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In the Shadow of Brothers: Sibling Spillovers in Migrant Families

Anna Hasselqvist*

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Abstract: Academic inequality between migrants and natives is often attributed to family dynamics that are difficult to observe. Siblings provide a way to study them: I estimate the effect of having a high-achieving sibling on the educational outcomes of children in migrant and native families. Using exogenous variation in sibling achievement from Sweden's school-entry cutoff in a Regression Discontinuity Design, I show that second-generation migrant girls face a unique disadvantage. A high-achieving brother lowers their grades, while a high-achieving sister has a small positive influence. Spillover effects are negligible for boys and native children regardless of sibling gender. Heterogeneity analysis suggests that traditional cultural norms contribute to this disadvantage, and parental labor market integration substantially attenuates it.

JEL Classification: I24 J13 J15

Keywords: sibling spillovers, second-generation migrants, gender norms, school starting age

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1 Introduction

School-performance gaps between migrant and native children have long been at the center of public debates (OECD 2018, 2019). Beyond differences in socioeconomic status and language proficiency, these gaps are often linked to growing up in families with different cultural backgrounds (Dustmann and Glitz 2011; Ichino et al. 2024). The educational and labor market trajectories of migrant girls and women are particularly influenced by gender norms from their countries of origin (Fernández and Fogli 2009). Yet the role of post-migration family dynamics in shaping academic inequality among girls and boys, within and across families from different backgrounds, remains poorly understood.

This paper studies how family dynamics shape the academic opportunities of girls and boys in migrant families and how these differ from native children. Because these dynamics are difficult to observe, I study sibling spillovers to capture within-family interactions. An emerging literature shows that sibling spillovers are typically positive, with improvements in one child's human capital or health benefiting their siblings (Qureshi 2018; Nicoletti and Rabe 2019; Figlio et al. 2023). These effects may be particularly salient in migrant families, where siblings are the first generation to grow up together in the host country. However, spillovers need not be uniform. A shock to one child may induce parents to reallocate investments across children because family resources are finite (Currie and Almond 2011; Bharadwaj et al. 2018). In migrant families, such reallocations may reflect gender norms retained from their countries of origin (Giavazzi et al. 2019; Kleven forthcoming), leading parents to invest differently in sons and daughters (Almond et al. 2013; Anukriti et al. 2022; Dahl et al. 2022). Spillover effects can therefore differ by sibling gender composition if parents respond differently to shocks affecting sons and daughters (Dossi et al. 2021; Adamecz et al. 2025).

This paper estimates the causal effect of having a high-achieving older sibling on girls and boys' grade outcomes in migrant and native families. To do so, I exploit Sweden's strict school-entry cutoff, under which children enter public education in the year they turn seven.

The policy creates a sharp cutoff around January 1st that the vast majority of families follow. As a result, children born in late December and early January start school one year apart, and a large literature shows that being older at school entry improves early educational outcomes.[1] This generates plausibly exogenous variation in older siblings' achievement, which I use to estimate spillover effects on younger siblings' outcomes. I also provide evidence that being older at school start improves school outcomes for both native and migrant older siblings in the sample.

The strict school-entry cutoff allows me to compare children with older siblings born just before and just after the January 1st cutoff in a Regression Discontinuity Design. Theoretically, the spillovers may operate through role-model effects (Karbownik and Özek 2023; Zang et al. 2023) and through changes in parental investment decisions (Currie and Almond 2011; Bharadwaj et al. 2018). These channels can differ between migrant and native families if, as discussed above, parental investment responses reflect gender norms retained from the country of origin. Such differences may be particularly salient in Sweden, a country consistently ranked among the most gender-equal in the world while receiving refugees and migrants from countries with lower levels of gender equality.[2] This has led to an ongoing public debate in Sweden about gender norms among minority groups that diverge from those of the majority society, and their potential consequences for girls' outcomes.[3]

The analysis makes use of detailed Swedish administrative data that link siblings within families and provide rich information on parental origins. This allows for separate regressions by migrant background and sibling-gender composition. Outcomes include students' final grade-point average (GPA), Swedish and math grades when they leave compulsory school at 15/16 years old. I also consider whether the student was enrolled in the regular Swedish

[1] Several studies document positive effects in the short run (Bedard and Dhuey 2006; Mühlenweg and Puhani 2010; Dhuey et al. 2019; Cook and Kang 2020; Cavallo et al. forthcoming, e.g.) and, to some extent, in the long run (Angrist and Krueger 1991; Black et al. 2011; Fredriksson and Öckert 2014), with mixed evidence on heterogeneity (Datar 2006; McEwan and Shapiro 2008; Puhani and Weber 2008; Cook and Kang 2020; Elder and Lubotsky 2009; Fredriksson and Öckert 2014; Suziedelyte and Zhu 2015; Leuven et al. 2010).

[2] Appendix Table A1 provides comparative measures of human development and gender inequality.

[3] Consistent with this, Swedish policymakers have repeatedly revisited legislation addressing gender-based coercive control linked to family norms in migrant communities (SOU 2020:57; SOU 2025:59).

track as opposed to the "Swedish as a Second Language" track at the start of the final year.

The migrant sample consists of all siblings born in Sweden to two non-Nordic parents between 1988-2004. I refer to them as second-generation migrants.[4] In order to have a comparable sample of natives I include all siblings born to at least one Swedish born-parent in families with average family incomes at the 20th percentile or below. I refer to these as native families with low socioeconomic status.

The main findings show that second-generation migrant girls face a unique disadvantage as spillovers depends critically on the sibling's gender. Strikingly, having a high-achieving older brother reduces a girl's GPA at the end of compulsory schooling by over 17 percent of a standard deviation. In contrast, having a high-achieving older sister has a small positive effect on the younger sister's school outcomes. For second-generation migrant boys, on the other hand, there are no spillover effects of having a high-achieving sibling, regardless of gender.

If generalizable to comparable native families, these spillover effects could be interpreted as consistent with the broader finding that opposite-sex siblings may exert more adverse influences than same-sex siblings (Adamecz et al. 2025). However, further analysis shows that girls in native families with low socioeconomic status are not disadvantaged by having a high-achieving brother. Instead, both native girls and boys are similarly (un)affected by a high-achieving older sibling, with effects being close to zero and statistically insignificant.[5] The stark negative effects of having a high-achieving older brother is thus unique for second-generation migrant girls.

One alternative explanation is that growing up with an older brother is in itself detrimental for second-generation migrant girls, irrespective of the older sibling's academic achievement. However, estimating the effect of having a first-born brother rather than a first-born

[4] This ensures accurate dates of birth and allows me to test for any birth-manipulation around the cutoff. Including first-generation migrants would lead to an over-representation of January 1st birthdates, often assigned to undocumented migrants in Sweden.

[5] These results differ from previous studies documenting positive spillover effects in among poor families in the US (Karbownik and Özek 2023; Zang et al. 2023), suggesting that spillovers may be context-specific.

sister on younger siblings' GPA shows that having an older brother negatively affects all children in Sweden, regardless of gender or family background. This suggests that the disadvantage faced by second-generation migrant girls is not driven by having a brother per se, but by having a high-achieving older brother.

Heterogeneity analysis on three potential channels point toward parental investment decisions as the key mechanism. First, the negative spillover of a high-achieving older brother is concentrated among families from more gender-traditional origins, as it is present for both younger sisters and brothers in the most traditional households. Second, parental labor market integration substantially attenuates the negative spillover for girls with high-achieving brothers. Third, neither family size nor living conditions appear to meaningfully influence sibling spillovers, which helps rule out resource dilution or crowding as alternative explanations.

These findings suggest that son-preferential investments reflect the salience of origin-country gender norms within the household, and that integration reduces this salience. The positive influence of parents' labor market integration on the family can operate through several channels. First off it is consistent with a conceptual framework where a parent invests in two sibling's human capital production function under a budget constraint. Increased family earnings relaxes this budget constraint alleviating more resources to the children. Second, labor market integration exposes migrant parents to host-country norms and expands their social and professional networks, potentially updating their beliefs about daughters' labor market prospects. Lastly, when both parents work full-time, children gain access to formal early childcare. Early childcare has been shown to generate particularly large human capital returns for children with migrant backgrounds (Drange and Telle 2015; Corazzini et al. 2021), and for daughters in households with a strong son preference, it may further substitute for parental investment that would otherwise fall short (Cunha and Heckman 2007).

More broadly, the results identify an overlooked source of educational inequality operating within the family. They suggest that second-generation migrant girls may face a systematic disadvantage when parental investments favor sons, particularly in households where traditional gender norms persist. That parental labor market integration substantially attenuates this disadvantage suggests that integration policies can promote not only parents' economic outcomes, but also more equal academic outcomes among their children.

This paper contributes to the growing literature on sibling spillovers. Policies that improve one sibling's school performance generally have positive spillovers on younger siblings' skill formation (Qureshi 2018; Nicoletti and Rabe 2019; Karbownik and Özek 2023; Figlio et al. 2023; Zang et al. 2023), and older siblings' choice of university major strongly influences younger siblings' choices (Altmejd et al. 2021).[6] Recent work shows that sibling influences can be heterogeneous by gender composition: son preference reduces girls' math performance (Dossi et al. 2021), and having a twin brother lowers girls' self-assessed math ability (Adamecz et al. 2025). This paper makes a novel contribution by showing that a positive shock to one sibling's human capital can instead harm the other's, when parents hold biased preferences across children. Migrant families offer an ideal setting for this analysis. Although siblings grow up in the host country, they are raised by parents whose gender norms may differ vastly from those of the majority society.

This paper also contributes to the literature on culture and the outcomes of girls and women with migrant backgrounds. Existing studies show that more traditional gender norms in parents' countries of origin adversely affect second-generation women's labor market outcomes (Fernández and Fogli 2009; Blau et al. 2013; Kleven forthcoming) and educational achievement (Nollenberger et al. 2016). Related work documents how norm and religious beliefs as well as policy changes shape migrant parents' investments in daughters (Mitrut and Wolff 2014; Dahl et al. 2022), for example that migrant girls especially benefit from early external investments such as access to childcare (Drange and Telle 2015; Corazzini et al.

[6] Sibling health and school performance are also positively correlated: negative health shocks to one child harm siblings' school performance (Fletcher et al. 2012; Black et al. 2021), while positive health shocks and medical treatment have positive spillovers on siblings (Bharadwaj et al. 2018; Daysal et al. 2022).

2021). Bergvall (2024) exploits a Swedish refugee placement policy and shows that traditional maternal gender norms widen the sibling-gender gap in mathematics, but that access to more gender-equal local labor markets mitigates these effects. Whereas this literature primarily examines the effects of inherited cultural norms on female outcomes, I focus on how culture interacts with the post-migration family environment. I also identify measures that can alleviate inequalities for girls that may arise from these dynamics during childhood.

The remainder of this paper is organized as follows: Section 2 presents a simple theoretical framework to motivate the empirical analysis. Section 3 describes the institutional setting and data, and Section 4 the empirical strategy. Section 5 presents the results and additional robustness tests. Section 6 explores mechanisms and provides a discussion after which Section 7 concludes.

2 Conceptual Framework

To motivate the empirical analysis, I outline a simple framework that illustrates how an educational shock for one child may affect the human capital of their sibling (Becker 1981; Currie and Almond 2011; Karbownik and Özek 2023). Consider a family with one parent and two children (i = 1, 2), where the parent is altruistic and values the children's lifetime earnings. These earnings are determined by the children's human capital, which is developed during childhood. For simplicity, I assume a single time period. The human capital production function for sibling i is expressed as follows:

$$H_i = f^i(I_i, \sigma_1, \sigma_2) \tag{1}$$

where I_i represents parental investment, and σ_1 and σ_2 are the school starting ages of each child. The production function of child $i's$ human capital, $f^i(\cdot)$, is assumed to be strictly increasing in all of its arguments and strictly concave in I_i. Additionally, I assume a higher school starting age increases the marginal return to parental investments, meaning that I_i

and σ_i complement each other in the production of human capital. This assumption captures the notion that if a child enters school later, they will require greater parental investment beforehand to fully benefit from late school entry.

The parent derives utility from their children's human capital, subject to a budget constraint:

$$U = U(\gamma_1 H_1, \gamma_2 H_2) \quad \text{s.t} \quad y = I_1 + I_2. \tag{2}$$

The utility function is assumed to be strictly increasing and concave in its arguments. The parameters $\gamma_1 = \gamma$ and $\gamma_2 = 1 - \gamma$ represent the parent's preferences for each child's human capital. I will refer to the parent's preferences as *neutral* if they value both children's human capital equally ($\gamma_1 = \gamma_2$). In contrast, the parent is considered to have *biased* preferences if they place greater value on one child's human capital over the other ($\gamma_1 > \gamma_2$ or $\gamma_1 < \gamma_2$). The first-order condition that characterizes the optimal level of parental investment becomes $I_1^* = I_1^*(\sigma_1, \sigma_2, \gamma_1, \gamma_2, y)$.[7] For more details see Appendix B.

I examine how an increase in the school starting age for child 1, σ_1, influences the human capital of both that child and their sibling, child 2, and to explore the role of parental investment adjustments in this process. The effect on the focal child ($i = 1$) is given by:

$$\frac{\partial H_1^*}{\partial \sigma_1} = \underbrace{\frac{\partial f^1(I_1^*, \sigma_1, \sigma_2)}{\partial \sigma_1}}_{\substack{\text{maturity} \\ \text{effect}}} + \underbrace{\frac{\partial f^1(I_1^*, \sigma_1, \sigma_2)}{\partial I_1} \frac{\partial I_1^*}{\partial \sigma_1}}_{\substack{\text{investment} \\ \text{adjusmtent}}}. \tag{3}$$

The first term represents the direct impact of the policy, which can be interpreted as the maturity advantage effect of late school entry, an effect frequently emphasized in the empirical literature. The second term shows how this effect may be either amplified or reduced through adjustments in parental investments.

[7] For simplicity, I abstract from two-parent households, in line with the literature. In practice, parents may have different preferences, and parental investment decisions can reflect a combination of bargaining power, gender identity, and cultural norms (Bertrand et al. 2015; Cortés and Pan 2023; Ichino et al. 2024). Section 6 shows that the results are similar when heterogeneity is defined by either maternal or paternal employment.

Next, using that $\partial I_2^*/\partial\sigma_1 = -\partial I_1^*/\partial\sigma_1$, the effect on the non-focal child ($i = 2$) is described as:

$$\frac{\partial H_2^*}{\partial\sigma_1} = \underbrace{\frac{\partial f^2(I_2^*, \sigma_1, \sigma_2)}{\partial\sigma_1}}_{\substack{\text{role model}\\ \text{effect}}} - \underbrace{\frac{\partial f^2(I_2^*, \sigma_1, \sigma_2)}{\partial I_2}\frac{\partial I_1^*}{\partial\sigma_1}}_{\substack{\text{investment}\\ \text{spillover}}}. \tag{4}$$

In this case, the first term represents a role model effect, capturing the direct effect of child 1's late school entry on child 2's human capital. The second term accounts for the impact of parental investment spillovers, showing how adjustments in parental investment in response to changes in σ_1 affect the human capital of child 2.[8]

The overall effect on both children depends on the sign and magnitude of the parental investment response, $\partial I_1^*/\partial\sigma_1$, which I formally derive in Appendix B. Assuming symmetric production functions ($f^i(\cdot) = f(\cdot)$), the results can be summarized as follows. When preferences are neutral ($\gamma_1 = \gamma_2$), the investment response is small. The complementarity between I_1 and σ_1 incentivizes greater investment in the focal child, but this is offset by the equal utility cost of reducing I_2. The dominant forces are therefore the maturity advantage effect for the focal child (first term in eq. 3) and the role model effect for the sibling (first term in eq. 4).

When preferences are biased toward the focal child ($\gamma_1 > \gamma_2$), the utility cost of reducing I_2 receives less weight, so the parent reallocates investment toward child 1. This amplifies the maturity advantage effect for the focal child while generating a negative investment spillover on the sibling. If the role model effect is also small, the net effect on the sibling's human capital may be negative.[9]

In summary, the model shows how sibling spillovers from late school entry can be tied to parental investment decisions, which in turn may be shaped by both cultural background

[8] Older school entry may affect younger siblings through multiple channels. It improves the older sibling's educational outcomes but also keeps the sibling at home for an additional year. Since most Swedish children attend formal childcare before school, the latter channel is likely limited, but may be more relevant when parents are not employed. Section 6 examines this possibility through heterogeneity by parental employment during the preschool years.

[9] The symmetric case, where preferences are instead biased toward the sibling ($\gamma_1 < \gamma_2$), reverses this logic, attenuating the focal child's gains while benefiting the sibling.

and economic circumstances. In the context of this paper, native and migrant families may differ along both dimensions: parents who have grown up in different cultures may hold different norms and values regarding the allocation of investments across children, and migrant families may face different economic conditions and labor market opportunities than native families. To address the latter in the empirical analysis, I restrict the native comparison group to families with comparable annual earnings to migrants.[10] Nevertheless, differences in labor market integration between the two groups may remain, as most migrant parents must integrate into the host country labor market over time, while native parents face no such integration process.

These factors can influence both the direct effect of late school entry on the focal child and the spillover to the younger sibling. In Section 4.1 I present estimates of the direct effects for first-born children in native and migrant families. In Section 6 I explore several potential mechanisms, including how family cultural origin and parental labor market integration impacts the main results.

