 6 summarizes and discusses implications of finding significant spillover effects.

## 2. Background

### 2.1 Background on T1D

The International Diabetes Federation (2021) Diabetes Atlas reports that globally there are 1,211,900 existing T1D cases among children under 19 and the number of new cases among this age group is 149,500 annually. T1D is an auto-immune disease in which the insulin-producing beta cells in the pancreas are destroyed. These beta cells are needed to maintain a stable blood glucose level (often referred to as blood sugar) and allow the body to transform food into energy. After disease onset, the individual needs to administer insulin (through a syringe or insulin pump) for the rest of his or her life as there is no cure. T1D is not congenital, and the sudden and rapid onset can occur throughout childhood. Childhood onset T1D can also lead to numerous complications including retinopathy leading to blindness, nephropathy leading to kidney failure, cardiovascular disease, an increased risk of psychiatric disorders such as anxiety, depression and eating disorders, and four times increased mortality and substantial loss of life expectancy (Rawshani, et al., 2018, Dybdal et al., 2017, White, Sun, and Cleary, 2010, Cameron, Northam, and Ryan, 2019, Sandahl et al., 2016, and Writing Group for the DCCT/EDIC Research Group, 2015).

The main identifying assumption of our paper is that T1D is an unforeseeable disability shock of which the unknown origin is not related to anything that would independently impact educational outcomes. First, if there was a high degree of inheritability than perhaps these children perform worse not because of their siblings but rather because their parents or they themselves are in worse health. There is only a 2-3 percent risk of T1D in children of mothers with T1D and there is only a five percent risk in children of fathers with T1D (Pociot and Lernmark, 2016). In comparison, Starck, Grünwald, and Schlarb (2016) show that among children with ADHD, 41 percent of mothers and 51 percent of fathers also have ADHD. Also, T1D onset can occur in children who have no immediate family member with T1D.

If onset is related to socio-economic status, then these children may perform worse because parental socio-economic status impacts educational outcomes directly, and not because of the sibling's shock. Prætorius, Urhoj and Andersen (2022) specifically test for evidence of this using full population data from Denmark and find that maternal and paternal income and education levels are not effective predictors of T1D onset in children and young adults. Consistent with the lack of socio-economic gradient in onset, Eriksen et al. (2021) find the income levels and trends were not significantly different for treatment and control mothers and fathers prior to disease onset.

It would be a concern if these siblings had different underlying health such that parental resources would have needed to be reallocated to health management even in the absence of T1D onset. Eriksen et al. (2021) find that children who are later diagnosed with T1D have similar APGAR scores as children who will not be diagnosed, and they are not more likely to have low birthweight. Eriksen et al. (2023) use event studies and monthly health data to test for differences in underlying health from two-years prior to T1D onset to two-years after onset. They find no significant impacts prior to onset on the probability of a hosptial admission, the probability of a visit to the general practitioner or the probability of a pharmacy claim.

Thingholm, Gaulke, Eriksen, Svensson, and Skipper (2020) study school absenteeism among Danish children who were diagnosed with T1D from 2010 to 2017 compared with sex and age matched controls that did not develop T1D (see Figure 1 for a reproduction of the results). The figure is informative about three important points regarding the nature of T1D: 1) That school absenteeism was similar 12 to 5 months prior to the clinical diagnosis further suggests that the condition is not tied to underlying health or health conditions. 2) The onset is sudden. Symptoms (severe enough to affect school absenteeism) are only present from around 4 months prior to diagnosis. 3) The children who are affected by T1D have more absenteeism after the onset (roughly 50% more than the non-treated children). This highlights that something is now different in these families and that parental resources are plausibly steered towards the affected child. Taken together, this evidence supports the use of T1D as a quasi-random shock.

### 2.2 Theoretical Predictions

A disability shock such as T1D could result in sibling spillovers through changes in both time and monetary investments by parents. Becker and Tomes (1976) discuss how parents may act in a compensatory way to even out inequalities between siblings or how parents may act to exacerbate inequality among siblings. It is theoretically unclear whether there should be a positive, negative, or null causal impact of having a disabled sibling.

While much of the empirical research suggests a compensatory approach (for example, see Loughran, Datar, and Kilburn, 2008), there is also heterogeneity in parental responses. For example, Hsin (2012) studies low birthweight children and finds that mothers with more education tend to compensate while the mothers with the lowest education levels behave in ways that exacerbate the differences. Figlio, Guryan, Karbownik, and Roth (2014) find larger impacts of being low birthweight for those living in zip codes with higher median income. Bernardi (2014) finds more educated mothers are able to mitigate the negative impacts of being young for one's grade in school through the use of a regression discontinuity design.

In terms of adjustments to time investments, medical professionals state that children cannot be expected to oversee their own diabetes management, so parents are expected to provide support (Silverstein et al., 2005 and Solowiejczyk, 2004). Specifically, Soloweijczyk (2004) explains that T1D requires a large amount of disease management from those diagnosed and their families. Silverstein et al. (2005) state, "Young children, including school-aged children, are unable to provide their own diabetes care, and middle school and high school students should not be expected to independently provide all of their own diabetes management care." Some examples of how parents help their children include planning healthy meals, counting carbohydrates, measuring and administering insulin, monitoring blood glucose (also at night), scheduling and providing transportation to medical appointments, picking up or ordering medicine, and assisting in case of severe hypoglycemia (low blood sugar) or hyperglycemia (high blood sugar). Additionally, given that parents can be reported for child abuse if their child's T1D is not well managed, there are limits to how much parents can cut back on disease management without being reported to local governments.

In terms of financial impacts in the Danish context, parents of children who are diagnosed with T1D are offered 4-8 weeks leave paid by the government, so they can settle and get used to the new treatment regimen. However, recent research suggests that the need for the family to steer parental resources towards the affected child perpetuates long after onset. Eriksen et al. (2021) finds that mothers are more likely to shift from full-time to part-time work and that this reduces wage income by 4-5 percent for at least ten years after the diagnosis, on average. However, fathers adjust so that there is no significant overall impact on family income if one conditions on the parents living together in the year prior to diagnosis.

Additionally, Denmark has universal health care paid for by taxes. As a result, in-patient and out-patient hospital care have no copayment. The cost of medical equipment employed for T1D management is free of charge. Insulin is not free; however, the mean and median 2016 out of pocket cost was only $239 and $229, respectively. Low-income families can request a waiver of these costs.

Taken together, this suggests that T1D should have little impact on overall financial resources, meaning that our estimates are likely driven by time constraints and not financial constraints in a Becker-Tomes type model. Our results are likely smaller in magnitude than cases where disability also negatively impacts financial resources, which would arguably be even more detrimental to siblings. As T1D does not directly affect the cognitive functioning of the affected child, we do not expect parents to change the composition of their investments in the human capital of their children due to differential marginal returns. However, the total amount of parental time available for investing in the human capital of their children is arguably reduced due to caregiving responsibilities related to T1D and impacts on parental mental health documented in Eriksen et al. (2021).

Parental time has been suggested as the key determinant in the healthy development of a child (Monna and Gauthier, 2008). The literature suggests that parental socio-economic status, such as education, matters for both the level and quality of time spent with their children and that less educated mothers struggle more with work-parenting balance (for example, see Zick and Bryant, 1996, Bianchi, Cohen, and Raley, 2004, Sayer, Gauthier, and Furstenberg, 2004, Guryan, Hurst, and Kearney, 2008, Hsin and Felfe, 2014, and Thomsen, 2015). Thus, we expect penalties to differ by maternal education and wage income. While higher wages may allow mothers to invest more in their children, employment may be an important parameter, as it will tend to leave mothers less flexible. Eriksen et al. (2021) show that mothers tend to shift to part-time work when their child is diagnosed with diabetes, likely because disease management requires parents to be alert throughout the day and night.

The quantity-quality model (Becker, 1960) suggests that children's human capital formation is a decreasing function of family size as parents will have less time to invest per child. When a sibling has T1D, the time spent with the focal child is likely reduced. If we expect that time investment in the child with T1D is independent of family size, then the relative time forgone from the focal child will be smaller the larger the family size. To investigate heterogeneity by family size, we construct a dummy variable equal to one if the child has more than one sibling. Along the same line of reasoning, we also investigate heterogeneity in whether the child lives with a single parent or in a family with two parents (may be either biological parents, or parents where either the mother or father is cohabitating with a new partner) as we hypothesize that single parents have less time to invest in their children and thus those children may be even more impacted by a sibling's diagnosis.

We hypothesize that impacts may vary by the sex of the child because Baker (2021) finds differences in parental investments immediately after birth depending on whether the child is a girl or boy. Also, Baker and Milligan (2016) find differences in investments in preschool children by sex such that investments in teaching activities favor girls. Similarly, one can imagine that a child's reaction to the reduction in time spent with their parents may differ depending on the sex of the child.

We also hypothesize that characteristics of the sibling pair matter for spillovers. Given the related literature on birth order effects and the importance of early childhood environments, we hypothesize that the cost of forgone time will be higher among younger siblings than older siblings. We also expect spillovers to be larger in magnitude between closely spaced siblings because they may interact with each other to a larger degree than siblings of very different ages, and the type of attention they require from their parents may be very similar, making it more obvious if the parents are redirecting attention away from one child to the other. Bharadwaj, Eberhard, and Neilson (2018) find a compensatory approach is used in Chile when the health shock is low birthweight, except in the case of twins. This suggests that parents respond differently by sibling spacing.