3 Institutional Setting and Data

3.1 Institutional Setting

In Sweden education from first grade onwards is compulsory for nine years and publicly funded.[11] Compulsory school is comprehensive and all students follow the same curriculum. Students attend their local public school or can opt out to a voucher-funded independent school, or a public school in a different neighborhood. After graduating from ninth grade,

[10] This also relates to a more theoretical concern. The discussion above assumes a symmetric human capital production function $f(\cdot)$ across children. When production technologies differ, however, the parental investment response to an increase in σ_1 can become non-neutral even under neutral preferences. For instance, if the focal child enjoys a large maturity advantage (first term in eq. 3), the parent may reduce investments in that child and redirect them toward the sibling to equalize human capital outcomes. An ideal test of the preference-based explanation would therefore require identifying families with identical production technologies to the treatment group but without gender-biased preferences. In practice, I address this by comparing migrant families to native families with similar socioeconomic characteristics.

[11] In 2018 the pre-school class became mandatory and thus extended compulsory schooling to ten years.

almost all students move on to upper-secondary education which includes academically oriented programs, vocational programs and preparatory programs for ineligible students. Since 1998 there are formal eligibility criteria for upper-secondary education, consisting of a lower performance threshold (passing mathematics, Swedish and English). Students who do not meet the eligibility criteria typically do not re-take year nine—instead they participate in a preparatory upper-secondary program. However, it is not impossible to skip or retake a grade in the Swedish system, nor is it impossible to delay school start.

All education systems have school-entry cutoff rules, but how strict the rules are is at the hand of policy makers (Puhani and Weber 2008; Oosterbeek et al. 2021). In Sweden, children start first grade in the year they turn seven.[12] This rule allows minimal discretion for parents to delay or advance their child's school entry, and nearly all children start on time.[13] It is also uncommon that children face retention during school. There is no formal criteria for 'passing' a grade and to move up to the next year group.

The only tracking in Swedish compulsory schools is for migrant students who are deemed not able to follow the standard Swedish curriculum. They are offered an alternative course plan in the Swedish subject ("Swedish as a second language"). Students who follow the alternative course plan are graded according to the criteria of the "second language" course track, but these students take the same centralized exams as the students on the standard course track.

Sweden has a long tradition of receiving migrants, particularly refugees from conflict-affected countries. Over time, the share of children with migrant backgrounds has increased steadily, reaching approximately 24 percent in 2018 (Statistics Sweden 2020).[14] These children are more likely to grow up in low-income households and to have parents with at most a secondary-level education.

[12] A year of "pre-school class" has been offered to six-year-olds since 1998. The children often attend the pre-school class in the same building as the elementary school children, though it is considered its own school form. Between 1998-2018 the pre-school class was not mandatory.

[13] Among school starters in the 2002-2004 birth cohorts, 99 percent of both natives and migrant students started school on time. First-grade enrollment is available for these cohorts in the dataset 'Elevregistret'.

[14] Refers to first- and second-generation migrants combined.

Appendix Figure A1 compares migrant and native families. Figure (a) shows that migrant families have lower average earnings when the child is of childcare age. This is driven partly by migrant mothers earning significantly less than native mothers at this stage, as shown in Figure (b). The large mass point at zero indicates many migrant mothers do not work at all before their child starts school. Figure (c) shows that most migrant mothers come from low- to medium-HDI countries, including all African countries plus Middle Eastern countries such as Iran, Iraq, and Turkey. Meanwhile a minority comes from high/very-high-HDI countries, including larger migrant-sending countries like Chile, Poland, and former Yugoslavia.[15]

These socioeconomic differences have two important implications. First, many second-generation migrant children grow up with mothers who are only weakly integrated into the labor force, which functions as a proxy for overall integration in society. Second, since childcare access in many Swedish municipalities depends on parental employment, these children likely spend more time at home before school start. I do not observe childcare attendance in the data, but migrant children's enrollment rates today are known to fall well below the 95% national average (Hall et al. 2025).

Migrant and native families also differ in fertility patterns. Appendix Figure A2 shows evidence of son preference among migrant families that is absent for native families. Figure (a) plots confidence intervals for the average number of siblings of first-born girls and first-born boys. In migrant families, first-born girls have almost one more sibling (0.8) than first-born boys, and this difference is statistically significant since the confidence intervals do not overlap. In contrast, first-born boys are slightly more likely to have more siblings than first-born girls in native families, though this difference is small in absolute terms. Figure (b) plots confidence intervals for birth spacing, defined as the number of years between the births of the first and second child. Migrant families with a first-born daughter have their second child about 7 months earlier, on average, than migrant families with a first-born son. Among native families, there is no significant difference.

[15] HDI classifications follow definitions from the United Nations Development Programme (UNDP) which publishes the index. Appendix Table A1 details the classification of all country groups in the sample.

3.2 Data and Summary Statistics

The paper uses administrative data from Sweden, including school records for all children matched with population and employment data from several registers covering the population.[16] I link all siblings by their parents' unique id-numbers in the data and define their migrant status based on detailed information on the family's migration background.

The main sample consists of all siblings born in Sweden to two foreign-born non-Nordic parents between 1988-2003. The exclusion of first-generation migrant children is motivated by the practice of subscribing children a birthdate of January 1st if they arrive in Sweden without proper documentation. Children of Nordic migrants are also excluded from the sample due to the close proximity in language, social institutions and culture among the Nordic countries.[17] In order to have a comparable sample of natives I restrict the sample of native families to those with comparable socioeconomic background to migrants. This includes families whose annual earnings are at the 20th percentile or below when the first-born child was of childcare age.[18] I discuss this further in section 4.1 and provide additional tests.

The main outcomes include the students' final grade point average (GPA), and their Swedish and math grades at the end of compulsory school.[19] The final GPA is particularly important as it determines the upper-secondary school track the student can enter. While the Swedish grade reflects language proficiency, the math grade captures cognitive skills that depend less on language. All grade outcomes are standardized to have a mean of zero and a standard deviation of one.[20] As an additional outcome, I consider whether the student was

[16] From the 'Multiple Generations' population register, education records for the students' final year of compulsory school, and the longitudinal 'LOUISE' database on education, earning and occupation.

[17] This includes Denmark, Norway and Finland. Majority of excluded observations have Finnish parents, many of whom are likely to be part of the Swedish-Finnish minority population.

[18] The earning percentiles are jointly calculated for the families in the native and second-generation migrant samples.

[19] The grades are set by the students' own teachers but are (in part) based on national standardized tests.

[20] This is standard practice due to some changes in the grading scale during the 20-year long time window. Outcomes for students with Swedish as a second language are standardized within its specific distribution.

enrolled in the regular Swedish track or the "Swedish as a Second Language" track at the start of their final year of compulsory school.

The data contains detailed information on parents' background. Importantly, it includes parents' "country group" origin and the year they arrived in Sweden.[21] The data also includes detailed information on parents' education and earnings measured after the child is born (and birthdate is realized), but before the child enters school.[22] For balance tests I use measures of parents' earnings and years of education when their first-born child is of daycare age.

Table 1 presents summary statistics for younger siblings. Column (1) covers all second-generation migrants while columns (2)–(3) split the estimation sample, those with oldest siblings born November through February, by gender. Column (4) covers all natives, and columns (5)–(6) restrict the sample to families with low socioeconomic status.

In terms of school outcomes, second-generation migrant girls receive higher grades at the end of compulsory school than migrant boys and natives in families with low socioeconomic status. Around 65 percent of second-generation migrant girls and boys attend the standard Swedish education track, as opposed to the "Swedish as a second language" track.

The education level of parents in migrant families and low-income families averages about one year less than the native population overall. Migrant fathers' earnings rank at a relatively higher percentile than those of native fathers in low-income families. This is largely mechanical, since the native estimation sample is selected on low family earnings, which are primarily driven by fathers. Migrant mothers, by contrast, earn less than native mothers in low-income families.

Compared to the average native family, both second-generation migrant families and low-income native families have more siblings, younger mothers, and more migrant neigh-

[21] Country groups are predefined in the data and consist of countries with close geographical and cultural identities. All country groups are listed in Appendix Table A1.

[22] Ideally, parental background should be measured before the first-born child's birth., Mother's and father's years of schooling is measured when the first-born child is 5 years old, and parental earnings are the mean of labor earnings when the first-born child is aged 3–5. I percentile rank parental earnings within the birth cohort of the child to facilitate comparisons of status across birth years.

Table 1: Summary Statistics Younger Siblings

	Second-Generation Migrants			Natives			
	(1) All	(2) Girls	(3) Boys	(4) All	(5) Low-SES	(6) Girls	(7) Boys
School outcomes							
GPA	-0.175	-0.015	-0.344	0.001	-0.435	-0.262	-0.620
	(1.044)	(1.044)	(1.043)	(0.974)	(1.123)	(1.135)	(1.087)
Swedish grade	-0.257	-0.026	-0.486	-0.005	-0.330	-0.054	-0.610
	(0.956)	(0.976)	(0.893)	(0.984)	(1.004)	(1.034)	(0.901)
Math grade	-0.234	-0.219	-0.239	0.011	-0.338	-0.312	-0.380
	(0.958)	(0.973)	(0.959)	(0.987)	(0.949)	(0.956)	(0.938)
Std. Swedish track	0.655	0.675	0.630	0.996	0.986	0.984	0.984
	(0.475)	(0.468)	(0.483)	(0.063)	(0.119)	(0.124)	(0.126)
Background characteristics							
Father years school	11.221	11.220	11.150	12.022	11.183	11.167	11.178
	(2.505)	(2.530)	(2.490)	(2.081)	(1.907)	(1.917)	(1.908)
Mother years school	10.870	10.881	10.829	12.220	11.299	11.281	11.281
	(2.444)	(2.464)	(2.398)	(1.903)	(1.821)	(1.837)	(1.851)
Father earnings (pctl)	22.102	22.080	21.551	53.354	13.624	13.605	13.558
	(22.603)	(22.490)	(22.074)	(27.094)	(8.637)	(8.703)	(8.613)
Mother earnings (pctl)	21.253	20.998	21.205	51.502	27.150	26.915	27.060
	(21.553)	(21.044)	(21.399)	(25.485)	(18.203)	(18.007)	(18.075)
Migrants neighborhood	0.346	0.351	0.345	0.078	0.101	0.102	0.101
	(0.242)	(0.247)	(0.242)	(0.081)	(0.124)	(0.124)	(0.123)
Number of siblings	1.851	1.905	1.856	1.442	1.562	1.579	1.583
	(1.035)	(1.091)	(1.057)	(0.690)	(0.832)	(0.864)	(0.864)
Birth spacing	46.079	46.138	46.685	40.285	41.307	41.421	41.625
	(29.719)	(29.571)	(30.464)	(24.242)	(27.206)	(27.638)	(27.498)
Mother age first birth	25.229	25.322	25.282	27.002	25.601	25.632	25.554
	(4.633)	(4.700)	(4.648)	(4.257)	(4.810)	(4.831)	(4.841)
Mother age birth obs.	29.066	29.166	29.170	30.359	29.044	29.084	29.026
	(4.902)	(4.963)	(4.878)	(4.434)	(5.001)	(5.049)	(5.042)
Observations	46,641	7,525	7,653	481,645	63,625	10,151	10,293

Notes: This table provides sample means and standard deviations (in parentheses) for younger siblings. Column (1) includes all second-generation migrant children. Columns (2)-(3) include girls and boys in the estimation sample, i.e. those whose first-born sibling was born in November-February. Column (4) includes all children with at least one Swedish-born parent. Column (5) includes children in families with low socioeconomic status and Columns (6)-(7) restrict this sample by gender. All grade outcomes are standardized to have a mean of zero with a standard deviation of one. Parental years of schooling and earnings are measured when the first-born child is age 3-5. Neighborhoods are measured as Small Areas for Market Statistics (SAMS).

bors. Children in migrant families average 1.8 siblings versus 1.6 among low-income natives. Meanwhile residential segregation is pronounced. Migrant families live in neighborhoods that are 35% migrant on average, compared to 10% for low-income natives. Mothers in both groups have their first child roughly two years earlier than the native average.

4 Method

4.1 Empirical Strategy

The aim of this paper is to study the spillover effect of having a high-achieving sibling on the school outcomes of girls and boys in migrant and native families. Since siblings' cognitive skills are likely similarly influenced by both nature and nurture, one needs to have some quasi-random assignment of a high-achieving sibling.

For this reason, I leverage exogenous variation in achievement for children born close in time around the Swedish cutoff for compulsory education. In Sweden, all children start school in the year they turn seven, which means that January 1st is the school-admission cutoff. Although most children adhere to the rule, some children may be allowed to start school early based on their anticipated academic ability and school readiness, while other children may be held back one year. Due to this potential endogeneity issue I use "expected" school starting age given by date of birth. Those born in the January will be older at school entry in September than those born a few weeks before in December.

Following previous literature, I employ a regression discontinuity design (RDD) which considers children born just around the cutoff (Black et al. 2011; Fredriksson and Öckert 2014; Karbownik and Özek 2023). Their birth year and school starting age is as good as random, under the assumption that parents cannot exactly plan the conception and birthdate of their child. Since I am interested in the sibling spillovers, I estimate the effect of having a first-born sibling i born after the January 1st cutoff on the younger siblings' j's outcomes:

$$y_j = \alpha + \beta_1 After_{ic} + \beta_2 f(r_i) + \beta_3 (After_{ic} \times r_i) + \theta_c + \epsilon_{jc} \tag{5}$$

where y_j refers to the school outcomes of younger sibling j. Treatment variable $After_i$ takes the value 1 if first-born sibling i in school-cohort c is born after the cutoff and is expected to be relatively older at school start than those born before. β_1 is the coefficient of interest.[23] $f(r_i)$ represents a linear control function in the baseline analysis, where r_i is the running variable, the first-born's birthdate, normalized around the January 1st cutoff. θ_c is a birth-cohort fixed effect.

At baseline, I employ a linear estimation with a triangular kernel for weighting observations inside the window around the cutoff. The standard errors are robust to heteroskedasticity but not clustered on the running variable, since the running variable (birth month) is discrete and only takes a limited number of values (Kolesár and Rothe 2018). The bandwidth selected for the main analysis is +/- 60 days around January 1st. In section 5.1 I perform data-driven bandwidth selection which yields marginal-squared-error optimal bandwidths within 48-67 days from the cutoff. This lends support to the choice of 60 days.

I estimate equation (5) separately by subgroups. Specifically, the sample is divided by i) the child's gender, ii) the gender of the first-born sibling, and iii) migrant versus native family background. I focus on first-born siblings since, conditional on having an older sibling, the gender of the first-born is plausibly exogenous and unlikely to be influenced by parental gender preferences. In section 5.1 I include controls for number of sibling and birth spacing as robustness checks.

4.2 Specification Checks

The validity of the empirical strategy relies on the assumption that pre-determined characteristics vary smoothly at the cutoff. I assess this by reporting a number of balance tests in Table 2 for second-generation migrant siblings, and Appendix Table A2 for native siblings in low-income families. These tests regress the first-born sibling's treatment status on characteristics of younger siblings and parents. All tests are conducted separately for girls and

[23] Note that the school-entry age literature has established three different age effects that may influence outcomes in this framework. Apart from the absolute age effect at school start, the relative age of a student compared to classmates, and age at test day may impact outcomes (Cavallo et al. forthcoming). Though not attempted in this paper, some studies have tried to decompose the age effects in different ways (Black et al. 2011; Fredriksson and Öckert 2014; Cascio and Schanzenbach 2016). This paper has a slightly different focus, as the analysis mainly focuses on heterogeneous sibling spillovers across gender and family background. It is likely that the three age effects would impact all children of certain gender and social group the same in the absence of different family structure.

boys in families with oldest brothers, in Panel A., and sisters, in Panel B.

Estimates from balance tests for younger sibling characteristics in columns (1)-(3) examine whether the first-born's school-starting age affects parents' fertility choices. The results show that for the vast majority of younger siblings treatment status is unrelated to whether the younger sibling is born after the cutoff, their birth month, or the spacing between births. The estimate in column (1) of panel A. shows that second-generation migrant boys are less likely to be born after the cutoff if their oldest brother did, significant on the 10-percent level. Column (3) in Panel A. of Appendix Table A2 shows that having a brother born after the cutoff in native families significantly reduces the birth spacing to their younger brothers.

Columns (4)–(7) present estimates from balance tests for parental characteristics. These tests examine whether the first-born's school starting age is related to parental earnings and years of education, both measured while the first-born was of childcare age. Most estimates are statistically insignificant in Table 2 but a few exceptions appear. Their fathers have fewer years of education when the oldest sibling is a brother and more years of education when the oldest sibling is a sister. For second-generation migrant boys, fathers have lower earnings when the oldest sibling is a brother. Appendix Table A2 tells us that for native boys, fathers have higher earnings when the oldest sibling is a sister.

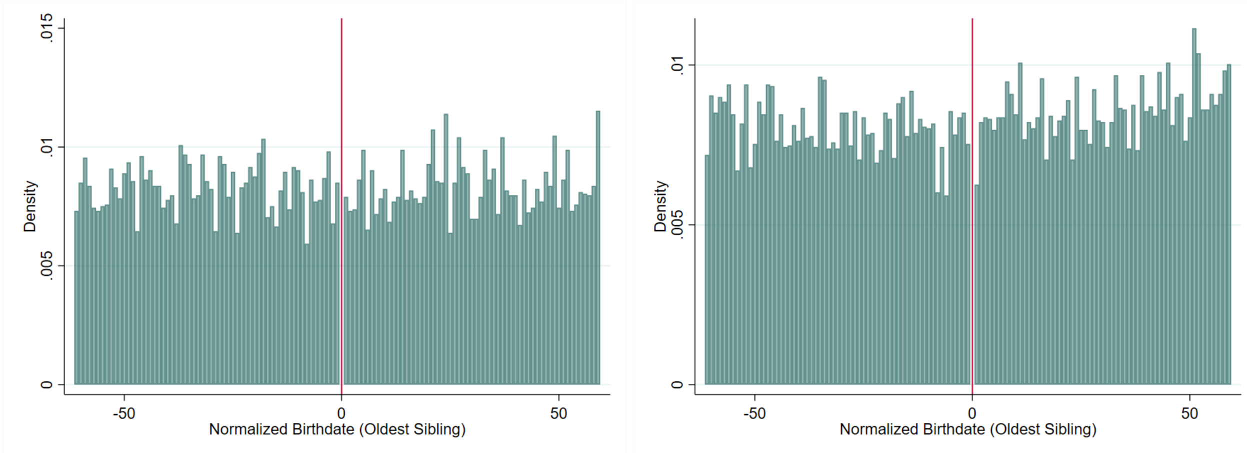
It is worth noting the parental characteristics are measured after the birth of the first-born child and before school entry. This is due to a data limitation since many migrants in the earlier cohorts arrived in Sweden shortly before the birth of their first child, which limits the ability to construct time-consistent measures of earnings and education prior to birth. As a result, the few significant estimates may not necessarily be indicative of systematic sorting around the cutoff. Nevertheless, in Section 5.1 I show that controlling for these variables does not affect the main results.

Validity also relies on a smooth distribution of observations around the cutoff void of manipulation of treatment status (McCrary 2008). Figure 1 shows the distribution of younger siblings over the birthdates of the first-born child and tests for smoothness. The top panel

Table 2: Balance Tests – Second-Generation Migrant Siblings

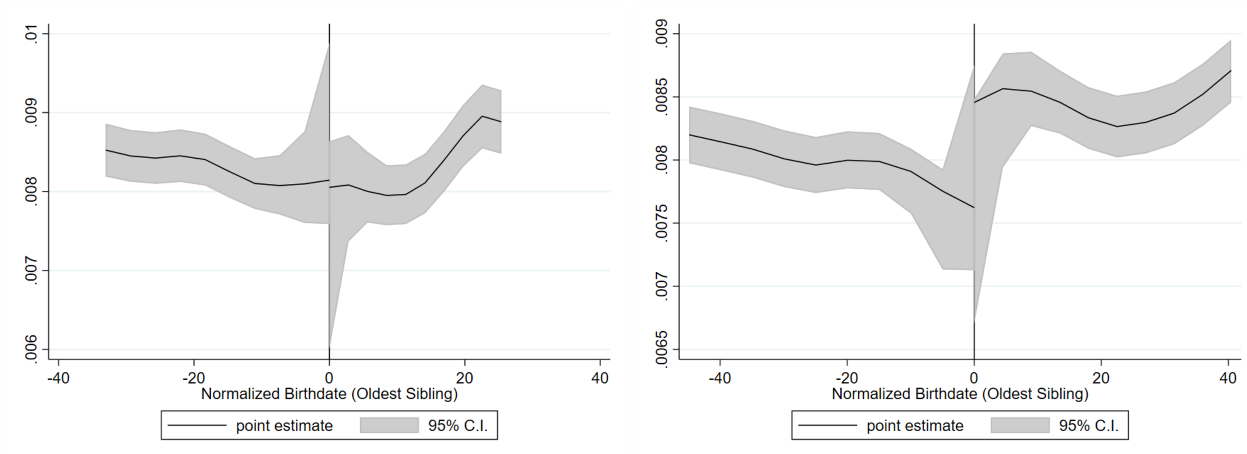
	Siblings			Mothers		Fathers	
	(1) After Cutoff	(2) Birth Month	(3) Birth Spacing	(4) Earnings (Pctl)	(5) Education (Years)	(6) Earnings (Pctl)	(7) Education (Years)
A. Families with oldest brothers							
Younger sisters							
After	-0.020	0.266	1.825	-2.406	0.028	-0.762	-0.348*
	(0.037)	(0.257)	(2.044)	(1.609)	(0.172)	(1.656)	(0.183)
Observations	3,582	3,582	3,582	3,582	3,582	3,582	3,582
R-squared	0.005	0.006	0.113	0.023	0.031	0.031	0.013
Outcome mean	0.505	6.491	45.50	21.10	10.93	22.62	11.27
Younger brothers							
After	-0.070*	0.236	-0.817	-1.487	-0.051	-3.650**	-0.283
	(0.037)	(0.254)	(2.166)	(1.703)	(0.163)	(1.649)	(0.181)
Observations	3,612	3,612	3,612	3,612	3,612	3,612	3,612
R-squared	0.010	0.011	0.125	0.016	0.034	0.016	0.021
Outcome mean	0.506	6.436	46.78	21.13	10.87	22.07	11.21
B. Families with oldest sisters							
Younger sisters							
After	0.044	-0.406	3.244	1.650	0.091	-0.330	0.389**
	(0.037)	(0.254)	(2.113)	(1.524)	(0.170)	(1.592)	(0.190)
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.006	0.009	0.116	0.015	0.019	0.021	0.017
Outcome mean	0.499	6.508	46.68	20.96	10.85	21.65	11.20
Younger brothers							
After	-0.005	0.003	0.212	-1.077	0.094	-0.485	-0.105
	(0.036)	(0.242)	(1.958)	(1.485)	(0.165)	(1.472)	(0.172)
Observations	3,856	3,856	3,856	3,856	3,856	3,856	3,856
R-squared	0.004	0.007	0.111	0.015	0.027	0.027	0.030
Outcome mean	0.506	6.473	46.62	21.31	10.78	21.10	11.11

Notes: The table provides balance tests for the sample of second-generation migrant younger siblings. Estimations include a linear control function and a 60-day bandwidth around the cutoff. Outcomes relating to the younger sibling are indicators for being born after cutoff, birth month, and birth spacing. Outcomes relating to the parents are earnings percentiles and years of education at the time the oldest sibling was of daycare age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.



(a) Second-generation migrants (b) Low-SES natives

A. Distribution of younger siblings around cutoff



(c) Second-generation migrants (d) Low-SES natives

B. Density test

Figure 1: Test for Manipulation of Treatment Status

Notes: The figure explores the validity of the empirical specification by whether observations can manipulate treatment status. Panel A. shows the distribution of younger siblings by oldest sibling's birth date each day between November 1st and February 28th normalized around the cutoff. Leap-year births are re-coded to February 28th. Panel B. shows the density discontinuity of the running variable (birthdate) at the January 1st cutoff. Following Cattaneo et al. (2018) the test uses local-polynomial density estimators. The left column includes second-generation migrant siblings born in Sweden between 1988-2003 to two non-Nordic migrant parents. The right column includes native siblings born in families where parents' average annual earnings are at the 20th percentile of below while the child is of childcare age. Panel (c) test-statistic: -1.5729, p-value: 0.1157. Panel (d) test-statistic: -0.5540, p-value: 0.5796.

describes the density of younger sibling observations normalized around January 1st. There is no obvious mass of observations after the cutoff in neither migrant families nor native families with low socioeconomic status. The bottom panel provides a manipulation test for the smoothness of these densities (Cattaneo et al. 2018). The test statistics are not statistically significant, with p-value 0.1157 in panel (c) and 0.5796 in panel (d), meaning I cannot reject the hypothesis that the densities of the running variable are smooth around the cutoff.

The specification tests for natives only hold when the sample is restricted to families with low socioeconomic status. Appendix Figure A3 shows evidence of manipulation around the cutoff in the full native sample. Placebo tests in Appendix Table A3 suggests that this behavior is partly driven by higher-earning and more highly educated parents. As a result, positive school-starting-age effects in the full native sample may partly reflect differences in family socioeconomic status rather than causal age effects. Avoiding this bias in the regression discontinuity design provides an additional reason to focus on low–income native families.

4.3 Confirming School-Starting-Age Effects

To interpret the estimated sibling spillover effects as the influence of a higher-achieving older sibling, two conditions must hold. First, an older school starting age must improve the educational achievement of first-borns. Second, these effects should not differ systematically across the subgroups considered in the spillover analysis. Otherwise, heterogeneous spillover effects could simply reflect differences in the effect of school starting age on the older sibling's own achievement. I examine these conditions by estimating equation (5) using the first-born sibling's end-of-compulsory-school GPA as the outcome.

Appendix Table A4 presents the results. For both girls and boys, a higher school-starting age is associated with an increase in final GPA. The estimates are similar for second-generation migrant and native children but differ somewhat by gender. For girls, older school start increases end-of-compulsory-school GPA by 12 percent of a standard deviation among native first-borns and by 17 percent of a standard deviation among second-generation migrant first-borns. Both estimates are statistically significant at the five-percent level. For boys, the estimated effects are smaller, ranging between 6 and 8 percent of a standard deviation, and are imprecisely estimated. However, back-of-the-envelope calculations indicate that none of the subgroup estimates are statistically different from one another.

The effects of school starting age could also vary depending on the gender of the younger sibling. To examine this possibility, I run regressions separately by the gender of the second-born sibling. The results are reported in columns (2)–(3) for first-born boys and columns (5)–(6) for first-born girls. The estimates suggest that first-borns experience somewhat larger gains from an older school start when they have a younger sister rather than a younger brother. However, these differences are not statistically significant, and I cannot reject that younger sisters and younger brothers have the same influence on their older siblings' outcomes across subgroups.

Taken together, these results are consistent with the existing literature showing that older school starters achieve higher academic performance. A limitation of the analysis is that I observe GPA only at the end of compulsory school, nine years after school entry. Previous research generally finds that school-starting-age effects are largest in the early school years and fade over time (Elder and Lubotsky 2009; Fredriksson and Öckert 2014). Thus, the imprecisely estimated effects for first-born boys observed nine years after school entry are not unexpected. Importantly, I find no evidence that the effect of school starting age on GPA differs across migrant status, gender, or the gender of the younger sibling. This reduces the concern that heterogeneous sibling spillovers are driven by differences in the extent to which older school starting age improves the older sibling's academic achievement.

Similar direct effects do not, however, rule out other mechanisms through which school starting age could generate heterogeneous sibling spillovers. School starting age could for example affect grade progression differently across groups. I therefore examine two additional outcomes: grade retention, defined as being old for grade in the final year of compulsory schooling, and redshirting, defined as being old for grade upon entry into compulsory schooling. Note that redshirting can be examined only for the subset of first-borns whose first-grade enrollment is observed.[24] Using U.S. data, Dhuey et al. (2019) show that older school starters are less likely to experience either outcome and find no differences in effects between minority and non-minority students. If these effects differ between migrant and native first-borns in my setting, differences in sibling spillovers could reflect differential effects on grade progression rather than the influence of a higher-achieving sibling.

Appendix Figure A4 reports the corresponding estimates. Consistent with previous evidence, older school starting age reduces the likelihood of both grade retention by ninth grade and redshirting at school entry. Boys are slightly less likely than girls to experience grade retention. I find no evidence that these effects differ across subgroups. Hence, differences in sibling spillovers are unlikely to be explained by heterogeneous effects of school starting age on grade progression.

The analysis in this paper focuses on educational outcomes, although school starting age may also affect broader non-cognitive outcomes. Studies of the effects on criminal behavior find that older school starters are less likely to engage in crime. Although heterogeneity by migrant background has not been studied, effects appear larger for boys (Landersø et al. 2017), Black males in the United States (Peña 2019), and children from low-socioeconomic backgrounds (Cook and Kang 2016). Other work finds that older school starting age improves children's mental health. Younger school starters are more likely to exhibit symptoms of inattention and hyperactivity (Dee and Sievertsen 2018), receive an ADHD diagnosis (Persson et al. 2025), and experience poorer mental health more broadly (Lubotsky and Kaestner 2016). Examining disability receipt, Dhuey et al. (2019) find no evidence of heterogeneous effects by minority status but do find differences by gender and socioeconomic status. Whether school starting age has differential effects on the mental health and broader well-being of migrant and native students remains an important open question, but addressing it is beyond the

[24] First-grade enrollment is recorded only in the separate dataset Elevregistret, which covers first-borns who entered first grade between 2008 and 2012. Because Elevregistret does not contain exact birthdates, identification relies on birth month.

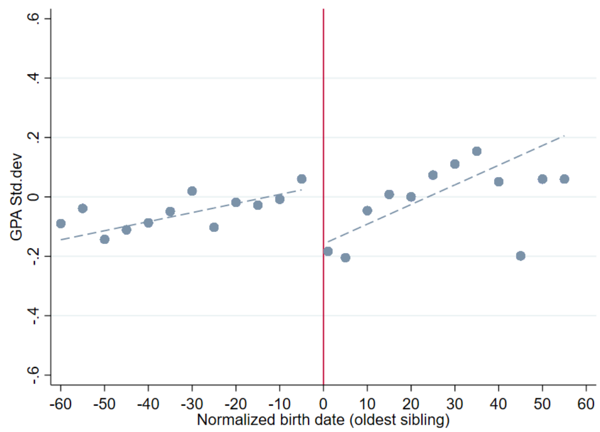
scope of this paper.

5 Results

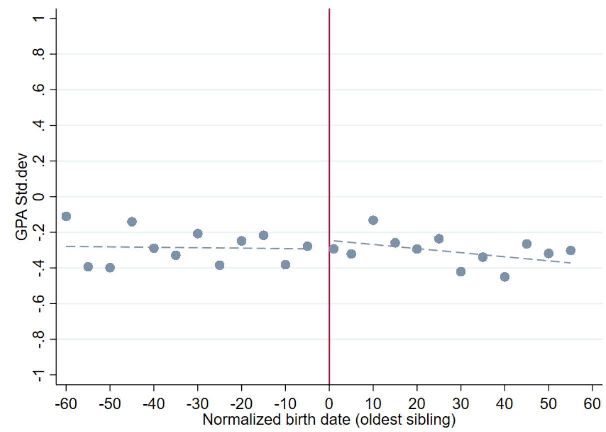
I begin by comparing the effect of having a high-achieving older sibling on girls in migrant and low-income native families. Figure 2 provides a graphical representation of the RDD results where the X-axis displays the birthdate of the oldest brother or sister and the Y-axis displays the final GPA of the younger sister. Table 3 provides the corresponding estimates for second-generation migrant and native girls in panels A. and B. respectively, as well as the results for the additional outcomes.

The top panel in Figure 2 shows the effects for girls with an oldest brother. Figure (a) reveals a clear negative discontinuity at the cutoff for second-generation migrant girls. This means that having a high-achieving older brother has a negative effect on these girls' GPA. In contrast, Figure (b) shows no discontinuity for native girls.

Turning to the point estimates in Table 3 the results indicate that having a high-achieving oldest brother has a sizable negative effect for second-generation migrant girls but no effect on the GPA for native. The estimate in column (1) tells us that having a high-achieving older brother reduces second-generation migrant girls' GPA by 17.9 percent of a standard deviation, statistically significant on the five-percent level. For native girls, the effect is close to zero and statistically insignificant. Similar patterns emerge for the additional outcomes reported. Column (4) shows that having a high-achieving older brother reduces second-generation migrant girls' participation in the standard Swedish track by eight percentage points. This corresponds to a 12 percent reduction relative to the outcome mean and is statistically significant on the five-percent level. Second-generation migrant girls are also worse off in terms of Swedish and math grades, although the estimates lack precision. For native girls, having a high-achieving older brother has small positive yet statistically insignificant effects on all outcomes.