Cuhna and Heckman (2007) note the effect of an investment in children may differ substantially depending on the timing of the investment. They argue that due to dynamic complementarities, childhood investments are more beneficial during early childhood. The magnitude of sibling spillovers may therefore be very different depending on the child's age when the shock occurs. We contribute to the literature by investigating whether the magnitude of the sibling spillover depends on the age at sibling's diagnosis.

To assess the potential impact from having a sibling diagnosed with T1D, we investigate outcomes related to completion of compulsory school. Specifically, we look at the 9$^{th}$ grade exit exam GPA, whether one passes the exam, on-time completion of 9$^{th}$ grade, and enrollment in high school or vocational school by age 18.

## 3 Data & Methodology

We merge several administrative registers to construct our analysis data. From the population register we identify all singletons born in Denmark from 1988 to 2002, and their immediate family members. Thus, we have data on siblings, mothers, and fathers. In Denmark, the 9th grade Exit Exam marks the end of compulsory schooling. Since children are to enter school the year they turn six, they will typically take the Exit Exam the year they turn 16. Thus, to ensure that the children had time to finish compulsory schooling we limit the sample to children born in 2002 or earlier.

We know which children are diagnosed with T1D through the clinical register DanDiabKids (see Svensson et al., 2016). This register contains information on the exact date of diagnosis and type of diabetes diagnosis for all Danish children and adolescents seen at pediatric endocrinology clinics throughout Denmark.[8] Since we can only observe records for health care received in Denmark and Colding, Husted, and Hummelgaard (2009) document large differences in the educational progress of native Danes versus immigrant children, we restrict our sample to native Danes. We further delete all focal children diagnosed with T1D as this in itself impacts 9th grade Exit Exam performance and completion of compulsory schooling (Lindkvist et al., 2021). We then drop individuals from families where the focal child has more than one sibling diagnosed with T1D, which amounts to only 0.61 percent of the sample.

For each remaining sibling pair, we calculate the completed family size and sibling spacing (years between their births). Our sample of treated focal children are those who have one sibling diagnosed with T1D before the focal child turns 16 – the typical age of finishing 9th grade. As a comparison group is essential, we match (without replacement) each member of our treatment group to five individuals among the remaining sibling pairs where no child in the

[8] Generally, this means children ages 0-18 years, although some children may transfer to adult clinics at age 16.

family is diagnosed with T1D. To ensure that differences in outcomes are not driven by differences in birth year, sibling spacing, or completed family size, we match on these three characteristics. Matching on birth year ensures that the focal children should be taking the exact same national 9th grade Exit Exam and thus helps rule out differences being driven by differences in national exams across years. As sibling spacing likely impacts the amount of interaction siblings have, even in the absence of one having T1D, we match on sibling spacing to make sure we are comparing more similar sibling pairs.

The reason for matching on family size is twofold. First, families with more children are more likely to have a child who is diagnosed with T1D. This is not due to family size causing T1D, but rather since if you have more draws from a distribution then you are more likely to get at least one draw of T1D. Second, if we only match on sibling spacing, then differences could be due to variation in parental resources by family size (i.e., parents may face a quality-quantity tradeoff). Sibling spillovers related to educational outcomes would likely vary across family size, regardless of whether one sibling is diagnosed with T1D or not.

We can match 3,068 children out of 3,070 children who have a sibling with T1D. For each non-treated focal child, we then assign a pseudo year of onset to his/her sibling that is equivalent to the date of onset for the treated focal child's sibling. This ensures the pseudo year of onset also occurs before the exit exam. Finally, as siblings with very large gaps in spacing likely interact much less with each other (and thus not impact each other) we restrict the sample to siblings where the focal child is five or less years older or five or less years younger than the sibling with T1D. It is important to note that we are not conditioning the sample on having taken either the Danish language or Math 9th grade exit exam, because that in and of itself could be impacted by the sibling's diagnosis. Thus, our sample size is slightly smaller for those outcomes.

The remaining sample thus consists of 13,752 children, out of which 16.67 percent have a sibling diagnosed with T1D.

*Outcomes*

We construct our educational outcomes from the registry on elementary school grades (UDFK, Statistics Denmark). The registry contains the grades of all students taking at least one of the exams in the 9th grade Exit Exam. We measure student *GPA* as the average grade in the mandatory Danish language exams (oral and written), and the mandatory mathematics exam (written).[9] We standardize the GPA within each year. The outcome *passed* is an indicator variable equal to one if the student maintained a GPA (in Danish and mathematics) greater than or equal to 2, the cutoff for passing. The outcome *on-time graduation* is an indicator for whether 9th grade was completed by age 16. To measure enrollment into further education past elementary school (in Denmark there are two options: high school or vocational school) we rely on the education registry (UDDA, Statistics Denmark). The indicator variable *further education* is equal to one if the child is, at any time, enrolled into high school or vocational school before the age of 18. The variable *high school* investigates the type of enrollment for those who enroll. It is equal to one if the first education enrolled into post elementary school and before the age of 18 was high school and equal to zero if the child instead enrolled into vocational school.

[9] Since 2007 the mandatory part of the 9th-grade exit exam comprises of five pre-determined exams (two oral exams in Danish and English, and either joint physics/chemistry or biology and geography and two written exams are in Danish and mathematics) and two exams drawn from the pool of the remaining obligatory courses. Since 2007 the ministry has evaluated different versions of the joint physics/chemistry or biology and geography exam. In 2015 the Danish government further introduced an entry requirement for vocational educations of at least obtaining a grade of 2 (equivalent to an E) in mathematics and Danish. We therefore decide to focus on the two core qualifications, Danish and Mathematics in our GPA measure. Before 2007 the exams where not mandatory but there appears to be no shift in the number of pupils sitting the Danish and Mathematics exams.

*Additional characteristics*

We merge a wide range of characteristics to our matched sample of children using registry data from Statistics Denmark. In addition to the matching characteristics, we also observe the child's sex, information pertaining to the birth of the child e.g., birthweight and whether their biological parents are living together. For the mothers we observe their age at birth of the child, wage income, whether they are employed (wage income > 0) and their highest completed education. We separate education into no qualifying education, short qualifying education (includes vocational training and academies of professional higher education) and long qualifying education (bachelor's degree and any type of graduate degree). We observe the same characteristics for fathers, unless there is no registered father. During this time, it was not required to list the father and thus there are some fathers who are not recorded. Also, if the child was born through a sperm donation, then the father would be anonymous. All characteristics are measured the year before the child is born except age at the birth of the child.

*Summary statistics*

Table 1 shows the summary statistics of the sample separated by whether the child has a sibling with T1D or not. When we compare the characteristics across the two groups, they appear very similar. About ten percent of the children live with a single parent the year they turn five and less than one percent of the children do not have a registered father. Information regarding the birth of the child is similar across treated and control children.

We next conduct a balance test by running a regression to determine what variables predict whether the sibling will be diagnosed with T1D. Results are shown in Table 2. Only the coefficient on maternal employment at birth is significant at a 5-percent level. The joint F-test suggests that there are no differences between the treatment and control groups, overall.

*Matched Regression*

We use the following regression to estimate the sibling spillovers in education from a disability shock

$$\boldsymbol{y_{im} = \alpha_o + \alpha_1 * Diabetes + \beta X_{im} + \tau_n + \gamma_c + \delta_o + \rho_s + \varepsilon_{imcos}}$$

Where $\boldsymbol{y_{im}}$ is either the standardized 9th grade exit exam GPA (Math, Danish or both) for individual *i* with mother *m*, a dummy variable for passing the 9th grade exit exam, a dummy variable for on-time completion of 9th grade, a dummy variable for any enrollment by age 18 or a dummy variable for whether the enrollment was into high school or vocational school by age 18. Diabetes is a dummy variable set equal to one if the focal child's sibling was diagnosed with T1D before the focal child was 16 years old. $\boldsymbol{\tau_n}$ are family size fixed effects, $\boldsymbol{\gamma_c}$ are birth cohort fixed effects, $\boldsymbol{\delta_o}$ are birth order fixed effects, and $\boldsymbol{\rho_s}$ are sibling spacing fixed effects. To increase our precision, $\boldsymbol{X_{im}}$ is a vector of characteristics we include in the adjusted regressions such as child sex, whether the parents live together when the child is 5 years old, maternal and paternal age at birth, and maternal and paternal wage income and education measured the year before the child's birth. We also test how robust our results are to including group fixed effects (where a group is the treated child and the matched untreated children). We cluster our standard errors at the matched group level to be consistent with the recommendation in Abadie and Spiess (2022).

# 4 Results

## 4.1 Main Results

Table 3 reports the impact of having a sibling with T1D on 9th grade exit exam performance (Panel A) and enrollment into further education by age 18 (Panel B). For each outcome we present the results with and without adjustment for covariates (other than our matching variables). While the point estimates decrease slightly as covariates are added, the results are quite robust. As we are not conditioning on having taken either subject's exam, note the sample size is slightly smaller for the Danish Exit Exam GPA, Math Exit Exam GPA, and passing the Exit Exam.

To allow for a clearer comparison with the related literature, we first test for impacts on the aggregated subjects. Black et al. (2020) find the relative effect of having a disabled sibling is a decline of 3.4% of a standard deviation on the 9th grade Exit Exam, and we find the total exposure to a disabled sibling leads to a decline of 3.8% of a standard deviation (with all covariates). The estimate is significant at a ten percent level. As one would expect the total effect to be larger than the relative effect, our estimated effect seems reasonable. Both Black et al. (2020) and this paper find very different results from Persson, Qui, and Rossin-Slater (2021), which focuses on marginal cases of ADHD and finds no impact on educational attainment. However, our results should be larger in magnitude as there is no judgement involved in diagnosing T1D and thus no marginal T1D patient. Our results also relate to studies on peer effects in classrooms and school performance. Kristoffersen et al. (2015) and Zhao and Zhao (2021) find that adding a disruptive peer to the classroom reduces student performance by about 2% of a standard deviation. This suggests that having a sibling with T1D exerts a larger spillover to school performance than a disruptive peer, although the underlying mechanisms may be quite different (for instance teacher vs. parental investment).

Column six and column eight in panel A show the impact on math and Danish language with all covariates included, respectively. Having a sibling with T1D significantly reduces the GPA in the 9th grade Danish language Exit Exam by 5.0% of a standard deviation. The impact on math is smaller and not significant (2.1% of a standard deviation decline). One potential reason for the larger impacts on Danish language compared to mathematics is that parents would have spent more of the time being allocated to T1D management on language skills than mathematics skills. Aucejo and Romano (2016) find that school absenteeism has larger negative impacts on math achievement compared with reading achievement. They argue that math skills are more sensitive to educational inputs whereas reading and literacy skills are more sensitive to exposures outside of the classroom; for instance, time spent on the activity with parents at home.

Although focal children with a sibling diagnosed with T1D perform worse on the 9th grade Exit Exam, it does not translate into a lower probability of passing the 9th grade Exit Exam (column ten, panel A) or impact on-time completion of 9th grade (column two, panel A). On the other hand, the lower performance in the 9th grade Exit Exam appears to affect post-compulsory schooling decisions. While enrollment into further education is not affected, the probability of enrolling into academic high school versus vocational school significantly decreases by 3.1 pp with controls (shown in column four, panel B of Table 3). Since a high school diploma is the primary entry requirement for enrollment into college and university, the result suggest that having a sibling with T1D reduces the level of attempted education. Unfortunately, we cannot investigate completed education as the cohorts in our sample are too young at present time. All the results are robust to the inclusion of matched group fixed effects.[10]

Our findings would be consistent with a compensatory approach, as opposed to an exacerbating approach, as we find negative sibling spillovers. This could suggest that parents are reallocating resources away from the child without T1D. However, parents may also have less time and energy

[10] Results available from the authors upon request.

due to increased mental burdens after the diagnosis. In fact, Eriksen et al. (2021) find both parents are significantly more likely to visit a psychologist after the child's diagnosis. Since we do not have detailed data on parental investments by child, we cannot determine whether parents are in fact reallocating time away from the child without T1D or whether the parents are cutting back equally across both children due to a smaller time budget to allocate towards children's human capital accumulation.

### 4.2 Falsification Test

To address the concern that there may be unobservable differences driving our results, we next conduct a falsification test in which our treatment children have a sibling diagnosed with T1D, but the diagnosis appears after the 9$^{th}$ grade Exit Exam (they were 17 years or older at their sibling's diagnosis).[11] We again match the treated and non-treated focal children based on the same set of characteristics (sibling spacing, family size, and year of birth). Table 4 shows the results for all our outcomes of interest. Having a sibling diagnosed after the Exit Exam neither significantly impacts the 9$^{th}$ grade Exit Exam related outcomes (GPAs, on-time graduation, and passing the exam) nor significantly impacts post-compulsory school enrollment and all the coefficients are small in magnitude. This suggests the previously found impacts are not driven by unobservable differences between children in families where a child will be diagnosed compared with children in families where no child will be diagnosed.

### 4.3 Heterogeneity by Sex, Family and Maternal Characteristics

[11] To further test for robustness related to omitted variable bias we have also followed the methodology outlined in Oster (2019). The results from this exercise did not support that the estimated effects could be due to omitted variables. Results are available upon request.

Table 5 and 6 show the results of the eight heterogeneity analyses. Table 5 shows heterogeneity in sex and family characteristics. Panel A investigates if the effects differ depending on the sex of the child, while panel B investigates the effects depending on whether the focal child is a younger or older sibling to the one diagnosed, panel C investigates if the effects differ depending on whether the spacing between the two siblings is three or fewer versus more than three years, and Panel D investigates the effects depending on whether the child has more than one sibling.

In panel A the coefficient on the interaction term between male and T1D is negative and significant at a ten percent level for Math. The total effect for boys is a 5.8% of a standard deviation decline in the Math GPA (also significant at a ten percent level). Males are also less likely to pass the exam (1.8 pp) compared to females, with the total effect being a marginally significant 1.2 percentage point decline (significant at the ten percent level). While the interaction effects are not significant for other outcomes, and thus we cannot rule out differences by sex, the total effect for boys is a marginally significant 6.5% of a standard deviation decline in the Danish language GPA, and a significant 4.1pp decline in high school versus vocational enrollment. Thus, our results seem to be driven by male focal children.

In panel B of Table 5, we find that if the focal child is an older sibling, the interaction term for Math exam GPA is sizeable, albeit insignificant. All other interaction terms are small and insignificant. The total effect on younger siblings does suggest that the negative performance effects are driven by focal children who are younger siblings. The main effect (for younger siblings) shows that the Danish scores decrease by 5.1% of a standard deviation (significant at a ten percent level) and the math scores decrease by 6.0% of a standard deviation. The interaction terms for T1D and being an older sibling are positive for math and Danish scores, leading to insignificant impacts on older siblings. Given the research on birth order and test scores, this suggests the children most negatively impacted were those who would have performed worse even in the absence of the sibling's disability shock. Thus, sibling onset of T1D seems to further exacerbate pre-existing inequality in educational outcomes.

Panel C of Table 5 shows the results by whether siblings are born three or fewer years apart versus more than three years apart.[12] None of the interaction terms for diabetes and three or fewer years apart are statistically significant for any outcome of interest. However, it is large in magnitude for Math, which has a total effect of 5.9% of a standard deviation penalty. We find a marginally significant (at the ten percent level) total effect for Danish language exam GPAs, with the penalty being 5.2% of a standard deviation, but as the interaction term is very close to zero this does not indicate any potential difference in the consequences of being closely spaced or not.

Panel D of Table 5 investigates differences in effects by whether there are two or more children in the family. None of the interaction terms are significant, but the total effect of just having one sibling compared to more siblings is negative and statistically significant (6.5% of a standard deviation decrease) for the Danish score. This could indicate that relative forgone time matters since parents would have to reduce time by a larger amount per child with fewer children to take on increased caregiving responsibilities, all else equal.

Table 6 shows heterogeneity by parental characteristics measured the year before sibling's (pseudo) diabetes onset. Panel A investigates if the effects differ depending on whether the mother has completed at least a bachelor's degree, while panel B investigates the effects depending on whether the mother is employed. Panel C investigates if the effects differ depending on whether the mothers wage income is in the bottom versus top quartile of the wage distribution and finally,

[12] Given our restriction of no more than five years apart, this means comparing three or fewer years apart with four to five years apart.

Panel D investigates the effects depending on whether the child is living in a single parent household.

The coefficient on the interaction term in panel A shows the effect of having a sibling with T1D does not differ by mother's education, except for the high school versus vocational school enrollment outcome. However, the magnitude of the effect on the math outcome is meaningful as children whose mothers have at least a bachelor's degree score 6.2% of a standard deviation better on the Math exam, which completely offsets the 3.7% of a standard deviation decline due to having a sibling with T1D. The total effect is an insignificant 2.5% of a standard deviation increase. In terms of the Danish GPA, the interaction term is a 5.3% of a standard deviation decline, which results in a negative and statistically significant total decline of 8.5% of a standard deviation when the mother has at least a bachelor's degree. Children whose mothers have at least a bachelor's degree are 4.9 pp more likely to enroll in high school versus vocational school, which again completely offsets the 4.7 pp decrease in enrollment due to being a child of a lower educated mother and having a sibling with T1D. As a result, there is no significant impact on the type of enrollment among children with more educated mothers. Thus, having a sibling with T1D more negatively impacts those most disadvantaged to begin with, which further exacerbates inequality.

Panel B shows differences in effects depending on whether the mother is employed or not. None of the interaction terms are significant when analyzing performance outcomes. However, the interaction on Danish is sizeable and shows a 7.5% of a standard deviation decrease in Danish scores, which results in a significant total effect of a 6.2% of a standard deviation decrease in Danish scores when the mother is employed. The interaction of further education shows a 3.4pp decrease in enrollment into further education (significant at a ten percent level) offsetting an apparent, albeit only marginally significant, increase in enrollment among unemployed mothers.

Similarly, children of employed mothers who have a sibling with T1D show a 4.1pp (insignificant) decrease in high school versus vocational school enrollment compared to children of unemployed mothers who have a sibling with T1D, which results in a 3.7pp significant decrease in high school versus vocational enrollment. The results suggest that employment may not be an advantage when the family is hit by a health shock, at least not in a system where access to health care is free and unrelated to employment. As employed mothers are less flexible and spend more time away from the child these results indicate that time may also play an important role.

Panel C investigates differences by whether the mother is in the bottom quartile of the income distribution (low wage income) or the top quartile of the income distribution (high wage). The interaction term for the outcomes pertaining to the 9$^{th}$ grade exit exam is never significant. However, the interaction on enrollment into further education shows a 5.9 pp statistically significant decrease in enrollment for children of low wage income mothers. The interaction on high school versus vocational school enrollment is insignificant but substantial in magnitude, resulting in a marginally significant total effect of a 6.6 pp decrease. These results suggest that the negative consequences on enrollment into further education for children with employed mothers are driven by low income working mothers.