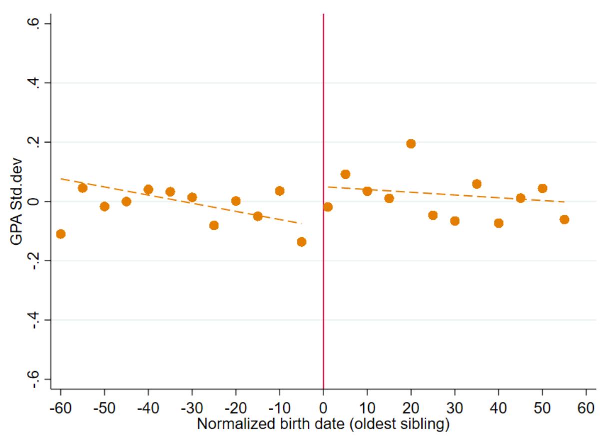


(a) Second-gen migrant girls

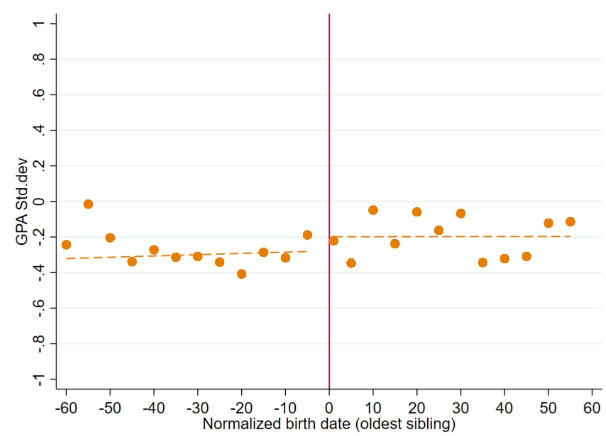


(b) Low-SES native girls

A. Girls with older brother



(c) Second-gen migrant girls



(d) Low-SES native girls

B. Girls with older sister

Figure 2: Sibling Spillovers on Girls' Final GPA

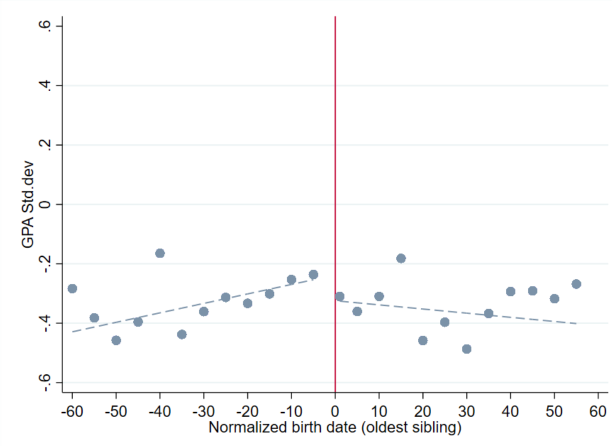
Notes: The figure shows the effect of having an oldest sibling born after the January 1st cutoff on girls' final GPA, standardized to have a mean of zero and a standard-deviation of one. The estimation includes a linear control function and a 60-day bandwidth around the cutoff. The X-axis displays the running variable birthdate of the oldest sibling, normalized to zero around the cutoff, represented by the vertical red line. Each dot represents the average for a five-day birth bin. The left column includes second-generation migrant siblings born in Sweden between 1988-2003 to two non-Nordic migrant parents. The right column includes native siblings born in families where parents average annual earnings are at the 20th percentile of below while the oldest was of daycare age.

The bottom panel of Figure 2 presents results for girls with an oldest sister. Figure (c) shows a positive discontinuity for second-generation migrant girls, while the corresponding discontinuity for native girls is again modest. Columns (5)-(7) of Table 3 show that GPA and and grade outcomes improve for second-generation migrant girls with a high-performing older sister, but the effects are statistically insignificant. Column (8) shows that having a high-achieving older sister significantly increases the probability that these girls attend the standard Swedish track by 17 percent relative to the outcome mean, significant on the one-percent level. For native girls, the effects are again positive yet small and statistically insignificant.

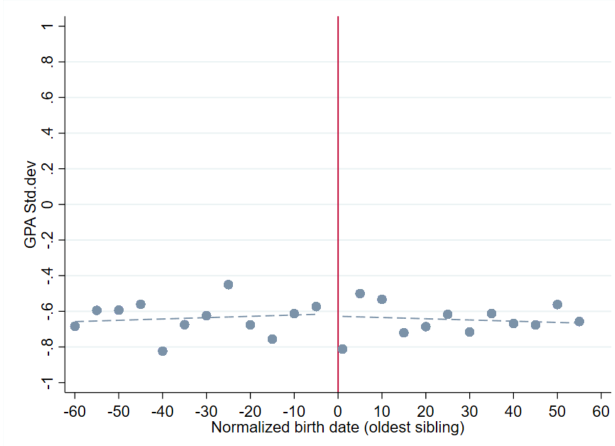
The results for boys are shown in Figure 3 and in Panels C and D of Table 3. A high-achieving older sibling, whether a brother or sister, has little to no effect on GPA for neither second-generation migrant boys nor native boys. This pattern is consistent across most other outcomes, with one exception. Having an older brother slightly improves math grades for second-generation migrant boys, statistically significant at the ten-percent level.

Overall, the results suggest that having a high-achieving older brother creates a disadvantage that is specific to second-generation migrant girls. The finding that native girls from comparable families do not experience this disadvantage indicates that it is not simply a matter of gender, that is, having a high-achieving older brother does not automatically disadvantage a younger sister. Similarly, the lack of effects for second-generation migrant boys shows that the negative impact is not driven by growing up with a high-achieving sibling in a migrant family in general. Instead, the disadvantage appears to be specific to girls in these families.

Comparing the effect sizes to two American studies on sibling spillovers related to school entry cutoffs points to similarities. Karbownik and Özek (2023) reports a positive spillover effect of 14.8 percent of a standard deviation on younger siblings' test scores when an older sibling enters school late, specifically in families with low socioeconomic status. Similarly, Zang et al. (2023) finds that spillover effects of an older sibling entering school late range from 3.6 to 6.5 percent of a standard deviation in younger siblings' reading and math scores

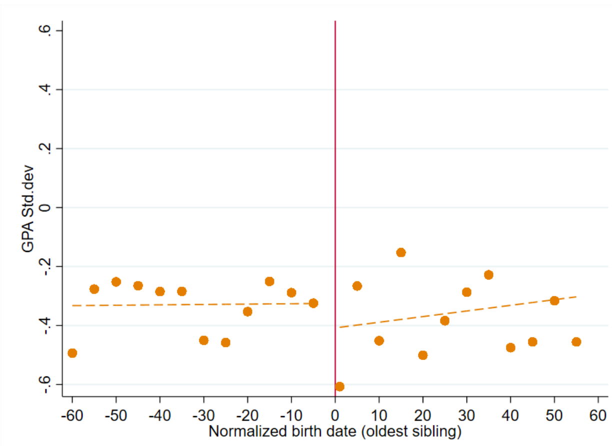


(a) Second-gen migrant boys

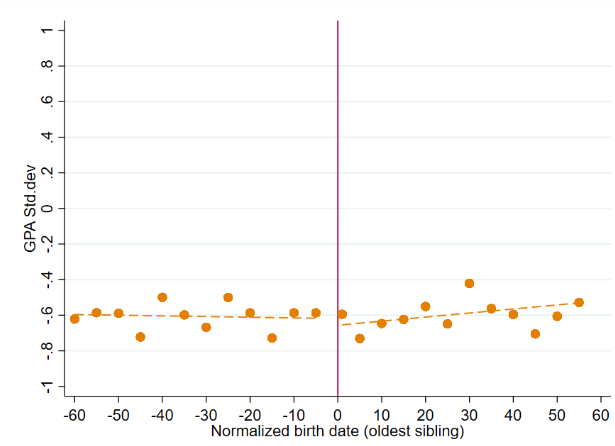


(b) Low-SES native boys

A. Boys with older brother



(c) Second-gen migrant boys



(d) Low-SES native boys

B. Boys with older sister

Figure 3: Sibling Spillovers on Boys' Final GPA

Notes: The figure shows the effect of having an oldest sibling born after the January 1st cutoff on boys' final GPA, standardized to have a mean of zero and a standard-deviation of one. The estimation includes a linear control function and a 60-day bandwidth around the cutoff. The X-axis displays the running variable birthdate of the oldest sibling, normalized to zero around the cutoff, represented by the vertical red line. Each dot represents the average for a five-day birth bin. The left column includes second-generation migrant siblings born in Sweden between 1988-2003 to two non-Nordic migrant parents. The right column includes native siblings born in families where parents average annual earnings are at the 20th percentile of below while the oldest was of daycare age.

in families with low socioeconomic status.[25]

[25] Studies on the spillover effects of various educational or health shocks to one sibling show impacts on sibling school performance ranging from 1 to 15 percent of a standard deviation (Breining 2014; Qureshi 2018; Nicoletti and Rabe 2019; Black et al. 2021).

Table 3: Sibling Spillovers on School Outcomes

Younger Sibling	With Oldest Brother				With Oldest Sister			
	(1) GPA	(2) Swedish grade	(3) Math grade	(4) Std. track (Swedish)	(5) GPA	(6) Swedish grade	(7) Math grade	(8) Std. track (Swedish)
A. Second-generation migrant girls								
After	-0.179**	-0.120	-0.082	-0.082**	0.123	0.085	0.129	0.120***
	(0.081)	(0.075)	(0.074)	(0.037)	(0.085)	(0.079)	(0.079)	(0.038)
Observations	3,121	3,146	3,146	3,118	3,254	3,287	3,287	3,250
R-squared	0.009	0.007	0.005	0.008	0.009	0.006	0.009	0.012
Outcome mean	-0.0277	-0.0384	-0.224	0.681	-0.00143	-0.00935	-0.214	0.672
B. Native girls in low-SES families								
After	0.054	0.055	0.068	-0.005	0.090	0.048	0.024	0.004
	(0.076)	(0.068)	(0.063)	(0.007)	(0.073)	(0.068)	(0.061)	(0.010)
Observations	4,687	4,790	4,790	4,786	4,365	4,459	4,459	4,439
R-squared	0.004	0.004	0.006	0.004	0.008	0.009	0.006	0.007
Outcome mean	-0.295	-0.0914	-0.327	0.985	-0.231	-0.0143	-0.301	0.984
C. Second-generation migrant boys								
After	-0.092	0.024	-0.082	-0.054	-0.080	0.003	-0.126*	0.048
	(0.079)	(0.070)	(0.074)	(0.038)	(0.080)	(0.069)	(0.072)	(0.037)
Observations	3,101	3,128	3,128	3,103	3,286	3,331	3,331	3,301
R-squared	0.011	0.010	0.013	0.008	0.009	0.007	0.009	0.008
Outcome mean	-0.335	-0.482	-0.231	0.633	-0.350	-0.489	-0.240	0.632
D. Native boys in low-SES families								
After	-0.032	-0.087	-0.063	-0.010	-0.025	0.021	-0.068	-0.006
	(0.070)	(0.058)	(0.059)	(0.008)	(0.074)	(0.061)	(0.062)	(0.009)
Observations	4,618	4,754	4,754	4,738	4,396	4,523	4,523	4,507
R-squared	0.009	0.006	0.007	0.003	0.004	0.002	0.005	0.006
Outcome mean	-0.639	-0.625	-0.396	0.985	-0.605	-0.602	-0.368	0.984

Notes: The table shows the effect of having an oldest sibling born after the January 1st cutoff on younger siblings' end-of-compulsory school outcomes. Results are presented for girls and boys in migrant and low-SES native families by the gender of the first-born sibling. Linear regressions with kernel-triangular weights and a 60-day bandwidth around the cutoff. GPA, Swedish and math grades are standardized to have a mean of zero and a standard deviation of one. The outcome "Standard track (Swedish)" is a dummy which takes on the value 1 if the younger sister was enrolled in the regular Swedish track in the final year of compulsory school, instead of the "Swedish as a second-language" track. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.1 Robustness

This section examines the robustness of the main results. First, I extend the baseline specification by including a series of covariates, with final GPA as the outcome variable. The results are presented in Appendix Table A5, where each column introduces a separate covariate. Columns (1)-(5) report results for siblings with an oldest brother, and columns (6)-(10) for siblings with an oldest sister. The first three columns include controls specific to the younger sibling. The baseline estimates remain robust to the inclusion of controls for the number of siblings, the younger sibling's birth month and year, and birth spacing. Similarly, the results are unaffected by adding parental characteristics, including years of education and earnings, measured when the oldest sibling is of childcare age.

In addition, I perform a number of robustness checks that are typical for the Regression Discontinuity Design. Appendix Figure A5 tests robustness of the effects on final GPA by introducing a quadratic specification instead of the linear one. The triangular dots depict the estimates from regressions with quadratic specification, and the circular dots depict the baseline (main results). Although the quadratic estimates have larger standard errors overall, the effects for second-generation migrant girls remain robust in terms of both effect size and significance.

Appendix Figure A6 presents a series of donut regressions that re-estimate the main specification after excluding observations within 1–10 days of the cutoff. The x-axis reports the number of days from the cutoff that are excluded. In general, this robustness check can show whether manipulation of treatment status occurs. In the specific context of this study, this exercise is motivated by the fact that January 1st is preceded by several bank holidays, which may shift scheduled cesarean sections and other high-risk births to dates after New Year's. Because such births are more likely to be associated with older mothers, the estimates could otherwise reflect differences in family composition. The results remain robust across all exclusion windows.

Appendix Figure A7 reproduces the main results using a staggered expansion of the bandwidth +/− 5 days around the cutoff. The estimates are somewhat unstable for bandwidths below 30 days, likely due to small sample sizes, but stabilize at around 50 days. Consistent with this pattern, Appendix Table A6 reports the spillover effects using data-driven marginal-squared-error optimal bandwidths following Calonico et al. (2017). Across all samples and outcomes, this data-driven approach selects bandwidths around 60 days, lending support to the qualitative choice of a two-month bandwidth in the baseline specification. The estimates are robust to this approach, and the positive effect of having a high-achieving oldest sister on second-generation migrant girls' math grades is now statistically significant on the ten-percent level.

6 Mechanisms

This section examines potential mechanisms behind the finding that having a high-achieving older brother has negative effects on second-generation migrant girls' own school performance. I analyze the role of sibling gender composition and explore heterogeneity across family characteristics. I conclude by discussing the best-supported mechanisms and how they matter in a policy context.

6.1 Sibling Gender and Educational Outcomes

In addition to the sibling's ability, the sibling's gender can in itself influence family dynamics and children's outcomes. For example, growing up in families exhibiting son-biased fertility has been shown to have negative effects on girls' educational outcomes (Dossi et al. 2021), and the presence of an opposite-sex sibling can influence self-perceived ability (Adamecz et al. 2025).

One potential explanation to the main finding can therefore be that having an oldest brother has different implications in migrant and native families and may be particularly harmful for migrant girls. If so, the estimated effects of having a high-achieving brother could partly reflect the presence of a brother rather than his achievement.

I investigate this mechanism by examining whether having an oldest brother rather than an oldest sister, regardless of achievement, differentially affects girls and boys in migrant and native families. Appendix Figure A8 presents estimates from regressions of a binary indicator for the gender of the first-born child on younger siblings' school outcomes in migrant and native families.[26] Overall, younger siblings are either unaffected or slightly worse off when the oldest child is a brother. Consistent with the existing literature, opposite-gender sibling composition appears to matter, as girls' grade outcomes are more negatively impacted by the presence of an older brother, both in terms of magnitude and significance. Crucially, second-generation migrant girls are not more adversely affected by having an oldest brother than native girls. This suggests that the main results for second-generation migrant girls are not driven by having a brother per se, but rather by having a brother who is a high achiever.

6.2 Heterogeneity by Family Characteristics

That the effects for second-generation migrant girls are driven by having a high-achieving older brother rather than the mere presence of a brother points to the role of parents. This is consistent with the theoretical framework presented in section 2, in which children are not only impacted by the older siblings' own ability, but the potential preferences in parents' investment adjustment response as well.

Parents' preferences for their children can occur for many reasons and are difficult to test directly. I explore three important indirect channels by running regressions where the treatment variable is interacted with different indicators that proxy the underlying mechanisms. First, I examine the influence of cultural norms from parents' country of origin by adding multiple measures of origin-country gender norms from open-access data sources. Second, I explore the influence of parents' labor force participation and integration in Sweden. Third, I consider the family's living conditions and size.

[26] The results are robust to controlling for number of siblings and birth spacing.

Cultural background. In the light of international migration a prominent difference between native and foreign-born parents is that they mostly have grown up in different cultural environments. Traditional gender norms among migrants that stem from their origin countries have proven remarkably persistent over time (Giavazzi et al. 2019; Kleven forthcoming). This may lead parents—consciously or unconsciously—to allocate fewer resources to younger children when a high-achieving son is present.

I include multiple measures of cultural origin from various open-access data sources. Since I do not observe exact country of origin, all measures are constructed as weighted country-group averages over the period 1988-2003. Specifically, I construct four binary indicators. First, whether at least one parent originates from a refugee-sending country, based on large conflicts in the late 1980s through the early 2000s. Second, whether a parent originates from a country with an above-median score of traditional gender values based on a principal component analysis of the World Value Survey (WVS). [27] Third, whether a parent originates from a country with an above-median UNDP Gender Inequality Index (GII) value. Lastly, whether parents belong to migrant groups demonstrating son preference in fertility after they arrived in Sweden.[28] Corresponding values for all country groups, as well as their shares of the sample, can be found in Appendix Table A1.

Table 4 presents the results. Reflecting the smaller, unevenly split samples underlying each column, the baseline coefficients are less precisely estimated here than in Table 3, and I focus below on the direction and relative size of the interaction terms rather than on statistical significance alone. For girls, in the top panel, the interaction terms between the treatment variable and the cultural indicators are not statistically significant, indicating no detectable heterogeneity by parents' cultural background along this margin. For boys in the bottom panel, the interaction terms are larger in magnitude. In families from more

[27] Based on these statements from waves 3-6: "When jobs are scarce a man should have more right to a job than a woman", "men make better political leaders" and "University is more important for a boy than a girl". The first principal component explains 61% of variance with balanced loadings (0.57, 0.60, 0.56).

[28] Following Almond et al. (2013), where son preference is measured as the probability of having another child within six years when the firstborn is a girl. Groups with a significant estimate include those from the former Yugoslavia, the MENA region, Iraq, Japan, China, Hong Kong, and South/North Korea.