As shown in panel D of table 6, we find no significant interaction effects for single mothers, despite the hypothesis that single parents have less time to invest in their children, all else equal. However, this may be caused by a lack of power due to the rarity of single mothers in Denmark. The results suggest that they perform worse in math (an insignificant 5.6% of a standard deviation), but much better in Danish relative to two-parent households (an insignificant 9.0% of a standard deviation). We find suggestive evidence that they appear less likely to enroll into further education but are more likely to enter high school if enrolled. Thus, living in a single parent household and having a sibling being hit by a negative health shock does not have clear negative consequences for focal children.

To summarize, our heterogeneity results suggest that there are some important differences by maternal characteristics. While sibling onset of T1D appears to result in worse Danish Exit Exam GPAs for children of highly educated mothers and employed mothers, there are no differences in Danish scores between high-income and low-income mothers. Having a sibling with T1D does not appear to have consequences for children in families where the mother is unemployed. On the other hand, the results show that having an employed mother with a low wage income negatively impacts enrollment into further education. Children of less educated mothers, as well as children of employed low-income mothers, substitute away from an academic track when a sibling has T1D. This could lead to long-term consequences and is likely to exacerbate inequality over time.[13]

### 4.4 Heterogeneity by Age at Sibling's Diagnosis

We split the sample into four categories matching the different institutional settings the child experiences between the age of two and fifteen. To be clear, these are categories based on the focal child's age and not the age of the sibling who is diagnosed. In Denmark children aged two to five are mostly placed in kindergarten. The year they turn six they enter primary school (grades zero through three). By age ten they switch to middle school (grades four through six). While this does not usually result in changing schools, children in grades four to six will typically be placed in a separate location within the school and have different teachers. By age thirteen they switch to lower secondary school (grades seven through nine), which again usually

[13] Our results suggests that it would be interesting to investigate interactions between employment, income, and education further. However, our sample sizes limits us from doing so.

does not mean changing schools but could result in being moved to a different part of the school and having new teachers.

Table 7 shows that while the coefficients on the Danish language Exit Exam GPAs remain negative across all age groups, the only significant decline (at the 5 percent level) is for those aged six to nine. This is likely due to this age group being where reading is taught in school and schools recommending that parents of children in this age group spend twenty minutes each night reading with their child. The effect is also large in magnitude for children whose sibling was diagnosed around the time they sit the 9$^{th}$ grade Exit Exam. A larger magnitude around the time of the test would be consistent with Landersø, Nielsen, and Simonsen (2020), which uses variation in school starting age to find siblings close to taking their 9th grade Exit Exam benefit from their younger sibling delaying their entry into school. Thus, changes within the family near test time appear detrimental.  However, the standard errors are large enough that the 95% confidence intervals overlap for the different age groups. The impact on 9$^{th}$ grade math Exit Exam GPA follows roughly the same pattern, albeit the coefficients are smaller in magnitude and insignificant. The impact on passing the Exit Exam as well as graduating on time is insignificant and small in magnitude across the different age groups.

When turning to post-compulsory school enrollment, we find that the effect on enrollment into further education is positive and significant at a ten percent level for the two to five age group (2.5 pp increase). The magnitude is very small for the other groups which suggests the larger impacts on 9$^{th}$ grade Exit Exam GPAs for age groups six to nine and 13 to 15 are not translating to less education. For all four age groups we observe a substitution away from high school and into vocational school of roughly the same magnitude. The impact is, however, only marginally significant for the six to nine age group.

## 5 Well-being

In this section we test for whether a potential mechanism behind the impact on sibling's educational outcomes is well-being. The child may be worried about the health of the sibling, worried about whether he or she will also get a disability or health shock, or jealous of the time parents are reallocating towards disease management and away from the focal child.[14] This psychological burden may result in reduced well-being as well as taking time and energy away from focusing on schoolwork.

Since 2015 Danish children in public schools are surveyed about their well-being in school. The National Well-Being Survey consists of two surveys, one containing 20 items that is given to children in grades zero to three and one containing 40 items that is given to children in grades three through nine. The surveys cover topics related to the teaching environment, student well-being, and peace and order. Based on a factor analysis (discussed in more detail in Appendix A), we extract six factors: self-efficacy, academic confidence, intrinsic motivation, codetermination, social well-being, and somatic symptoms. We do not include codetermination or somatic symptoms in this paper because we have no clear theoretical reason to believe that having a sibling with T1D would impact teachers' willingness to let students have a say in how the classes are taught or cause headaches or stomach aches.

Results from the well-being analysis are shown in Table 8. We find a marginally significant (at the 10-percent level) worse reports of academic confidence for children whose sibling is diagnosed with T1D. Otherwise, there is no evidence of impacts on school well-being, indicating well-being is not a key mechanism behind the results.

[14] See Incledon et al. (2013) for an overview of determinants of mental health for siblings of children with a chronic health diagnosis.

## 6 Conclusion

This paper estimates the effect of having a disabled sibling on a variety of educational outcomes. We use Danish administrative registry data and T1D as our disability shock to estimate effects. We match focal children with a sibling diagnosed with T1D to focal children without a sibling diagnosed with T1D based on year of birth, family size, and sibling spacing. We find that having a sibling diagnosed with T1D leads to a significant 5.0% of a standard deviation decrease in the 9$^{th}$ grade Danish language Exit Exam GPA, with a smaller impact on Math (insignificant 2.1% of a standard deviation decline). The age group most negatively impacted on Danish GPAs corresponds to when children are learning to read and when parents are advised to spend time each day reading at home with their children. We contribute to the literature by documenting a significant 3.1 pp reduction in high school versus vocational school enrollment, which indicates educational trajectories are impacted as well.

These results indicate that sibling disability status plays an important role in educational inequality. While most interventions related to disability onset focus on the individual diagnosed, our results suggest that siblings may benefit from an intervention as well. While we cannot pinpoint the exact type of intervention needed, our results do suggest that an important mechanism behind the impact on siblings is reduced time investments from parents. Future research could test whether increased investments in these children from non-parental adults are effective at alleviating the negative spillovers.

Our results also suggest that when determining whether interventions aimed at helping the child who is diagnosed with the disability are cost-effective, it is important to not only focus on the benefits to the focal child, but siblings as well. Even an intervention that leads to equally good outcomes for the disabled child but is less time consuming to use from the parental standpoint, could lead to gains for the siblings of affected children. Discovering interventions to mitigate the sibling spillovers related to a disability shock is especially important given the economically meaningful impacts on post-compulsory school educational trajectories.

## Bibliography


Abadie, & Spiess. (2022). Robust Post-Matching Inference. *Journal of the American Statistical Association, 117*(538), 983–995.

Adhvaryu, A., Daysal, N. M., Gunnsteinsson, S., Molina, T., & Steingrimsdottir, H. (2022). Impact of Child Health on Families: Evidence from Childhood Cancers. *Working Paper*.

Altonji, J., Arcidiacono, P., & Maurel, A. (2016). Chapter 7 - The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects. In E. Hanushek, S. Machin, & L. Woessmann, *Handbook of the Economics of Education* (pp. 305 - 396). Elsevier.

Aucejo, E. M., & Romano, T. F. (2016). Assessing the effect of school days and absences on test score performance. *Economics of Education Review*, 70-87.

Baker, M. (2021). Gender Differences in (Some) Formative Inputs to Child Development. *NBER Working Paper 28382*.

Baker, M., & Milligan, K. (2016). Boy-Girl Differences in Parental Time Investments: Evidence from Three Countries. *Journal of Human Capital*.

Becker, G., & Tomes, N. (1976). Child Endowments and the Quantity and Quality of Children. *Journal of Political Economy, 84*(4), S143-S162. Retrieved from www.jstor.org/stable/1831106

Bernardi, F. (2014). Compensatory Advantage as a Mechanism of Educational Inequality: A Regression Discontinuity Based on Month of Birth . *Sociology of Education*, 74-88.

Bharadwaj, P., Eberhard, J. P., & Neilson, C. A. (2018). Health at Birth, Parental Investments, and Academic Outcomes. *Journal of Labor Economics*, 349-394.

Bianchi, Cohen, & Raley. (2004). Inequality in parental investments in child-rearing: Expenditures, time, and health. In K. (. Neckerman, *Social Inequality* (pp. 189–219). New York: Russell Sage Foundation.

Black, S. E., Breining, S., Figlio, D. N., Guryan, J., Karbownik, K., Nielsen, H., . . . Simonsen, M. (2020). Sibling Spillovers. *The Economic Journal*.

Breining, S. N. (2014). The presence of ADHD: Spillovers between siblings. *Economics Letters*, 469-473.

Breining, S., Doyle, J., Figlio, D. N., Karbownik, K., & Roth, J. (2020). Birth Order and Delinquency: Evidence from Denmark and Florida. *Journal of Labor Economics*, 95-142.

Breivik, A.-L., & Costa-Ramón, A. (2022). The Career Costs of Children's Health Shocks. *University of Zurich, Department of Economics, Working Paper No. 399, Revised version*.

Cameron, F. J., Northam, E. A., & Ryan, C. M. (2019). The effect of type 1 diabetes on the developing brain. *The Lancet Child & Adolescent Health*, 427-436.

Colding, B., Husted, L., & Hummelgaard, H. (2009). Educational progression of second-generation immigrants and immigrant children. *Economics of Education Review*, 434-443.

Conti, G., Heckman, J. J., & Pinto, R. (2016). The Effects of Two Influential Early Childhood Interventions on Health and Healthy Behaviour. *The Economic Journal, 126*(596), F28-F65. Retrieved from https://doi.org/10.1111/ecoj.12420

Conti-Ramsden, G., & Durkin, K. (2012). Language Development and Assessment in the Preschool Period. *Neuropsychol Rev*, 384–401.

Cuhna, F., & Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 31–47.

Cunha, F., Heckman, J., & Navarro, S. (2005). Separating uncertainty from heterogeneity in life cycle earnings. *Oxford Economic Papers, 57*(2), 191-261.

Daysal, M., Ding, H., Rossin-Slater, M., & Schwandt, H. (2021). Germs in the Family: The Long-Term Consequences of Intra-Household Endemic Respiratory Disease Spread. *NBER working paper 29524*. Retrieved from http://schwandt.sesp.northwestern.edu/papers/Childsick_HELP_webinar.pdf

Daysal, N. M., Simonsen, M., Trandafir, M., & Breining, S. (2020). Spillover Effects of Early-Life Medical Interventions. *The Review of Economics and Statistics*, 1-46.

Dybdal, D., Tolstrup, J., Sildorf, S., Boisen, K., Svensson, J., & Skovgaard, T. G. (2017). Increasing risk of psychiatric morbidity after childhood onset type 1 diabetes: a population-based cohort study. *Diabetologia*, 1-8.

Elango, S., Garcia, J. L., Heckman, J. J., & Hojman, A. (2016). Early Childhood Education. In R. A. Moffitt, *Economics of Means-Tested Transfer Programs in the United States, Volume 2* (pp. 235-297). University of Chicago Press. Retrieved from http://www.nber.org/chapters/c13489

Eriksen, T. L., Gaulke, A., Skipper, N., Svensson, J., & Thingholm, P. (2022). Long Run Labor Market Outcomes of a Childhood Health Shock: High Socio-Economic Status Parents Can Mitigate the Impact. *working paper*.

Eriksen, T. M., Gaulke, A., Skipper, N., & Svensson, J. (2021, July). The Impact of Childhood Health Shocks on Parental Labor Supply. *Journal of Health Economics, 78*. Retrieved from https://doi.org/10.1016/j.jhealeco.2021.102486

Fadlon, I., & Nielsen, T. H. (2019). Family Health Behaviors. *American Economics Review*, 3162-91.

Fadlon, I., & Nielsen, T. H. (2021). Family Labor Supply Responses to Severe Health Shocks: Evidence from Danish Administrative Records. *American Economic Journal: Applied Economics*, 1-30.

Figlio, D., Guryan, J., Karbownik, K., & Roth, J. (2014). The Effects of Poor Neonatal Health on Children’s Cognitive Development. *American Economic Review*, 3921–3955.

Garcia, J. L., Heckman, J. J., Leaf, D. E., & Prados, M. J. (2019). Quantifying the Life-cycle Benefits of a Prototypical Early Childhood Program. *NBER Working Paper*. doi:10.3386/w23479

Guryan, J., Hurst, E., & Kearney, M. (2008). Parental Education and Parental Timewith Children. *Journal of Economic Perspective*, 23– 46.

Hakim, N. S., Stratta, R. J., & Gray, D. (2010). *Pancreas, islet and stem cell transplantation for diabetes.*

Hsin, A. (2012). Is Biology Destiny? Birth Weight and Differential Parental Treatment. *Demography*, 1385-1405.

Hsin, A., & Felfe, C. (2014). When Does Time Matter? Maternal Employment, Children's Time With Parents, and Child Development. *Demography*, 1867-1894.

Huggett, M., Ventura, G., & Yaron, A. (2011). Sources of Lifetime Inequality. *American Economic Review, 101*(7), 2923-2954. doi:10.1257/aer.101.7.2923

Hyunkuk, C. (2021). Sibling Gender Effects on Test Scores. *Education Finance and Policy*, 1-34. doi:https://doi.org/10.1162/edfp_a_00352

Incledon, E., Williams, L., Hazell, T., Heard, T. R., Flowers, A., & Hiscock, H. (2013). A review of factors associated with mental health in siblings of children with chronic illness. *Journal of Child Health Care, 19*(2), 182-194.

International Diabetes Federation. (2021). *IDF Diabetes Atlas: 10th Addition.*

Joensen, J. S., & Nielsen, H. S. (2018). Spillovers in Education Choice. *Journal of Public Economics*, 158-183.

Karbownik, K., & Özek, U. (2021). Setting a Good Example? Examining Sibling Spillovers in Education using a Regression Discontinuity Design. *The Journal of Human Resources*.

Kristoffersen, J., Krægpøth, M., Nielsen, H., & Simonsen, M. (2015). Disruptive school peers and student outcomes. *Economics of Education Review*, 1-13.

Landersø, R., Nielsen, H. S., & Simonsen, M. (2020). Effects of School Starting Age on the Family. *Journal of Human Resources*, 1258-1286.

Lindkvist, E. B., Thorsen, S. U., Paulsrud, C., Thingholm, P. R., E. T., G. A., & Svensson, J. (2021). Association of type 1 diabetes and educational achievement in 16–20-year olds: A Danish nationwide register study. *Diabetic Medicine*.

Loughran, D. S., Datar, A., & Kilburn, M. R. (2008). The Response of Household Parental Investment to Child Endowments. *Review of Economics of the Household*, 223-242.

Lovén, I. (2017). Labor market consequences of growing up with a sibling with type 1-diabetes. *Social Science and Medicine*, 1-10.

Monna, B., & Gauthier, A. (2008). A Review of the Literature on the Social and Economic Determinants of Parental Time. *Journal of Family and Economic Issues*, 634-653.

Nicoletti, C., & Rabe, B. (2018). Sibling spillover effects in school achievement. *Journal of Applied Econometrics*.

Oster, E. (2019). Unobservable Selection and Coefficient Stability:. *Journal of Business & Economic Statistics,*, 187-204.

Persson, P., Qui, X., & Rossin-Slater, M. (2021). Family Spillover Effects of Marginal Diagnoses: The Case of ADHD. *NBER Working paper 28334*.

Pociot, F., & Lernmark, Å. (2016). Genetic risk factors for type 1 diabetes. *The Lancet, 387*(10035), 2331-2339. doi:10.1016/S0140-6736(16)30582-7

Prætorius, K., Urhoj, S. K., & Andersen, A.-M. N. (2022). Parental socio-economic position and the risk of type 1 diabetes in children and young adults in Denmark: A nation-wide register-based study. *Scandinavian Journal of Public Health*, Epub ahead of print.

Pruckner, G. J., Schneeweis, N., Schober, T., & Zweimüller, M. (2021). Birth order, parental health investment, and health in childhood. *Journal of Health Economics*.

Qureshi, J. (2018). Siblings, Teachers, and Spillovers on Academic Achievement. *Journal of Human Resources, 53*(1), 272-297.

Rawshani, A., Sattar, N., Franzén, S., Rawshani, A., Hattersley, A., Svensson, A., . . . Gudbjörnsdottir, S. (2018). Excess mortality and cardiovascular disease in young adults with type 1 diabetes in relation to age at onset: a nationwide, register-based cohort study. *Lancet.*, 392:10.

Regnell, S., & Lernmark, A. (2017). Early Prediction of Autoimmune (type 1) diabetes. *Diabetologia*, 1370-1381.

Rellstab, S., Bakx, P., García-Gómez, P., & Doorslaer, E. v. (2020). The kids are alright - labour market effects of unexpected parental hospitalisations in the Netherlands. *Journal of Health Economics*, 102275.

Rewers, M., & Ludvigsson, J. (2017). Environmental Risk Factors for Type 1 Diabetes. *The Lancet*, 2340-2348.

Ryan, C., Duinkerken, E. v., & Rosano, C. (2016). Neurocognitive consequences of diabetes. *American Psychologist*, 563–576.

Sandahl, K., Nielsen, L., Svensson, J., Johannesen, J., Pociot, F., Mortensen, H., . . . Olsen, B. (2016). Increased mortality in a Danish cohort of young people with Type 1 diabetes mellitus followed for 24 years. *Diabet Med.*, 380-386.

Sayer, Gauthier, & Furstenberg. (2004). Educational differences in parents' time with children: Cross-national variations. *Journal of Marriage and Family*, 1152–1169.

Silles, M. A. (2010). The implications of family size and birth order for test scores and behavioral development. *Economics of Education Review*, 795-803.

Silverstein, J., Klingensmith, G., Copeland, K., Plotnick, L., Kaufman, F., Laffel, L., . . . Clark, N. (2005). Care of Children and Adolescents with Type 1 Diabetes. *Diabetes Care, 28*(1), 186-212. doi:10.2337/diacare.28.1.186

Skipper, N., Gaulke, A., Sildorf, S., Eriksen, T., Nielsen, N., & Svensson, J. (2019). Association of Type 1 Diabetes with Standardized Test Scores of Danish Schoolchildren. *JAMA*, 484-492.

Solowiejczyk, J. (2004). The Family Approach to Diabetes Management: Theory into Practice Toward the Development of a New Paradigm. *Diabetes Spectrum*, 31-26. doi:10.2337/diaspect.17.1.31

Starck, M., Grünwald, J., & Schlarb, A. (2016). Occurrence of ADHD in parents of ADHD children in a clinical sample. *Neuropsychiatric disease and treatment*, 581–588.

Steingrimsdottir, H., & Gunnsteinsson, S. (2019). The Long-Term Impact of Child Disability of Families. *working paper*.

Svensson, J., Cerqueira, C., Kjærsgaard, P., Lyngsøe, L., Hertel, N., Maden, M., . . . Johannesen, J. (2016). Danish Registry of Childhood and Adolescent. *Clinical Epidemiology*, 679—683.

Thingholm, P., Gaulke, A., Eriksen, T., Svensson, J., & Skipper, N. (2020). Association of Prodromal Type 1 Diabetes with School Absenteeism of Danish Schoolchildren: A Population-Based Case-Control Study of 1,338 Newly Diagnosed Children. *Diabetes Care*, 2886-2888.