Table 4: Heterogeneity by Cultural Background

Younger Sibling	With Oldest Brother				With Oldest Sister			
	(1) Refugee	(2) WVS	(3) GII	(4) Son-pref.	(5) Refugee	(6) WVS	(7) GII	(8) Son-pref.
A. Second-generation migrant girls								
After	-0.335*	-0.150	-0.075	-0.112	0.319*	0.128	0.047	0.076
	(0.180)	(0.108)	(0.141)	(0.103)	(0.176)	(0.110)	(0.143)	(0.113)
More traditional	0.184	-0.069	-0.156	-0.144	-0.243	-0.016	0.115	0.099
	(0.202)	(0.164)	(0.176)	(0.165)	(0.201)	(0.174)	(0.182)	(0.173)
Observations	3,121	3,121	3,121	3,121	3,254	3,254	3,254	3,254
R-squared	0.024	0.010	0.013	0.016	0.022	0.009	0.009	0.014
Outcome mean	-0.0277	-0.0277	-0.0277	-0.0277	-0.00143	-0.00143	-0.00143	-0.00143
B. Second-generation migrant boys								
After	0.190	0.096	0.060	0.138	-0.417*	-0.281***	-0.281*	-0.159
	(0.203)	(0.111)	(0.141)	(0.103)	(0.219)	(0.108)	(0.145)	(0.106)
More traditional	-0.328	-0.448***	-0.224	-0.555***	0.409*	0.447***	0.308*	0.166
	(0.220)	(0.157)	(0.172)	(0.157)	(0.235)	(0.162)	(0.176)	(0.163)
Observations	3,101	3,101	3,101	3,101	3,286	3,286	3,286	3,286
R-squared	0.021	0.016	0.012	0.019	0.020	0.012	0.010	0.015
Outcome mean	-0.335	-0.335	-0.335	-0.335	-0.350	-0.350	-0.350	-0.350

Notes: The table shows the effect of having an oldest sibling born after the January 1st cutoff on GPA, when effect is allowed to differ by parents' cultural background. The baseline regression is fully interacted with the indicator. "More traditional" shows estimates from interaction between indicator and treatment. GPA is standardized to have a mean of zero and a standard deviation of one. "Refugee" includes families where one or both parents originate from the largest refugee-sending countries at the time. "WVS" is an indicator for scoring above the sample mean in terms of traditional gender attitudes from the World Value Survey, using principal component analysis. "GII" is an indicator of having an Gender Inequality Index value above the sample mean as measured by the UNDP. "Son-pref." in an indicator of whether parents belong to migrant groups demonstrating son preference in fertility in Sweden. Corresponding values for all country groups is found in Appendix Table A1. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

gender-traditional cultures, younger brothers are consistently disadvantaged by having a high-achieving older brother, but benefit from having a high-achieving older sister. WVS and son-preference are statistically significant for boys with older brothers, while refugee origin, WVS, and GII are significant for those with older sisters.

These findings suggest that preferential investment in a high-achieving first-born sons is stronger among families from more gender-traditional origins. Among families from the most traditional backgrounds, even younger brothers are disadvantaged by having a high-achieving older brother. Meanwhile, girls are disadvantaged by having a high-achieving older brother across the migrant sample, with no detectable variation by cultural background. This may partly reflect that most migrants in Sweden originate from relatively gender-traditional country groups, so the sample median, around which the interaction is centered, already corresponds to a high level of gender traditionalism. There is therefore limited variation at the lower end of the distribution to identify differential effects for girls, while for boys the negative spillover from having a high-achieving older brother becomes apparent at the more traditional margin.

Parents' Labor Force Participation. Parents' labor force participation matters for children because it shapes the resources and time available to them (Duncan et al. 2023). For children of migrants specifically, it can also affect how the family integrates into the host society. As discussed in section 3, migrant families in Sweden have lower annual earnings and mothers participate in the labor force at substantially lower rates than their Swedish-born counterparts. This gap is noteworthy, as Sweden has one of the highest female labor force participation rates in the OECD (Olivetti and Petrongolo 2017).

Labor force participation in itself not only functions as a measure of labor market integration, but can also capture a difference in how parents invest in their children. Put simply, employed parents can invest financial resources, while parents who are not employed can invest time more directly. This, in turn, shapes children's access to childcare, which can function as a supplementary investment made outside the household. Intra-family dynamics may thus be more influential for siblings who remain at home, and negative for girls, if resources are diverted toward an older brother instead.

I perform a heterogeneity analysis using two measures; a binary indicator of parental employment and an index of parental labor market integration. Because labor market participation varies systematically across migrant origin groups, I control for mothers' country group.[29] This lets me compare families from the same origin who differ in whether par-

[29] Estimates not included in paper show that the results are robust to allowing parental origin to vary by employment/integration status rather than entering additively.

Table 5: Heterogeneity by Parents' Labor Force Participation

Younger Sibling	With Oldest Brother				With Oldest Sister			
	Father		Mother		Father		Mother	
	(1) Employ	(2) Integrate	(3) Employ	(4) Integrate	(5) Employ	(6) Integrate	(7) Employ	(8) Integrate
A. Second-generation migrant girls								
After	-0.510	-0.367	-0.517	-0.112	0.544	0.535	0.638	0.590
	(0.556)	(0.548)	(0.551)	(0.562)	(0.553)	(0.540)	(0.554)	(0.545)
Higher participation	0.409**	0.246***	0.400**	0.177*	0.053	0.024	-0.090	-0.006
	(0.199)	(0.090)	(0.175)	(0.094)	(0.236)	(0.097)	(0.195)	(0.115)
Observations	3,121	3,121	3,121	3,121	3,254	3,254	3,254	3,254
R-squared	0.029	0.029	0.028	0.020	0.021	0.033	0.024	0.015
Outcome mean	-0.0277	-0.0277	-0.0277	-0.0277	-0.00143	-0.00143	-0.00143	-0.00143
Control origin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
B. Second-generation migrant boys								
After	0.209	0.070	0.128	0.249	-0.605	-0.549	-0.575	-0.549
	(0.577)	(0.550)	(0.581)	(0.558)	(0.564)	(0.529)	(0.564)	(0.538)
Higher participation	0.008	0.018	0.031	-0.041	-0.045	0.130	-0.029	0.150
	(0.187)	(0.088)	(0.171)	(0.094)	(0.207)	(0.091)	(0.183)	(0.108)
Observations	3,101	3,101	3,101	3,101	3,286	3,286	3,286	3,286
R-squared	0.033	0.028	0.030	0.026	0.029	0.035	0.029	0.020
Outcome mean	-0.335	-0.335	-0.335	-0.335	-0.350	-0.350	-0.350	-0.350
Control origin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows the effect of having an oldest sibling born after the January 1st cutoff on GPA, when the effect is allowed to differ by parents' employment, "Employ", and a labor market integration index, "Integrate". The baseline regression is fully interacted with the indicator. "Higher participation" shows estimates from interaction between indicator and treatment. GPA is standardized to have a mean of zero and a standard deviation of one. Employment is a dummy which takes on the value 1 if the father/mother earns at least half of the median earning for 45-year-old men/women in the Swedish labor force. This value was calculated using the average annual earnings of men and women aged 44-46 between 1985-2018, deflated to 2018 values. Fathers/mothers' integration index is a measure of earning more than expected based on his/hers origin, age, time in Sweden and number of children, standardized to have a mean zero and standard deviation of one. All regressions include a control for mothers' origin country group. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

ents are employed while the oldest child is of childcare age. Table 5 presents the results. The baseline coefficients are estimated less precisely in these specifications, reflecting the smaller and unevenly split samples. I therefore focus on the direction and magnitude of the interaction terms rather than on the statistical significance of the subgroup-specific effects.

I first consider parental employment. In Panel A, greater parental labor market attachment substantially attenuates the negative spillover from a high-achieving older brother to second-generation migrant girls. The estimated interaction is positive for both fathers and mothers, while interactions for girls with older sisters are small. In Panel B, the interaction terms are small across both sibling genders, suggesting little systematic heterogeneity in sibling spillovers for boys.

I next consider parental labor market integration, measured by an index of whether fathers and mothers earn more than expected given migrant origin, age, time in Sweden, and number of children. The results for girls with high-achieving brothers again indicate substantial attenuation of the negative spillover as parental integration increases. Greater maternal integration, in particular, moves the estimated effect close to zero. The interaction terms are small for girls with high-achieving sisters and for second-generation migrant boys. Appendix Table A7 shows similar patterns when parental earnings are used as an alternative measure of labor market attachment. Overall, the results are consistent with greater parental labor market integration attenuating the gender-specific disadvantage associated with a high-achieving older brother for girls.[30]

Living Conditions, Family Size and Birth Order. Family living conditions and size can also shape family dynamics. Parents who arrived earlier may be more culturally and socioeconomically similar to natives (Böhlmark 2008), while residing in more segregated areas can affect assimilation (Dustmann and Glitz 2011). In terms of family size and birth order, larger families and being born later in the sibling group are associated with worse educational outcomes, driven by quality-quantity tradeoffs in parental investment and increasing resource constraints (Becker 1960; Black et al. 2005; Breining et al. 2020; Kim and Wang 2023).

Appendix Table A8 reports heterogeneities by parental time in Sweden, neighborhood migrant share, and sibling characteristics. Panel A shows little heterogeneity for girls by parental time in Sweden or neighborhood migrant shares. For boys, some interactions are economically meaningful. Longer paternal time in Sweden attenuates the negative spillover from a high-achieving older brother, while the positive spillover from a high-achieving older

[30] See Table A9, Panel A., for low-SES native families. Employment appears to matter for those with older brothers, with a slight negative effect for girls and a positive one for boys.

sister is larger in more migrant-dense neighborhoods. Panel B shows little systematic heterogeneity by birth spacing, birth order, or number of siblings. Overall, the results provide limited evidence that family size or living conditions account for the gender-specific disadvantage for girls documented in the main results.[31]

6.3 Discussion

This paper documents that second-generation migrant girls are uniquely disadvantaged by having a high-achieving older brother, a pattern absent among migrant boys and natives. The analysis of potential mechanisms points to two underlying factors. First, son preference in parental investments is more pronounced in migrant families from more gender-traditional origins, generating negative spillovers of a high-achieving older brother for both younger sisters and brothers in the most traditional households. Second, parents' labor force participation and integration substantially attenuates the disadvantage for girls with high-achieving brothers.

In general, the moderating role of parental employment is consistent with the conceptual framework in Section 2. Full-time employment relaxes the household budget constraint, reducing the tradeoffs parents face when allocating resources across their children. On the other hand, when resources are scarce, a high-achieving first-born child may receive relatively more parental investments, crowding out investments in a younger sibling. Also the direct role model effect from the older sibling becomes relatively less salient when household resources are less limited (Karbownik and Özek 2023).

For migrant families, parental employment carries an additional return beyond the income effect. Parents who enter the labor market form social ties across cultural backgrounds and gain direct exposure to host-country norms (Dustmann and Glitz 2011; Boelmann et al. 2025), which can reduce information asymmetries about the school system and child-rearing practices more broadly. This greater exposure can lead parents to update their

[31] The results for natives from families with low socioeconomic status are reported in Panel B in Appendix Table A9. The null effects for girls and boys remain robust to interacting any of the indicators.

beliefs about daughters' labor market prospects, weakening the gender-biased investments that son preference would otherwise generate. This channel is consistent with evidence that parents' integration promotes assimilation for the family as a whole (Bleakley and Chin 2008; Blau et al. 2013; Åslund et al. 2015), and with findings that maternal labor market integration can fully offset the effect of cultural gender norms on the schooling gap between migrant girls and boys (Bergvall 2024).

The most concrete influence of parental employment for young children is access to childcare. In Sweden, the primary condition for childcare enrollment, especially during the sample period, was parental employment, as places were allocated on the basis of parents' working hours. To this day, childcare enrollment rates among children of migrants are substantially below the national average of approximately 95 percent (Hall et al. 2025), and the gap is largest for recently arrived migrant families. Meanwhile, children from minority backgrounds and with low socioeconomic status tend to be the ones who benefit the most from daycare (Havnes and Mogstad 2011; Cornelissen et al. 2018), with particularly positive effects for migrant girls (Drange and Telle 2015; Corazzini et al. 2021).

Early childcare access can benefit children in migrant families through multiple channels. It facilitates integration by exposing children to Swedish-speaking peers and educators, accelerating language acquisition, fostering social skills, and introducing institutional environments with gender norms that may differ from those in the home. Childcare also expands the set of human capital investments available to the child beyond the household (Cunha and Heckman 2007), reducing reliance on parental inputs during a critical stage of skill formation. This is likely to be especially valuable for girls in families with stronger son preference, who may receive fewer parental investments than their brothers.

7 Conclusion

This paper documents that spillovers from having an academically high-achieving older sibling depend critically on sibling gender composition and family background. Using detailed Swedish administrative data, I show that a high-achieving older brother substantially reduces school performance for second-generation migrant girls, with no comparable effect for migrant boys or native children. An exploration of mechanisms shows that while parents' origin-country cultural norms are one contributing factor, parents' labor market integration heavily attenuates this disadvantage for girls. Parental integration can lead to family assimilation, with parents updating their beliefs about girls' future opportunities in the host country. It also increases children's access to early childcare, which can serve as a supplementary early investment in their skill formation.

This paper highlights an overlooked source of inequality in the human capital accumulation of migrant children. Academic disparities can arise from family dynamics that are difficult to observe and that may persist because they are rooted in parental norms and preferences. As a result, migrant girls with high-achieving brothers may experience disadvantages that remain hidden in aggregate measures of educational inequality. Meanwhile, parental labor market integration can have positive and persistent effects on intra-family dynamics, improving daughters' educational opportunities well beyond the labor-market gains typically documented for migrant parents themselves.

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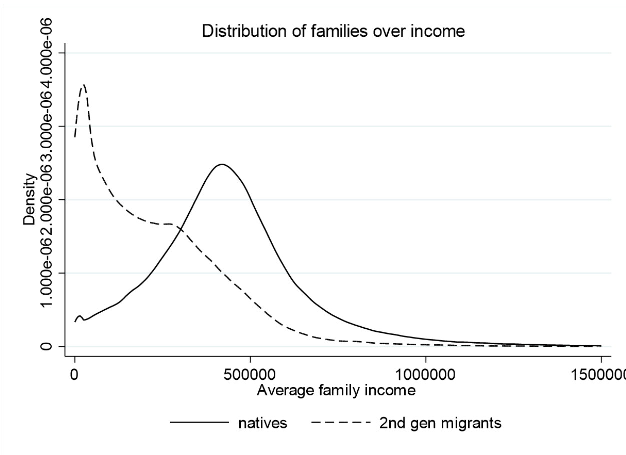
Appendices for Online Publication

A Appendix Tables and Figures

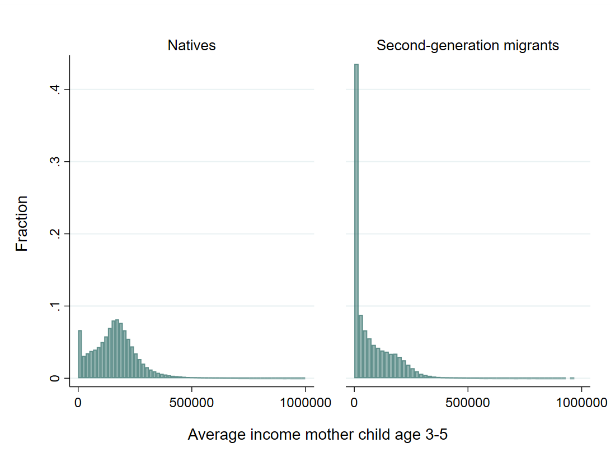
Table A1: Migrant Origin Countries

(1) ID	(2) Countries	(3) %	(4) Refugee	(5) HDI	(6) GII	(7) WVS	(8) Son pref.
00	Sweden			very high	0.055	1.391	
29	Bosnia-Herzegovina	4.2	X	medium	0.326	0.216	
30	Yugoslavia, Croatia, North Macedonia, Slovenia	9.0	X	high	0.221	0.210	X
31	Gdansk, Poland	2.4		high	0.216	0.063	
32	Ireland, Great Britain	0.4		very high	0.231	1.291	
33	Germany	0.9		very high	0.142	1.015	
34	Greece, Italy, Malta, Monaco, Portugal, San Marino, Spain, Vatican City	1.0		very high	0.207	0.668	
35	Estonia, Latvia, Lithuania	0.2		high	0.070	no	
36	Albania, Armenia, Azerbaijan, Bulgaria, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Romania, Russia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan, Belarus	2.1		high	0.416	-0.077	
37	Slovakia, Czech Republic, Hungary	0.9		high	0.295	0.426	
38	Andorra, Belgium, France, Liechtenstein, Luxembourg, Netherlands, Switzerland, Austria	0.5		very high	0.149	1.169	
39	Canada, USA	0.3		very high	0.269	0.937	
40	Antigua and Barbuda, Bahamas, Barbados, Belize, Costa Rica, Cuba, Dominican Republic, El Salvador, Grenada, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, St Lucia, St Vincent, St Kitt-Nevis-Anguilla, Trinidad and Tobago	0.7		medium	0.485	-0.079	
41	Chile	3.0	X	high	0.463	0.352	
42	Argentina, Bolivia, Brazil, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela	1.4		medium	0.515	0.491	
43	Djibouti, Eritrea, Ethiopia, Somalia, Sudan	13.8	X	low	0.249	0.652	
44	Algeria, Bahrain, Cyprus, Egypt, French Morocco, United Arab Emirates, Gaza, Israel, Yemen, Jordan, Kuwait, Lebanon, Libya, Morocco, Palestine, Qatar, Saudi Arabia, South Yemen, Syria, Tunisia	24.7	X	low	0.357	-0.406	X
45	Angola, Benin, Botswana, Burkina Faso, Burundi, Central African Rep., Comoros, Equatorial Guinea, Ivory Coast, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Cameroon, Cape Verde, Kenya, Congo, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Swaziland (Eswatini), South Africa, Tanzania, Chad, Togo, Uganda, DR Congo, Zambia, Zanzibar, Zimbabwe	2.0		low	0.599	-0.079	
46	Iran	5.3	X	medium	0.622	-0.837	
47	Iraq	8.7	X	medium	0.686	-1.179	X
48	Turkey	9.6	X	medium	0.584	-0.324	
49	Hong Kong, Japan, China, South Korea, North Korea	1.6		medium	0.231	0.023	X
50	Myanmar/Burma, Philippines, Indonesia, Laos, Malaysia, Singapore, Thailand, Vietnam	3.9		medium	0.414	-0.262	
51	Afghanistan, Bangladesh, Bhutan, Brunei, India, Kampuchea, Maldives, Mongolia, Nepal, Oman, Pakistan, Sikkim, Sri Lanka	3.7		low	0.435	-0.731	
52	Australia, Fiji, Kiribati, Micronesia, Nauru, New Zealand, Palau, Papua New Guinea, Solomon Islands, Tonga, Vanuatu, Samoa	0.05		very high	0.181	0.994	

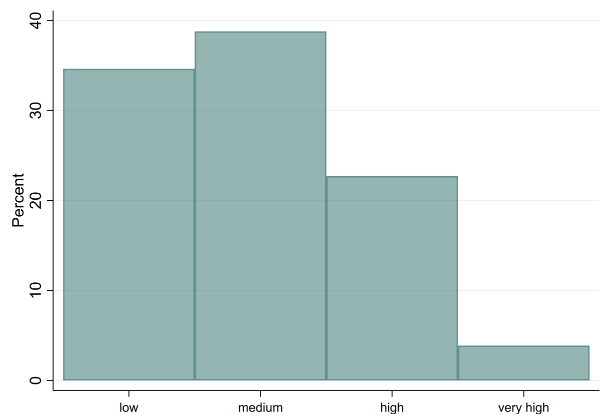
Notes: The table presents the country groups available in the data as well as relevant demographic measures. All are within-country group mean weighted by the total migrant population in Sweden during the sample period. Country groups with large refugee outflows during sample periods are indicated under "Refugee". Two measures provided by the UNDP, "HDI" and "GII", classifies countries by their human development and gender inequality. WVS measures the countries' values/beliefs over time from the World Value Survey, constructed using principal component analysis. Statements used from waves 3-6: "When jobs are scarce a man should have more right to a job than a woman", "men make better political leaders" and "University is more important for a boy than a girl". The first principal component explains 61% of variance with balanced loadings (0.57, 0.60, 0.56). A higher value indicates that the country group is more gender-egalitarian. "Son pref." indicates a significant estimate from regressing subsequent births within six years on first-born gender, a measure of cultural son-preference (Almond et al. 2013).



(a) Density annual family earnings



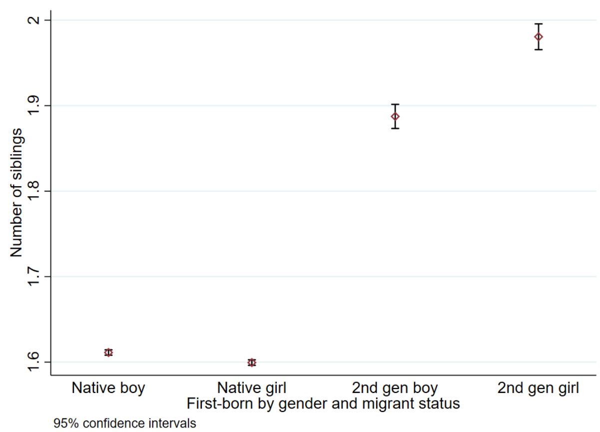
(b) Differences in mother's earnings when child age 3-5



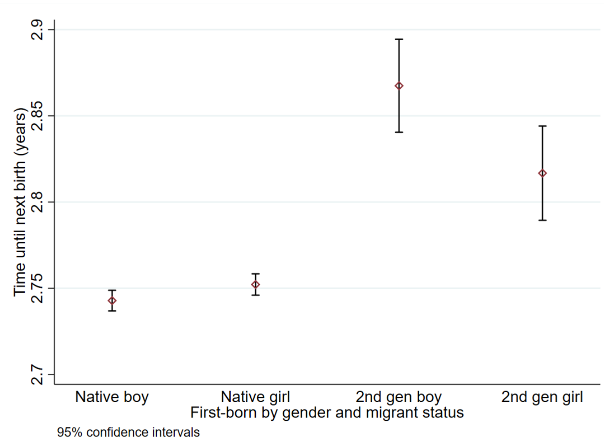
(c) Human development of mother's origin

Figure A1: Migrant and Native Families' Socioeconomic Backgrounds

Notes: The figure provides descriptives on migrant and native families in Sweden during sample period. Panel (a) shows the average annual family earnings for migrant and native families when child is age 3-5. Migrant families include those with children born in Sweden to parents born in non-Nordic countries. Panel (b) shows the fraction of mothers with average earnings between 0-1 000 000 SEK for native and second-generation migrant children when the child is of childcare age. Panel (c) shows the sample of second-generation migrant students divided by the human development index (HDI) of their mother's origin. HDI is the average over the 1988-2003 sample birth-period divided into UNDP categories: low < 0.550, medium 0.550-0.699, high 0.700-0.799, very high ≤ 0.800. For reference, Sweden's average HDI was 0.900 during the sample period.



(a) Number of siblings for first-born gender



(b) Birth spacing before first and second birth

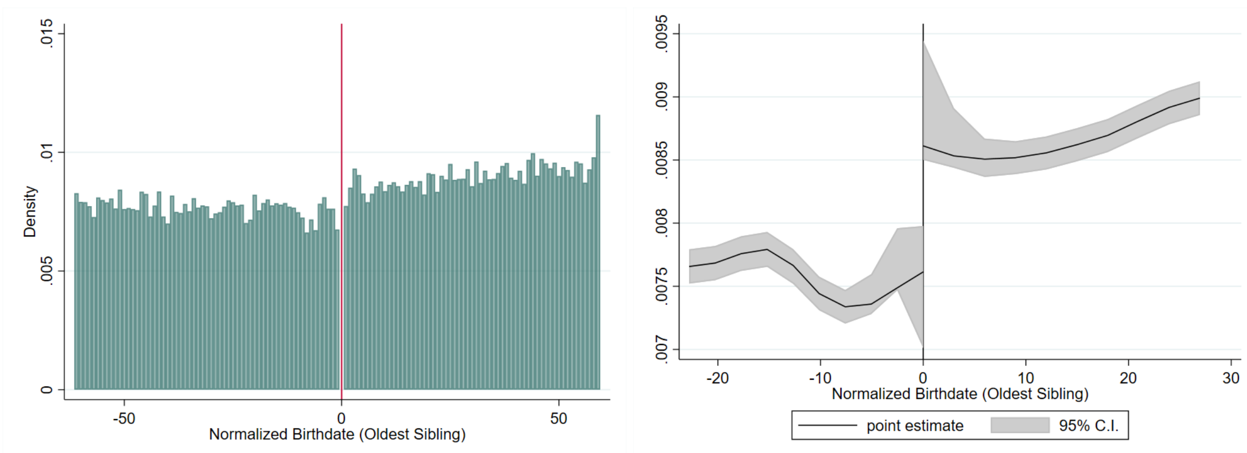
Figure A2: Fertility in Migrant and Native Families

Notes: The figure provides confidence-interval plots of the average number of siblings and birth spacing (in years) between first and second birth in families with either a first-born girl or boy. The estimates are displayed with 95 percent confidence intervals. Overlapping confidence intervals indicate insignificant estimates across sample groups. Families are included conditioning on having at least two children born between 1988-2003. Panel (a) shows the number of siblings by first-born girl and boy in native and migrant families. Panel (b) shows the birth space by first-born girl and boy in native and migrant families.

Table A2: Balance Tests for Native Siblings in Low-SES Families

	Siblings			Mothers		Fathers	
	(1) After Cutoff	(2) Birth Month	(3) Birth Spacing	(4) Earnings (Pctl)	(5) Education (Years)	(6) Earnings (Pctl)	(7) Education (Years)
A. Families with oldest brothers							
Younger sisters							
After	0.036	-0.166	-1.555	1.495	-0.033	0.083	-0.178
	(0.031)	(0.209)	(1.738)	(1.089)	(0.112)	(0.542)	(0.116)
Observations	5,130	5,130	5,130	5,130	5,130	5,130	5,130
R-squared	0.009	0.011	0.057	0.011	0.030	0.013	0.026
Outcome mean	0.516	6.377	41.43	26.77	11.27	13.69	11.14
Younger brothers							
After	0.022	-0.106	-4.873***	-0.615	-0.066	-0.115	0.023
	(0.031)	(0.208)	(1.635)	(1.113)	(0.114)	(0.545)	(0.121)
Observations	5,135	5,135	5,135	5,135	5,135	5,135	5,135
R-squared	0.009	0.009	0.066	0.015	0.033	0.008	0.023
Outcome mean	0.512	6.442	41.04	26.95	11.27	13.67	11.18
B. Families with oldest sisters							
Younger sisters							
After	0.005	-0.232	2.254	-0.569	0.162	-0.357	-0.184
	(0.032)	(0.213)	(1.725)	(1.144)	(0.117)	(0.544)	(0.122)
Observations	4,783	4,783	4,783	4,783	4,783	4,783	4,783
R-squared	0.007	0.009	0.059	0.014	0.025	0.008	0.017
Outcome mean	0.523	6.322	41.13	27.12	11.28	13.52	11.19
Younger brothers							
After	0.027	-0.246	-0.243	-0.554	-0.090	1.134**	0.036
	(0.032)	(0.216)	(1.667)	(1.115)	(0.118)	(0.531)	(0.120)
Observations	4,890	4,890	4,890	4,890	4,890	4,890	4,890
R-squared	0.006	0.009	0.070	0.016	0.019	0.016	0.023
Outcome mean	0.516	6.323	42.29	27.22	11.29	13.44	11.17

Notes: The table provides balance tests for the sample of younger siblings in native families with low socioeconomic status (SES). Estimations include a linear control function and a 60-day bandwidth around the cutoff. Outcomes relating to the younger sibling are indicators of being born after cutoff, birth month, and birth spacing. Outcomes relating to the parents are earnings percentiles and years of education at the time the oldest sibling was of daycare age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.



(a) Distribution of younger siblings

(b) Density test

Figure A3: Smoothness Full Native Sample

Notes: The figure explores the validity of the empirical specification by whether observations can manipulate treatment status for the full native sample. (a) shows the distribution of younger siblings by oldest sibling's birth date each day between November 1st and February 28th normalized around the cutoff. Leap-year births are re-coded to February 28th. (b) shows the density discontinuity of the running variable (birthdate) at the January 1st cutoff. Following Cattaneo et al. (2018) it uses local-polynomial density estimators. With test-statistic 4.2503 with p-value 0.0000 the test rejects the hypothesis that density is smooth around the cutoff.

Table A3: Balance Tests – Full Native Sample

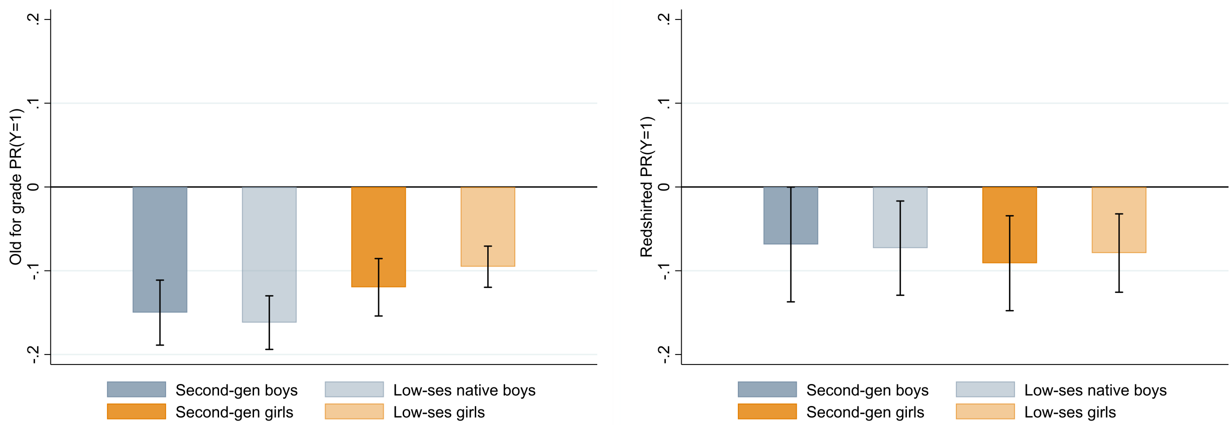
	Younger Sibling			Mothers		Fathers	
	(1) After Cutoff	(2) Birth Month	(3) Birth Spacing	(4) Earnings (Pctl)	(5) Education (Years)	(6) Earnings (Pctl)	(7) Education (Years)
A. Families with oldest brothers							
Younger sisters							
After	-0.004	-0.018	-0.135	1.750***	0.036	0.288	-0.029
	(0.013)	(0.083)	(0.603)	(0.613)	(0.048)	(0.601)	(0.053)
Observations	31,307	31,307	31,307	31,307	31,307	31,307	31,307
R-squared	0.006	0.007	0.050	0.002	0.033	0.002	0.014
Outcome mean	0.535	6.223	40.37	55.53	12.35	59.21	12.13
Younger brothers							
After	-0.003	-0.017	-0.170	1.305**	0.022	0.652	-0.005
	(0.012)	(0.081)	(0.561)	(0.604)	(0.046)	(0.590)	(0.052)
Observations	33,189	33,189	33,189	33,189	33,189	33,189	33,189
R-squared	0.005	0.007	0.049	0.001	0.037	0.002	0.014
Outcome mean	0.539	6.190	40.35	55.43	12.35	59.50	12.15
B. Families with oldest sisters							
Younger sisters							
After	0.024*	-0.183**	0.048	1.033	0.002	0.649	0.015
	(0.013)	(0.087)	(0.594)	(0.644)	(0.049)	(0.617)	(0.055)
Observations	29,446	29,446	29,446	29,446	29,446	29,446	29,446
R-squared	0.005	0.006	0.051	0.002	0.035	0.001	0.016
Outcome mean	0.536	6.223	40.18	54.83	12.33	59.36	12.14
Younger brothers							
After	0.025*	-0.218***	-0.018	1.462**	0.097**	2.309***	0.083
	(0.013)	(0.084)	(0.587)	(0.621)	(0.046)	(0.601)	(0.052)
Observations	31,235	31,235	31,235	31,235	31,235	31,235	31,235
R-squared	0.007	0.008	0.048	0.002	0.031	0.004	0.017
Outcome mean	0.534	6.245	40.10	55.12	12.33	59.29	12.13

Notes: The table provides balance tests for the sample of younger siblings in the full sample of native families. Estimations include a linear control function and a 60-day bandwidth around the cutoff. Outcomes relating to the younger sibling are indicators of being born after cutoff, birth month, and birth spacing. Outcomes relating to the parents are earnings percentiles and years of education at the time the oldest sibling was of daycare age. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Effect of Older School Starting Age on Final GPA First-Borns

	First-Born Boys			First-Born Girls		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Brother	Sister	All	Brother	Sister
A. Second-generation migrants						
After	0.048	0.029	0.052	0.170**	0.080	0.248**
	(0.073)	(0.101)	(0.107)	(0.069)	(0.098)	(0.097)
Observations	3,943	1,981	1,962	3,986	2,007	1,979
R-squared	0.039	0.038	0.047	0.045	0.060	0.045
Outcome mean	-0.213	-0.211	-0.215	0.141	0.111	0.171
A. Natives from low-SES families						
After	0.084	0.047	0.118	0.123**	0.138	0.111
	(0.056)	(0.081)	(0.078)	(0.060)	(0.084)	(0.085)
Observations	6,763	3,361	3,402	6,345	3,162	3,183
R-squared	0.037	0.041	0.042	0.043	0.051	0.041
Outcome mean	-0.474	-0.466	-0.482	-0.0692	-0.0882	-0.0504

Notes: The table shows the effect of being born after the January 1st cutoff on first-born children's GPA at the end of compulsory school. Estimations include a linear control function and a 60-day bandwidth. GPA is standardized to have a mean of zero and a standard deviation of one. Columns (2)-(3) and (4)-(5) divides first borns by the gender of their second-born sibling. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.