Thomsen, M. (2015). Parental time investments in children: Evidence from Denmark . *Acta Sociologica*, 249-263.

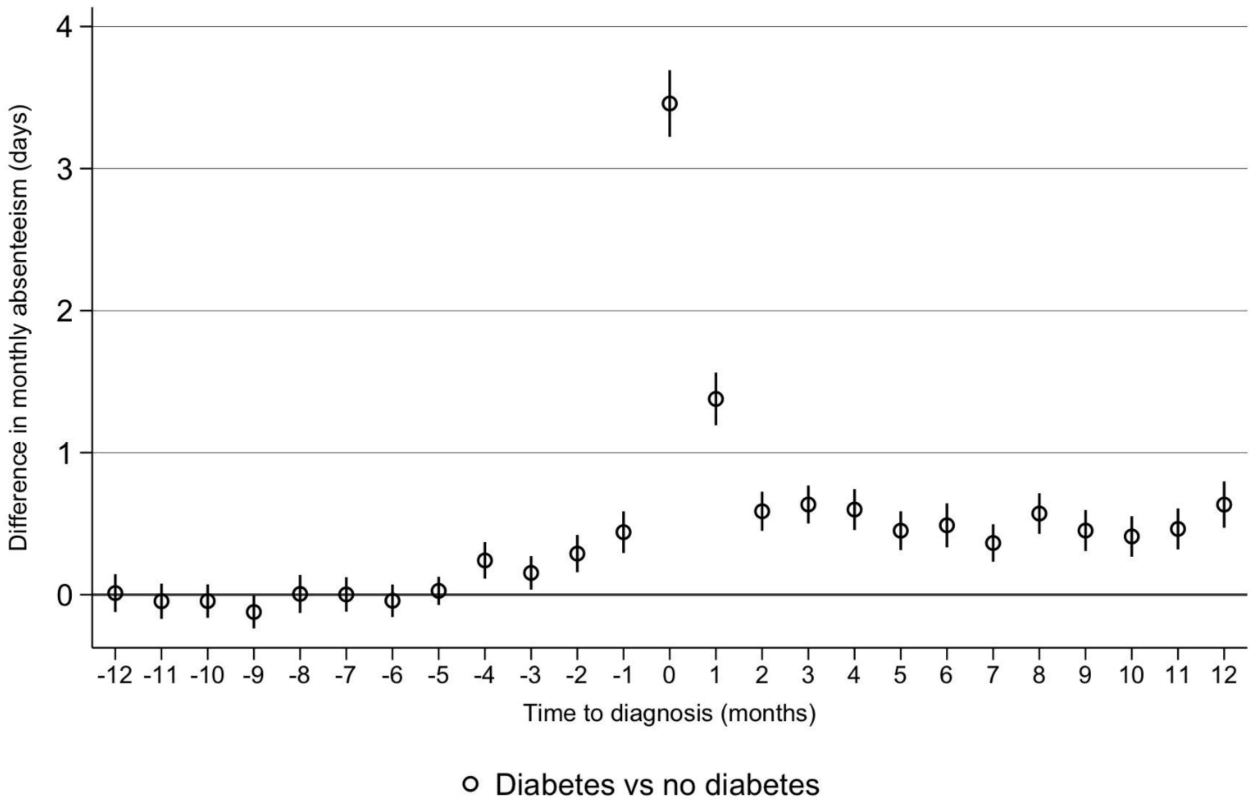
White, N., Sun, W., & Cleary, P. (2010.). Effect of Prior Intensive Therapy in Type 1 Diabetes on 10-Year Progression of Retinopathy in the DCCT/EDIC: Comparison of Adults and Adolescents. *Diabetes.*, 59(5): 1244–1253.

Writing Group for the DCCT/EDIC Research Group. (2015). Association Between 7 Years of Intensive Treatment of Type 1 Diabetes and Long-term Mortality. *JAMA*, 45-53.

Zhao, L., & Zhao, Z. (2021). Disruptive Peers in the Classroom and Students' Academic Outcomes: Evidence and Mechanisms. *Labour Economics*, 101954.

Zick, C., & Bryant, W. (1996). A New Look at Parents' Time Spent in Child Care: Primary and Secondary Time Use. *Social Science Research*, 260-280.

Figure 1: Mean difference (95% CI) in days absent from school during a given month relative to diagnosis of type 1 diabetes (diabetes vs. no diabetes)




Notes: n= 1,338 children diagnosed with type 1 diabetes from August 1 2010 to June 30 2017 compared with n= 6,690 age and sex matched controls. Mean (95% CI) difference in number of days absent from school relative to diabetes diagnosis (month 0). The mean differences are adjusted for calendar-month and school grade specific effects. As the month of July is the only month of year with no school days in Denmark, it was left out of the analysis. Months -12 to -5 showed non-significant differences (with a level of significance at $p<0.05$).

*Published previously in Thingholm et al. Association of Prodromal Type 1 Diabetes with School Absenteeism of Danish Schoolchildren: A Population-Based Case-Control Study of 1,338 Newly Diagnosed Children. Diabetes Care 2020 Nov; 43(11): 2886-2888. Copyright 2020 by the American Diabetes Association.*

**Table 1 Summary Statistics**

| Child has sibling with diabetes: | NO | | YES | |
|---|---|---|---|---|
| Matching Variables: | | | | |
| Birthyear | 1,996 | (4.126) | 1,996 | (4.127) |
| Spacing | 3.018 | (1.115) | 3.018 | (1.115) |
| Number of children | 2.793 | (0.911) | 2.793 | (0.911) |
| Child's Characteristics: | | | | |
| Male (0/1) | 0.513 | (0.500) | 0.523 | (0.500) |
| Birthorder | 1.894 | (0.831) | 1.903 | (0.841) |
| Birthweight | 3,563 | (545.4) | 3,551 | (560.0) |
| Birthlength | 52.13 | (2.420) | 52.11 | (2.434) |
| Apgar Score | 9.855 | (0.785) | 9.832 | (0.886) |
| Birthweight missing | 0.006 | (0.079) | 0.009 | (0.095) |
| Child lives with one parent | 0.107 | (0.309) | 0.0999 | (0.300) |
| Age at onset | 9.285 | (3.842) | 9.285 | (3.842) |
| Sibling age at onset | 9.425 | (3.597) | 9.425 | (3.598) |
| Focal child is older sibling | 0.478 | (0.500) | 0.479 | (0.500) |
| Mother's characteristics | | | | |
| Age at birth | 29.02 | (4.221) | 28.90 | (4.299) |
| Employed | 0.852 | (0.355) | 0.835 | (0.371) |
| Wage income | 189.0 | (136.2) | 185.5 | (133.7) |
| Wage income - missing | 0.004 | (0.06) | 0.005 | (0.069) |
| *Highest completed education* | | | | |
| Short qualifying education | 0.368 | (0.482) | 0.373 | (0.484) |
| Long qualifying education | 0.230 | (0.421) | 0.217 | (0.412) |
| No qualifying education | 0.384 | (0.486) | 0.392 | (0.488) |
| Education - missing | 0.018 | (0.132) | 0.018 | (0.134) |
| Father's characteristics | | | | |
| Father Missing | 0.004 | (0.062) | 0.005 | (0.069) |
| Age at birth | 31.54 | (5.126) | 31.42 | (5.065) |
| Employed | 0.900 | (0.300) | 0.905 | (0.293) |
| Wage income | 300.2 | (193.6) | 295.7 | (183.0) |
| Wage income - missing | 0.01 | (0.098) | 0.012 | (0.108) |
| *Highest completed education* | | | | |
| Short qualifying education | 0.481 | (0.500) | 0.492 | (0.500) |
| Long qualifying education | 0.184 | (0.388) | 0.168 | (0.374) |
| No qualifying education | 0.306 | (0.461) | 0.315 | (0.465) |
| Education - missing | 0.028 | (0.166) | 0.025 | (0.156) |
| Observations | 11,460 | | 2,292 | |

Notes: Mean and standard deviations (in parentheses) split by whether a child has a sibling with diabetes or not.

**Table 2** Regression of sibling with diabetes (0/1) on the conditioning set

| | Sibling with diabetes (0/1) | |
|---|---|---|
| Matching variables: | | |
| birthyear | 0.000 | (0.000) |
| Spacing | 0.000 | (0.000) |
| Number of children | -0.004 | (0.002) |
| Child's characteristics: | | |
| Male | 0.005 | (0.006) |
| Birthorder | 0.007 | (0.004) |
| Birthweight | -0.000 | (0.000) |
| Birthlength | 0.002 | (0.002) |
| Apgar Score | -0.004 | (0.005) |
| Birth info. Missing | 0.053 | (0.044) |
| Child lives with one parent | -0.017* | (0.010) |
| Mother's characteristics: | | |
| Age at birth | -0.001 | (0.001) |
| Employed | -0.023** | (0.011) |
| Wage income | 0.000 | (0.000) |
| Wage income - missing | 0.030 | (0.077) |
| *Highest completed education (ref. No qualifying education)* | | |
| Short qualifying education | -0.000 | (0.008) |
| Long qualifying education | -0.004 | (0.010) |
| Education missing | 0.003 | (0.027) |
| Father's characteristics: | | |
| Age at birth | -0.000 | (0.001) |
| Employed | 0.017 | (0.013) |
| Wage income | -0.000 | (0.000) |
| Wage income - missing | 0.038 | (0.052) |
| *Highest completed education (ref. No qualifying education)* | | |
| Short qualifying education | 0.000 | (0.008) |
| Long qualifying education | -0.010 | (0.010) |
| Education missing | -0.040* | (0.023) |
| Father missing | 0.028 | (0.074) |
| | | |
| Constant | -0.013 | (0.280) |
| Observations | 13,752 | |
| R-squared | 0.002 | |
| Joint F-test | 0.963 | |
| Prob > F | 0.517 | |