(a) Grade retention (9th grade)

(b) Redshirting (1st grade)

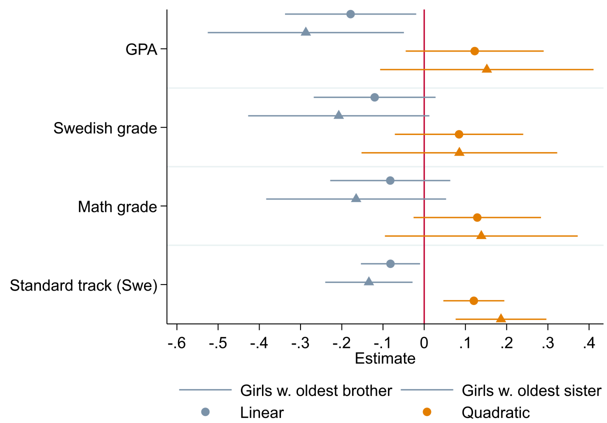
Figure A4: Effect of Older School Starting Age on Retention and Redshirting

Notes: The figure shows the effect of being older at school start on the probability of grade retention and redshirting for first-borns. The effect measured figure (a) is the probability of being old-for-grade, within the main sample of first-borns. This can occur due to have been redshirted at the beginning for compulsory school, or being held back one class sometime after school start. The effect measured in figure (b) is the probability of being redshirted, i.e. starting first grade one year late, at the beginning of compulsory school. First-grade school attendance is only observed in a separate dataset, Elevregistret, which is only available for first-borns who started first grade sometime between 2008-2012. Therefore, Figure (b) is only measured for a subset of the first-borns in the main sample. Elevregistret does not include exact birthdates, so estimations is made using birth month. Both estimations include a linear control function and kernel triangular weights.

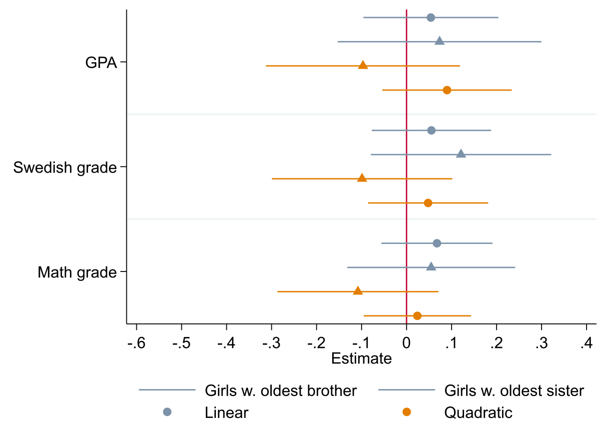
Table A5: Adding Controls to Baseline Regression

Younger Sib.	With Oldest Brother					With Oldest Sister				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Second-generation migrant girls										
After	-0.160**	-0.190**	-0.177**	-0.139*	-0.172**	0.133	0.123	0.127	0.063	0.112
	(0.080)	(0.081)	(0.081)	(0.080)	(0.080)	(0.084)	(0.087)	(0.085)	(0.082)	(0.084)
Observations	3,121	3,121	3,121	3,121	3,121	3,254	3,254	3,254	3,254	3,254
R-squared	0.033	0.019	0.009	0.084	0.048	0.036	0.017	0.011	0.092	0.050
Outcome mean	-0.0277	-0.0277	-0.0277	-0.0277	-0.0277	-0.00143	-0.00143	-0.00143	-0.00143	-0.00143
B. Native girls in low-SES families										
After	0.054	0.062	0.054	0.074	0.030	0.084	0.088	0.092	0.085	0.091
	(0.076)	(0.077)	(0.077)	(0.071)	(0.075)	(0.073)	(0.074)	(0.073)	(0.068)	(0.072)
Observations	4,687	4,687	4,687	4,687	4,687	4,365	4,365	4,365	4,365	4,365
R-squared	0.005	0.013	0.004	0.155	0.031	0.010	0.014	0.009	0.151	0.034
Outcome mean	-0.295	-0.295	-0.295	-0.295	-0.295	-0.231	-0.231	-0.231	-0.231	-0.231
C. Second-generation migrant boys										
After	-0.076	-0.089	-0.090	-0.019	-0.055	-0.077	-0.078	-0.081	-0.057	-0.072
	(0.079)	(0.078)	(0.079)	(0.077)	(0.077)	(0.078)	(0.080)	(0.080)	(0.076)	(0.079)
Observations	3,101	3,101	3,101	3,101	3,101	3,286	3,286	3,286	3,286	3,286
R-squared	0.022	0.024	0.011	0.089	0.050	0.041	0.023	0.009	0.097	0.059
Outcome mean	-0.335	-0.335	-0.335	-0.335	-0.335	-0.350	-0.350	-0.350	-0.350	-0.350
D. Native boys in low-SES families										
After	-0.031	-0.028	-0.036	-0.022	-0.026	-0.030	-0.021	-0.026	-0.019	-0.035
	(0.070)	(0.070)	(0.070)	(0.064)	(0.070)	(0.074)	(0.074)	(0.074)	(0.067)	(0.073)
Observations	4,618	4,618	4,618	4,618	4,618	4,396	4,396	4,396	4,396	4,396
R-squared	0.009	0.014	0.009	0.174	0.021	0.005	0.012	0.005	0.180	0.025
Outcome mean	-0.639	-0.639	-0.639	-0.639	-0.639	-0.605	-0.605	-0.605	-0.605	-0.605
Controls										
Nr. Siblings	Yes	No	No	No	No	Yes	No	No	No	No
Birth M/Y	No	Yes	No	No	No	No	Yes	No	No	No
Birth-space	No	No	Yes	No	No	No	No	Yes	No	No
Parent Edu.	No	No	No	Yes	No	No	No	No	Yes	No
Parent Earn.	No	No	No	No	Yes	No	No	No	No	Yes

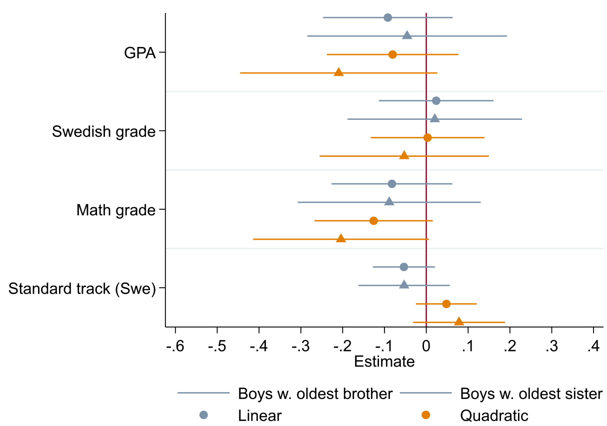
Notes: This table shows the main effects when adding control variables for number of siblings, birth month/year and birth spacing as well as parental education and earnings. Separate regressions for second-generation migrant siblings and native siblings in families with low socioeconomic status. Parents' earnings percentiles and years of education are measured when oldest sibling is of childcare age. The outcome variable is GPA, standardized to have a mean zero and a standard deviation of one. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.



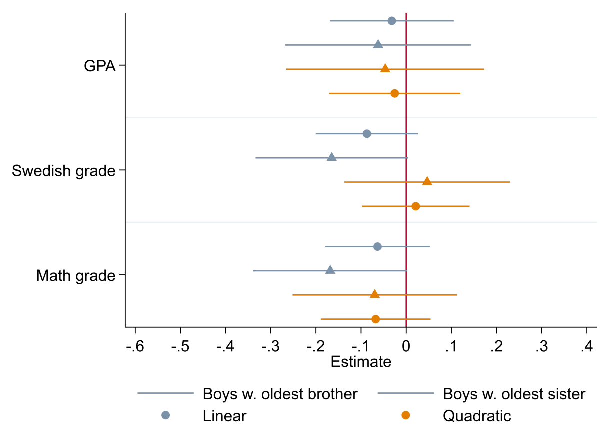
(a) Second-gen migrant girls



(b) Low-SES native girls



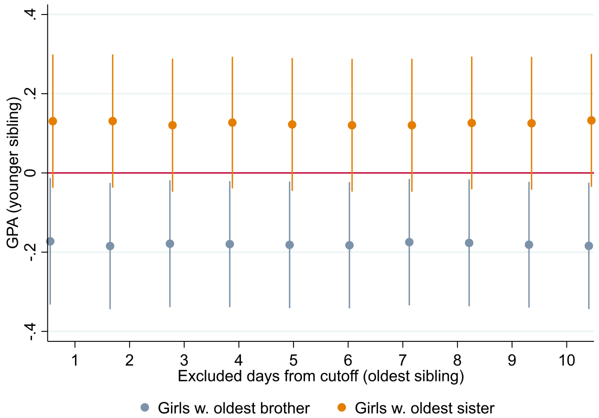
(c) Second-gen migrant boys



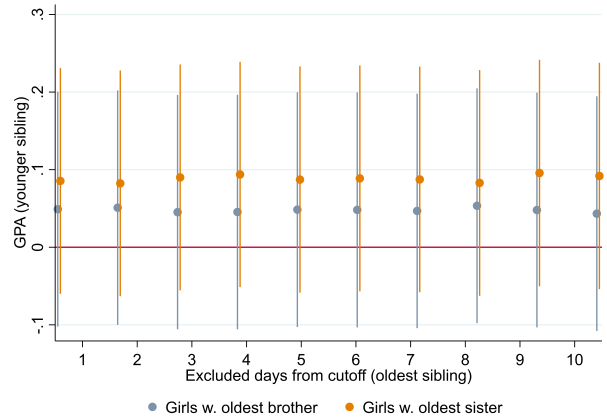
(d) Low-SES native boys

Figure A5: Robustness: Functional Form

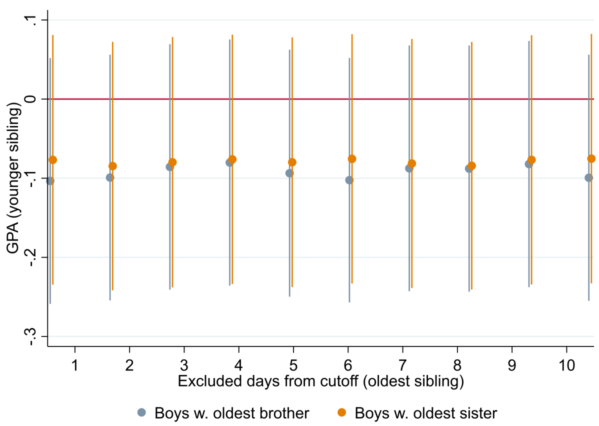
Notes: The figure tests robustness on the main results for final GPA when choosing a second-order polynomial control function. Baseline refers to the main specification, which includes a linear control function and kernel triangular weights. Each point represents a point estimate where the line represents the standard error. If an estimate shows a large deviation from the corresponding baseline estimate the results are not robust to the inclusion of a second-order polynomial.



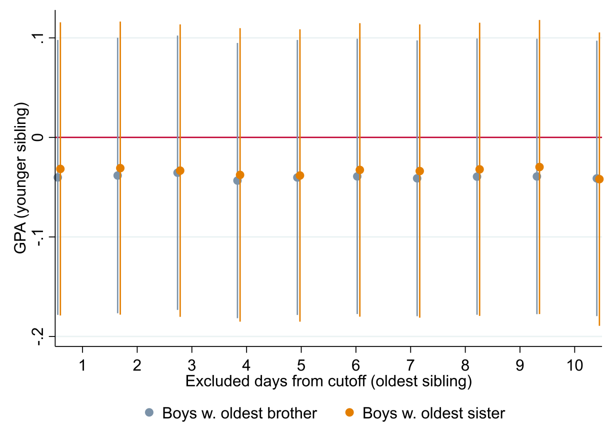
(a) Second-gen migrant girls



(b) Low-SES native girls



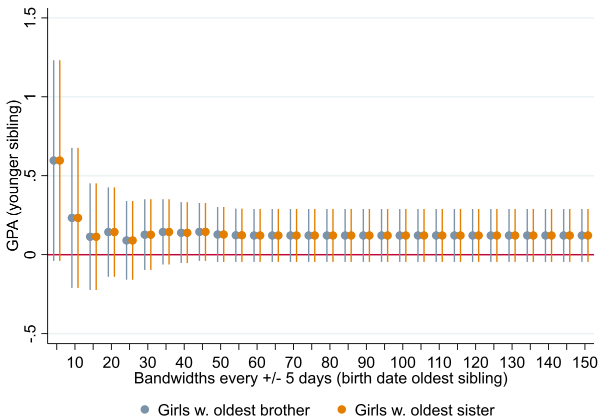
(c) Second-gen migrant boys



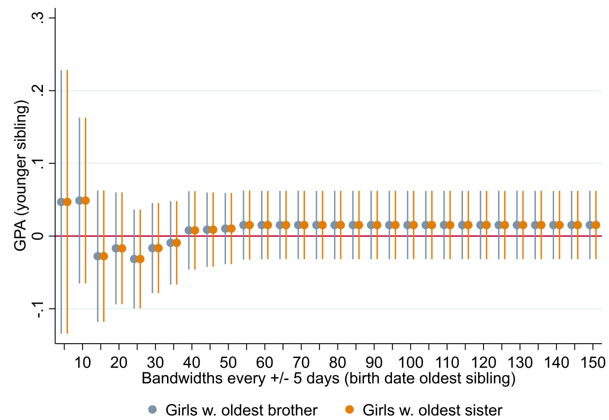
(d) Low-SES native boys

Figure A6: Robustness: Donut Regressions

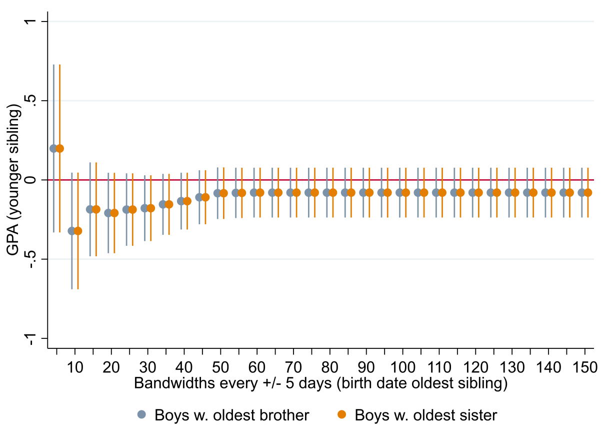
Notes: The figure tests robustness on the main results for final GPA when performing donut regressions. These regressions exclude 1-10 days around the cutoff. Baseline refers to the main specification, which includes all days around the cutoff. Each point represents a point estimate where the line represents the standard error. If an estimate show a large deviation from the corresponding baseline estimate the results are not robust to excluding days around the cutoff.



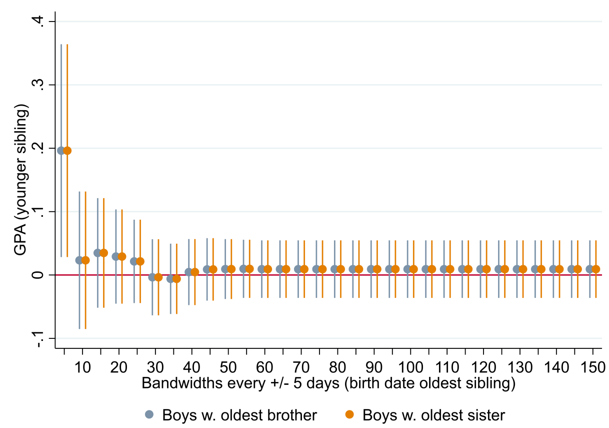
(a) Second-gen migrant girls



(b) Low-SES native girls



(c) Second-gen migrant boys



(d) Low-SES native boys

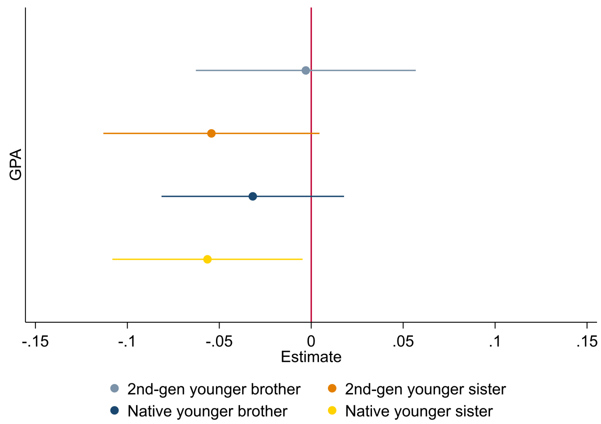
Figure A7: Robustness: Bandwidths

Notes: The figure tests robustness on the main results when choosing a flexible bandwidth every +/- 5 days around the cutoff. Baseline is 60 days around the cutoff. Each point represents a point estimate where the line represents the standard error. Each estimate from left to right adds 5 days to the regression until 150 days, about 4.5 months.