Note: Characteristics pertaining the parents are measured two years before (pseudo) onset of sibling's diabetes unless stated otherwise. Standard errors (in parentheses) are clustered at the matched group level.
*** p<0.01, ** p<0.05, * p<0.1

**Table 3** OLS regressions: The effects of having a sibling with diabetes on school performance and enrollment

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| A: 9th grade Exit Exam | On-time Graduation | | GPA | | Math | | Danish | | Passed | |
| Diabetes | 0.003 | 0.006 | -0.056** | -0.038* | -0.034 | -0.021 | -0.068*** | -0.050** | -0.004 | -0.003 |
| | (0.009) | (0.009) | (0.024) | (0.022) | (0.023) | (0.021) | (0.025) | (0.022) | (0.005) | (0.004) |
| | | | | | | | | | | |
| Adjusted | NO | YES | NO | YES | NO | YES | NO | YES | NO | YES |
| R-squared | 0.004 | 0.050 | 0.000 | 0.181 | 0.000 | 0.143 | 0.001 | 0.196 | 0.000 | 0.044 |
| Outcome mean | 0.797 | | 0.001 | | -0.001 | | 0.001 | | 0.967 | |
| Observations | 13,752 | | 12,650 | | 12,504 | | 12,584 | | 12,221 | |
| | | | | | | | | | | |
| B: Enrollment | Any further education | | High School | | | | | | | |
| Diabetes | 0.005 | 0.007 | -0.039*** | -0.031*** | | | | | | |
| | (0.006) | (0.006) | (0.011) | (0.010) | | | | | | |
| | | | | | | | | | | |
| Adjusted | NO | YES | NO | YES | | | | | | |
| R-squared | 0.008 | 0.051 | 0.024 | 0.156 | | | | | | |
| Outcome mean | 0.912 | | 0.716 | | | | | | | |
| Observations | 13,752 | | 12,542 | | | | | | | |

Notes: All regressions condition on characteristics pertaining the child and mother as well as cohort, spacing, parity and test year FE. GPA, Math GPA, and Danish GPA are all standardized and thus are measured as z-scores. Standard errors (in parentheses) are clustered at the matched group level.

*** p<0.01, ** p<0.05, * p<0.1

**Table 4 OLS regressions:** Falsification test - The effects of having a sibling with diabetes where onset happens after the 9th Grade Exit Exam

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 9$^{th}$ grade Exit Exam | | | | Enrollment | |
| Outcome | On-time Graduation | Math | Danish | Passed | Further Education | High School |
| Diabetes | -0.025 | -0.006 | 0.012 | -0.012 | 0.001 | 0.008 |
| | (0.025) | (0.066) | (0.062) | (0.011) | (0.009) | (0.027) |
| Outcome mean | 0.859 | 0.019 | 0.020 | 0.973 | 0.976 | 0.746 |
| Observations | 1,593 | 1,576 | 1,583 | 1,546 | 1,593 | 1,555 |

All regressions condition on characteristics pertaining the child and mother as well as cohort, spacing, parity and survey year FE. Math GPA and Danish GPA are standardized and are thus measured as z-scores. Standard errors (in parentheses) are clustered at the matched group level.

*** p<0.01, ** p<0.05, * p<0.1

**Table 5** OLS regressions: Heterogeneous effects of having a sibling with diabetes – child and family characteristics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 9th grade Exit Exam | | | | Enrollment | |
| Outcome | On-time Graduation | Math | Danish | Passed | Further education | High vs. Voc. School |
| A: Child is male (0/1) | | | | | | |
| (1) diabetes | 0.005 | 0.018 | -0.035 | 0.006 | 0.010 | -0.020 |
| | (0.010) | (0.028) | (0.030) | (0.005) | (0.008) | (0.014) |
| (2) diabetes x male | 0.002 | -0.075* | -0.030 | -0.018** | -0.005 | -0.021 |
| | (0.017) | (0.044) | (0.046) | (0.008) | (0.013) | (0.021) |
| (1) + (2) | 0.007 | -0.058* | -0.065* | -0.012* | 0.004 | -0.041*** |
| | (0.014) | (0.033) | (0.033) | (0.007) | (0.009) | (0.015) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 13,752 | 12,504 | 12,584 | 12,221 | 13,752 | 12,542 |
| B: Focal Child is an older sibling (0/1) | | | | | | |
| (1) diabetes | -0.001 | -0.051* | -0.060** | -0.001 | 0.009 | -0.032** |
| | (0.011) | (0.030) | (0.030) | (0.006) | (0.008) | (0.013) |
| (2) diabetes X focal older | 0.016 | 0.063 | 0.021 | -0.005 | -0.005 | 0.003 |
| | (0.018) | (0.042) | (0.044) | (0.009) | (0.012) | (0.020) |
| (1) + (2) | 0.015 | 0.012 | -0.039 | -0.006 | 0.004 | -0.029** |
| | (0.013) | (0.030) | (0.032) | (0.007) | (0.008) | (0.015) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 13,752 | 12,504 | 12,584 | 12,221 | 13,752 | 12,542 |
| C: Spacing 0-3 years (0/1) | | | | | | |
| (1) diabetes | 0.005 | 0.018 | -0.046 | -0.005 | 0.002 | -0.034** |
| | (0.015) | (0.039) | (0.038) | (0.008) | (0.010) | (0.017) |
| (2) diabetes X spacing 0-3 | 0.003 | -0.059 | -0.006 | 0.003 | 0.007 | 0.005 |
| | (0.018) | (0.046) | (0.047) | (0.010) | (0.013) | (0.021) |
| (1) + (2) | 0.007 | -0.040 | -0.052* | -0.002 | 0.009 | -0.029** |
| | (0.011) | (0.026) | (0.027) | (0.005) | (0.007) | (0.012) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 13,752 | 12,504 | 12,584 | 12,221 | 13,752 | 12,542 |
| D: More than one sibling (0/1) | | | | | | |
| (1) diabetes | 0.012 | -0.014 | -0.065** | -0.007 | 0.009 | -0.028** |
| | (0.012) | (0.030) | (0.032) | (0.006) | (0.008) | (0.013) |
| (2) diabetes X two or more siblings | -0.011 | -0.013 | 0.028 | 0.006 | -0.004 | -0.004 |
| | (0.017) | (0.042) | (0.044) | (0.009) | (0.011) | (0.020) |
| (1) + (2) | 0.001 | -0.027 | -0.037 | -0.000 | 0.005 | -0.032** |
| | (0.013) | (0.030) | (0.030) | (0.007) | (0.009) | (0.014) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 13,752 | 12,504 | 12,584 | 12,221 | 13,752 | 12,542 |

Notes: All regressions condition on characteristics pertaining the child and mother as well as cohort, spacing, parity and test year FE. Math GPA and Danish GPA are standardized and are thus measured as z-scores. Standard errors (in parentheses) are clustered at the matched group level. *** p<0.01, ** p<0.05, * p<0.1

**Table 6** OLS regressions: Heterogeneous effects of having a sibling with diabetes – mother characteristics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 9th grade Exit Exam | | | | Enrollment | |
| Outcome | On-time Graduation | Math | Danish | Passed | Further education | High vs. Voc. School |
| A: Mother has a bachelors degree or above (0/1) | | | | | | |
| (1) diabetes | 0.003 | -0.037 | -0.032 | -0.003 | 0.003 | -0.047*** |
| | (0.011) | (0.026) | (0.026) | (0.006) | (0.007) | (0.013) |
| (2) diabetes X bachelors degree | -0.003 | 0.062 | -0.053 | 0.003 | 0.002 | 0.049** |
| | (0.018) | (0.049) | (0.049) | (0.007) | (0.011) | (0.019) |
| (1) + (2) | 0.000 | 0.025 | -0.085** | 0.000 | 0.005 | 0.002 |
| | (0.015) | (0.04) | (0.040) | (0.004) | (0.009) | (0.013) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 13,538 | 12,369 | 12,444 | 12,090 | 13,538 | 12,397 |
| B: Mother is employed (0/1) | | | | | | |
| (1) diabetes | -0.013 | -0.029 | 0.013 | 0.006 | 0.032* | 0.004 |
| | (0.025) | (0.059) | (0.060) | (0.014) | (0.019) | (0.028) |
| (2) diabetes X mother employed | 0.017 | 0.009 | -0.075 | -0.011 | -0.034* | -0.041 |
| | (0.026) | (0.064) | (0.062) | (0.015) | (0.020) | (0.030) |
| (1) + (2) | 0.004 | -0.020 | -0.062*** | -0.005 | -0.002 | -0.037*** |
| | (0.009) | (0.023) | (0.023) | (0.004) | (0.006) | (0.011) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 13,590 | 12,417 | 12,494 | 12,135 | 13,590 | 12,443 |
| C: Low vs. high wage income (0/1) | | | | | | |
| (1) diabetes | 0.006 | -0.064 | -0.002 | -0.006 | 0.005 | -0.005 |
| | (0.019) | (0.055) | (0.054) | (0.007) | (0.011) | (0.019) |
| (2) diabetes X high income | 0.020 | 0.042 | -0.017 | 0.007 | -0.059** | -0.061 |
| | (0.034) | (0.090) | (0.083) | (0.018) | (0.026) | (0.041) |
| (1) + (2) | 0.026 | -0.022 | -0.019 | 0.001 | -0.053** | -0.066* |
| | (0.029) | (0.072) | (0.063) | (0.017) | (0.024) | (0.035) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 3,486 | 3,221 | 3,239 | 3,167 | 3,486 | 3,248 |
| D: Single parent household (0/1) | | | | | | |
| (1) diabetes | 0.006 | -0.017 | -0.063*** | -0.005 | 0.011* | -0.037*** |
| | (0.009) | (0.023) | (0.023) | (0.005) | (0.006) | (0.011) |
| (2) diabetes X single parent HH | -0.006 | -0.056 | 0.090 | 0.016 | -0.035 | 0.041 |
| | (0.030) | (0.069) | (0.068) | (0.015) | (0.023) | (0.032) |
| (1) + (2) | -0.000 | -0.073 | 0.027 | 0.011 | -0.023 | 0.004 |
| | (0.029) | (0.063) | (0.065) | (0.014) | (0.022) | (0.030) |
| Outcome Mean | 0.797 | -0.008 | -0.009 | 0.967 | 0.912 | 0.716 |
| Observations | 13,653 | 12,449 | 12,529 | 12,177 | 13,653 | 12,490 |

Notes: All regressions condition on characteristics pertaining the child and mother as well as cohort, spacing, parity and test year FE Math GPA and Danish GPA are standardized and are thus measured as z-scores. Standard errors (in parentheses) are clustered at the matched group level. *** p<0.01, ** p<0.05, * p<0.1

**Table 7** OLS regressions: Age at Sibling's onset

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Age at onset | | | |
| | 2-5 yrs | 6-9 yrs | 10-12 yrs | 13-15 yrs |
| A: On-time Graduation | | | | |
| Diabetes | -0.005 | 0.001 | 0.021 | -0.002 |
| | (0.022) | (0.017) | (0.016) | (0.018) |
| Outcome mean | 0.792 | 0.793 | 0.806 | 0.795 |
| Observations | 2,424 | 4,152 | 3,930 | 3,246 |
| A: Math 9th grade Exit Exam | | | | |
| Diabetes | 0.011 | -0.044 | -0.014 | -0.025 |
| | (0.054) | (0.040) | (0.043) | (0.044) |
| Outcome mean | -0.079 | -0.008 | -0.01 | 0.046 |
| Observations | 2,205 | 3,778 | 3,567 | 2,954 |
| B: Danish 9th grade Exit Exam | | | | |
| Diabetes | -0.031 | -0.077** | -0.010 | -0.067 |
| | (0.052) | (0.039) | (0.041) | (0.049) |
| Outcome mean | -0.052 | -0.017 | -0.003 | 0.026 |
| Observations | 2,227 | 3,798 | 3,588 | 2,971 |
| C: Passed 9th grade Exit Exam | | | | |
| Diabetes | -0.007 | -0.003 | -0.002 | -0.001 |
| | (0.011) | (0.008) | (0.009) | (0.009) |
| Outcome mean | 0.964 | 0.971 | 0.966 | 0.966 |
| Observations | 2,158 | 3,687 | 3,487 | 2,889 |
| D: Enrollment into further education | | | | |
| Diabetes | 0.025* | 0.011 | -0.011 | 0.010 |
| | (0.013) | (0.011) | (0.012) | (0.012) |
| Outcome mean | 0.906 | 0.912 | 0.912 | 0.917 |
| Observations | 2,424 | 4,152 | 3,930 | 3,246 |
| E: Enrollment into High School vs. Vocational school | | | | |
| Diabetes | -0.027 | -0.030* | -0.028 | -0.033 |
| | (0.023) | (0.018) | (0.018) | (0.021) |
| Outcome mean | 0.700 | 0.716 | 0.720 | 0.721 |
| Observations | 2,196 | 3,786 | 3,584 | 2,976 |
| Sibling with diabetes mean age at onset | 5.431 | 8.643 | 10.88 | 11.65 |

Notes: All regressions condition on characteristics pertaining the child and mother as well as cohort, spacing, parity and test year FE. Math GPA and Danish GPA are standardized and are thus measured as z-scores. Standard errors (in parentheses) are clustered at the matched group level. *** p<0.01, ** p<0.05, * p<0.1

**Table 8** OLS regressions: The effects of having a sibling with diabetes on school well-being

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Outcome | Self efficacy | Social wellbeing | Academic confidence | Intrinsic Motivation |
| Diabetes | -0.006 | -0.076 | -0.121* | 0.030 |
| | (0.057) | (0.057) | (0.065) | (0.056) |
| Outcome mean | 0.036 | 0.057 | -0.040 | -0.006 |
| Observations | 1,736 | 1,697 | 1,666 | 1,736 |

All regressions condition on characteristics pertaining the child and mother as well as cohort, spacing, parity and survey year FE. Standard errors (in parentheses) are clustered at the matched group level.

*** p<0.01, ** p<0.05, * p<0.1

## Appendix A: Factor Analysis

To construct our outcomes regarding the children's well-being in school we conduct an explorative factor analysis on the 2015-2017 National Well-being Surveys. The survey was first implemented in all public schools in the spring of 2015. We use the version targeted at fourth through ninth graders which consists of 40 items.

We initially exclude the questions related to the physical environment and peace and order. The remaining 33 questions show a Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) of 0.93 indicating excellent conditions for the use of factor analysis. We extract factors using maximum likelihood and subsequently rotate them using oblique (promax) rotation. We sequentially exclude items with loadings below 0.32 or items that cross load. The final model consists of six factors. To test internal reliability, we calculate Cronbach's alphas for each factor. The alphas range between 0.68 and 0.84 indicating good internal reliability. Finally, we assess whether the factors could be given reasonable names based on the wording of the items that are grouped together. The loadings of the final model including Cronbach's alphas are reported in Appendix Table A. The table show a clear factor structure with high loadings where no items load on multiple factors. As a final test we investigate the resulting factor structure in a confirmative factor analysis. The chi-square test highly rejects the hypothesis that the factor model is no better than the saturated model. Furthermore, the model has a root mean square of approximation (RMSEA) equal to 0.049, the comparative fit index (CFI) is equal to 0.953, and the standardized root mean square residual (SRMR) is equal to 0.036, all of which indicates good fit. We calculate summated scores for each of the variables (items are standardized within grade and cohort before calculating the scores). The final outcomes are standardized with mean zero and variance one.

*Appendix table A Factor analysis - The National Well-being Survey*

| | Factor 1 | Factor2 | Factor 3 | Factor 4 | Factor 5 | Factor 6 | Alpha |
|---|---|---|---|---|---|---|---|
| **Self efficacy** | | | | | | | 0.68 |
| q6: How often can you find solutions to problems as long as you try hard enough? | 0.027 | -0.007 | -0.010 | **0.666** | -0.006 | -0.029 | |
| q7:How often can you achieve your goals? | -0.031 | 0.163 | -0.025 | **0.613** | -0.036 | 0.014 | |
| q22: If something is difficult for me in the lesson I can help myself move on. | 0.007 | 0.161 | 0.088 | **0.429** | 0.028 | 0.033 | |
| **Academic confidence** | | | | | | | 0.80 |
| q28: What do your teachers think of your improvements in school? | -0.008 | **0.684** | 0.002 | -0.034 | 0.022 | -0.005 | |
| q29: I perform well in school. | -0.004 | **0.780** | -0.033 | 0.081 | -0.021 | 0.010 | |
| q30: I make good academic improvements in school. | 0.032 | **0.828** | 0.004 | -0.036 | 0.009 | -0.006 | |
| **Intrinsic motivation** | | | | | | | 0.82 |
| q19: Are the lessons boring? | -0.014 | -0.044 | **0.831** | -0.072 | -0.009 | 0.068 | |
| q20: Are the lessons exciting? | 0.007 | -0.037 | **0.868** | 0.057 | -0.033 | -0.034 | |
| q31: The teaching makes me want to learn more. | 0.045 | 0.200 | **0.565** | 0.002 | 0.061 | -0.028 | |
| **Codetermination** | | | | | | | 0.69 |
| q16: Are you and your classmates involved in deciding what to work on in class? | 0.016 | -0.047 | 0.097 | 0.056 | **0.497** | -0.014 | |
| q37: The teachers make sure that the students ideas are used in the lessons. | 0.007 | 0.006 | -0.027 | -0.028 | **0.966** | 0.020 | |
| **Social well-being** | | | | | | | 0.84 |
| q2: Do you like your class? | **0.760** | -0.043 | 0.045 | 0.002 | -0.036 | -0.053 | |
| q9: Do you feel lonely? | **0.522** | -0.033 | -0.090 | 0.018 | -0.036 | 0.232 | |
| q13: How often do you feel safe in school? | **0.526** | 0.004 | 0.032 | 0.103 | -0.019 | 0.106 | |
| q33: I feel that I belong at my school. | **0.688** | 0.093 | 0.062 | -0.072 | -0.004 | 0.030 | |
| q35: Most of the students in my class are friendly and helpful. | **0.787** | -0.0236 | 0.0141 | -0.0159 | 0.0473 | -0.1132 | |
| q36: Other students accept me for who I am. | **0.7416** | 0.035 | -0.063 | 0.015 | 0.032 | -0.012 | |
| **Somatic symptoms** | | | | | | | 0.67 |
| q10 How often do you have stomach aches? | -0.034 | 0.004 | -0.011 | 0.023 | 0.008 | **0.762** | |
| q11: How often do you have headaches? | -0.003 | 0.002 | 0.046 | -0.045 | 0.025 | **0.666** | |

Factorloadings from the factor analysis on the National Well-being Survey N=708,323. Factors are extracted using maximum likelihood and oblique (promax) rotation. Factor loadings above 0.32 in bold.