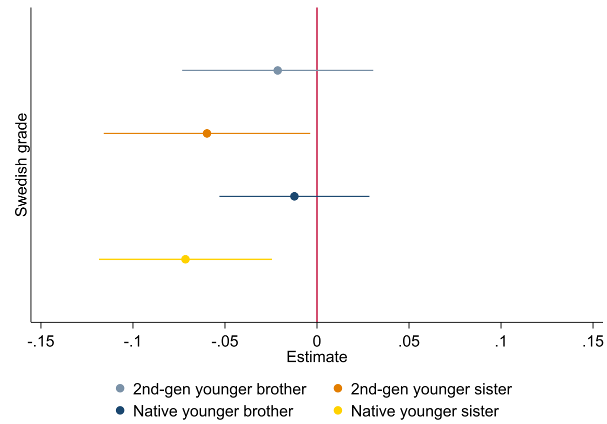
Table A6: Robustness: Main Results using Data-driven Bandwidths

Younger Sibling	With Oldest Brother				With Oldest Sister			
	(1) GPA	(2) Swedish grade	(3) Math grade	(4) Std. track (Swedish)	(5) GPA	(6) Swedish grade	(7) Math grade	(8) Std. track (Swedish)
A. Second-generation migrant girls								
After	-0.179**	-0.120	-0.086	-0.082**	0.123	0.085	0.137*	0.120***
	(0.081)	(0.075)	(0.075)	(0.037)	(0.085)	(0.079)	(0.080)	(0.038)
BW (Days)	63	67	54	62	63	67	54	62
Observations	3,121	3,146	2,885	3,118	3,254	3,287	3,016	3,250
R-squared	0.009	0.007	0.005	0.008	0.009	0.006	0.010	0.012
Outcome mean	-0.0277	-0.0384	-0.229	0.681	-0.00143	-0.00935	-0.215	0.672
B. Native girls in low-SES families								
After	0.056	0.055	0.079	-0.008	0.093	0.048	-0.007	0.004
	(0.077)	(0.068)	(0.071)	(0.008)	(0.074)	(0.068)	(0.068)	(0.011)
BW (Days)	56	63	42	40	56	63	42	40
Observations	4,465	4,790	3,342	3,185	4,157	4,459	3,150	2,986
R-squared	0.004	0.004	0.006	0.006	0.008	0.009	0.007	0.010
Outcome mean	-0.300	-0.0914	-0.324	0.984	-0.239	-0.0143	-0.312	0.983
C. Second-generation migrant boys								
After	-0.030	-0.087	-0.099	-0.012	-0.025	0.021	-0.077	-0.010
	(0.070)	(0.058)	(0.066)	(0.009)	(0.075)	(0.061)	(0.070)	(0.011)
BW (Days)	56	63	42	40	56	63	42	40
Observations	4,404	4,754	3,340	3,167	4,180	4,523	3,185	3,018
R-squared	0.009	0.006	0.009	0.003	0.004	0.002	0.006	0.008
Outcome mean	-0.640	-0.625	-0.399	0.983	-0.607	-0.602	-0.363	0.983
D. Native boys in low-SES families								
After	-0.030	-0.087	-0.099	-0.012	-0.025	0.021	-0.077	-0.010
	(0.070)	(0.058)	(0.066)	(0.009)	(0.075)	(0.061)	(0.070)	(0.011)
BW (Days)	56	63	42	40	56	63	42	40
Observations	4,404	4,754	3,340	3,167	4,180	4,523	3,185	3,018
R-squared	0.009	0.006	0.009	0.003	0.004	0.002	0.006	0.008
Outcome mean	-0.640	-0.625	-0.399	0.983	-0.607	-0.602	-0.363	0.983

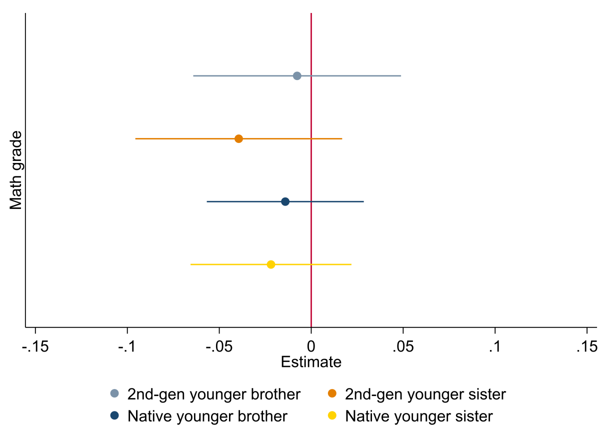
Notes: The table reproduces the main results in Table 3 using datadriven marginal-squared-error optimal bandwidths (BW) from Calonico et al. (2017). Bandwidths (in days) are symmetrical on either side of the cutoff, and chosen separately for the migrant and native sample and outcome variable. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.



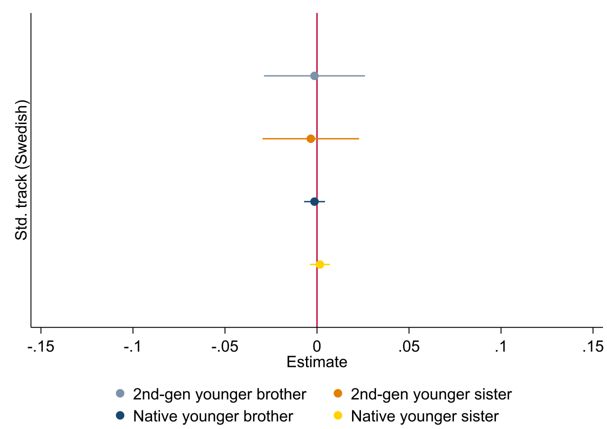
(a) Final GPA



(b) Swedish grade



(c) Math grade



(d) Standard track (Swedish)

Figure A8: The Effect of Having an Oldest Brother Instead of an Oldest Sister

Notes: The figure shows the effect of having a first-born brother instead of a sister on younger siblings' school outcomes on final GPA, Swedish grades, math grades and the probability of being enrolled in the standard Swedish track. Separate regressions by sibling-gender composition and family background. Results displayed here are from regressions that do not include any covariates, but they are robust to the inclusion of controls for number of siblings and birth spacing. Standard errors are heteroskedasticity robust.

Table A7: Heterogeneity by Parents' Earnings

Younger Sibling	With Oldest Brother				With Oldest Sister			
	Father		Mother		Father		Mother	
	(1) Above Median	(2) Earning Percentiles	(3) Above Median	(4) Earning Percentiles	(5) Above Median	(6) Earning Percentiles	(7) Above Median	(8) Earning Percentiles
A. Second-generation migrant girls								
After	-0.534	-0.671	-0.415	-0.343	0.585	0.610	0.720	0.649
	(0.565)	(0.563)	(0.561)	(0.556)	(0.557)	(0.562)	(0.572)	(0.563)
High earner	0.322**	0.009***	0.375**	.005	0.001	-0.001	-0.044	-0.001
	(0.161)	(0.003)	(0.163)	(0.003)	(0.171)	(0.004)	(0.175)	(0.004)
Observations	3,121	3,121	3,121	3,121	3,254	3,254	3,254	3,254
R-squared	0.039	0.045	0.033	0.035	0.040	0.052	0.039	0.028
Outcome mean	-0.027	-0.027	-0.027	-0.027	-0.001	-0.001	-0.001	-0.001
B. Second-generation migrant boys								
After	-0.003	-0.089	-0.029	0.120	-0.673	-0.666	-0.786	-0.689
	(0.575)	(0.571)	(0.577)	(0.585)	(0.555)	(0.547)	(0.564)	(0.569)
High earner	0.093	0.004	0.118	0.003	0.135	0.005	0.145	0.003
	(0.162)	(0.003)	(0.166)	(0.003)	(0.161)	(0.003)	(0.163)	(0.003)
Observations	3,101	3,101	3,101	3,101	3,286	3,286	3,286	3,286
R-squared	0.038	0.044	0.036	0.037	0.043	0.056	0.045	0.037
Outcome mean	-0.335	-0.335	-0.335	-0.335	-0.350	-0.350	-0.350	-0.350

Notes: The table shows the effect of having an oldest sibling born after the January 1st cutoff on GPA, when effect is allowed to differ by parents' earnings. The baseline regression is fully interacted with the indicator. "High earner" shows estimates from interaction between indicator and treatment. GPA is standardized to have a mean of zero and a standard deviation of one. Parents' earnings are measured when the first-born child is age 3-6. "Above median" is a binary measure taking on a value of one if fathers (mothers) earn above the median among migrant fathers (mothers). "Earning percentiles" is a continuous measure. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Heterogeneity by Living Conditions and Family Size

Younger Sibling	With Oldest Brother			With Oldest Sister		
	(1) Father Years	(2) Mother Years	(3) Migrant Neighbor	(4) Father Years	(5) Mother Years	(6) Migrant Neighbor
A. Living conditions						
Younger sisters						
After	-0.259**	-0.101	-0.388***	0.201	0.098	0.137
	(0.116)	(0.105)	(0.141)	(0.132)	(0.105)	(0.143)
After × Indicator	0.010	-0.022	0.483	-0.013	0.006	-0.084
	(0.013)	(0.018)	(0.350)	(0.015)	0.018)	(0.360)
Observations	3,121	3,121	3,121	3,254	3,254	3,254
R-squared	0.022	0.011	0.029	0.019	0.010	0.045
Outcome mean	-0.0277	-0.0277	-0.0277	-0.00143	-0.00143	-0.00143
Younger brothers						
After	-0.246**	-0.183*	0.077	-0.240**	-0.140	-0.348**
	(0.120)	(0.099)	(0.127)	(0.117)	(0.099)	(0.142)
After × Indicator	0.022*	0.021	-0.487	0.023*	0.015	0.779**
	(0.012)	(0.015)	(0.345)	(0.014)	(0.016)	(0.350)
Observations	3,101	3,101	3,101	3,286	3,286	3,286
R-squared	0.019	0.012	0.034	0.021	0.012	0.028
Outcome mean	-0.335	-0.335	-0.335	-0.350	-0.350	-0.350

	(1) Birth Spacing	(2) Birth Order	(3) Number Siblings	(4) Birth Spacing	(5) Birth Order	(6) Number Siblings
B. Family size						
Younger sisters						
After	-0.110	0.072	0.075	-0.009	-0.077	0.165
	(0.153)	(0.338)	(0.168)	(0.169)	(0.302)	(0.185)
After × Indicator	-0.002	-0.101	-0.130	0.003	0.084	-0.016
	(0.003)	(0.143)	(0.091)	(0.003)	(0.119)	(0.089)
Observations	3,121	3,121	3,121	3,254	3,254	3,254
R-squared	0.009	0.021	0.035	0.011	0.025	0.036
Outcome mean	-0.0277	-0.0277	-0.0277	-0.00143	-0.00143	-0.00143
Younger brothers						
After	-0.140	0.065	0.189	0.014	0.020	-0.119
	(0.145)	(0.256)	(0.165)	(0.151)	(0.269)	(0.155)
After × Indicator	0.001	-0.061	-0.155*	-0.002	-0.040	0.021
	(0.002)	(0.100)	(0.084)	(0.003)	(0.106)	(0.072)
Observations	3,101	3,101	3,101	3,286	3,286	3,286
R-squared	0.013	0.018	0.023	0.011	0.031	0.042
Outcome mean	-0.335	-0.335	-0.335	-0.350	-0.350	-0.350

Notes: The table provides heterogeneity analysis for migrant families by their living conditions (Panel A) and family size (Panel B). Baseline regression is fully interacted with the indicator. After × Indicator gives the difference in effects. Outcome is GPA, standardized to have a mean of zero and a standard deviation of one. "Father/Mother years" indicate years since migration to Sweden. Neighborhoods are measured as Small Areas for Market Statistics (SAMS). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Mechanisms Low-SES Natives

Younger Sibling	With Oldest Brother				With Oldest Sister			
	(1) Father Earn	(2) Mother Earn	(3) Father Employ	(4) Mother Employ	(5) Father Earn	(6) Mother Earn	(7) Father Employ	(8) Mother Employ
A. Parents' labor force participation								
Younger sisters								
After	0.008	0.085	0.027	0.039	-0.091	0.005	0.008	-0.053
	(0.064)	(0.060)	(0.038)	(0.048)	(0.069)	(0.063)	(0.038)	(0.049)
After × Indicator	-0.001	-0.002**	-0.122**	-0.098*	0.001	-0.000	-0.039	0.056
	(0.001)	(0.001)	(0.048)	(0.055)	(0.001)	(0.001)	(0.050)	(0.057)
Observations	30,319	30,319	30,319	30,319	28,461	28,461	28,461	28,461
R-squared	0.054	0.033	0.017	0.012	0.042	0.029	0.015	0.009
Outcome mean	0.234	0.234	0.234	0.234	0.274	0.274	0.274	0.274
Younger brothers								
After	0.094	-0.113*	-0.080**	-0.094**	-0.073	0.002	0.030	0.017
	(0.063)	(0.059)	(0.036)	(0.045)	(0.066)	(0.059)	(0.036)	(0.047)
After × Indicator	-0.002	0.002**	0.138***	0.136***	0.001	-0.000	-0.078	-0.034
	(0.001)	(0.001)	(0.047)	(0.053)	(0.001)	(0.001)	(0.048)	(0.054)
Observations	31,887	31,887	31,887	31,887	30,033	30,033	30,033	30,033
R-squared	0.053	0.034	0.016	0.011	0.059	0.034	0.014	0.009
Outcome mean	-0.143	-0.143	-0.143	-0.143	-0.130	-0.130	-0.130	-0.130

	(9) Migrant Neighbor	(10) Birth Space	(11) Birth Order	(12) Number Siblings	(13) Migrant Neighbor	(14) Birth Space	(15) Birth Order	(16) Number Siblings
B. Living conditions and family size								
Younger sisters								
After	0.071	0.010	-0.156	-0.204	-0.012	0.147	0.260	0.105
	(0.098)	(0.142)	(0.308)	(0.157)	(0.098)	(0.142)	(0.300)	(0.157)
After × Indicator	-0.287	0.001	0.093	0.170*	1.248*	-0.001	-0.075	-0.012
	(0.716)	(0.003)	(0.133)	(0.092)	(0.712)	(0.003)	(0.129)	(0.090)
Observations	4,406	4,687	4,687	4,687	4,113	4,365	4,365	4,365
R-squared	0.020	0.005	0.006	0.007	0.020	0.009	0.013	0.011
Outcome mean	-0.300	-0.295	-0.295	-0.295	-0.238	-0.231	-0.231	-0.231
Younger brothers								
After	-0.114	-0.070	-0.160	-0.178	-0.124	0.055	0.054	0.161
	(0.090)	(0.136)	(0.287)	(0.150)	(0.096)	(0.137)	(0.289)	(0.152)
After × Indicator	0.835	0.001	0.055	0.094	0.735	-0.002	-0.037	-0.121
	(0.586)	(0.003)	(0.125)	(0.086)	(0.638)	(0.003)	(0.122)	(0.083)
Observations	4,369	4,618	4,618	4,618	4,170	4,396	4,396	4,396
R-squared	0.013	0.010	0.010	0.010	0.012	0.005	0.007	0.007
Outcome mean	-0.639	-0.639	-0.639	-0.639	-0.608	-0.605	-0.605	-0.605

Notes: The table provides heterogeneity analysis for native families with low socioeconomic status, by parents' labor force participation (Panel A) and the family's living conditions and size (Panel B). Baseline regression is fully interacted with the indicator. Outcome GPA is standardized to have a mean of zero and a standard deviation of one. Parents earnings measured when the first-born is age 3-6. Employment takes on the value 1 if the father/mother earns at least half of the median earning for 45-year-old men/women in the Swedish labor force. This was calculated using the average annual earnings of men/women aged 44-46 in 1985-2018, deflated to 2018 values. Neighborhoods are measured as Small Areas for Market Statistics (SAMS). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B Conceptual Framework

This appendix provides details on the theoretical framework discussed in Section 2. By using the budget constraint to express I_2 in terms of I_1 and substituting it into the utility function, I transform this constrained optimization problem into an unconstrained one with respect to I_1. The first-order condition that characterizes the optimal level of parental investment, $I_1^* = I_1^*(\sigma_1, \sigma_2, \gamma_1, \gamma_2, y)$, is given by:

$$G \equiv \gamma_1 U_1 f_1^1 - \gamma_2 U_2 f_1^2 = 0 \tag{D.1}$$

Here, U_i represents the partial derivative of $U(\cdot)$ with respect to H_i $(i = 1, 2)$, while f_k is the derivative of $f^i(\cdot)$ with respect to kth argument $(k = 1, 2, 3)$. The arguments of these functions are omitted for simplicity of exposition.

Next, I provide details on the comparative statics. Specifically, I formally derive $\partial I_1^*/\partial\sigma_1$, capturing the parental investment response to an increase in child 1's school starting age. By the implicit function theorem, the sign of $\partial I_1^*/\partial\sigma_1$ is determined by the sign of $\partial G/\partial\sigma_1$, where G is defined in eq. D.1. This derivative is given by:

$$\frac{\partial G}{\partial \sigma_1} = \gamma_1 \left[U_1 f_{12}^1 + f_1^1 \left(\gamma_1 U_{11} f_2^1 + \gamma_2 U_{12} f_2^2\right)\right] - \gamma_2 \left[U_2 f_{12}^2 + f_1^2 \left(\gamma_1 U_{12} f_2^1 + \gamma_2 U_{22} f_2^2\right)\right], \tag{D.2}$$

where the derivatives of $U(\cdot)$ and $f^i(\cdot)$ are defined analogous to those in the main text. Consider first the limiting case where $\gamma_2 \to 0$, i.e., the case of biased parental preferences where only the human capital of child 1 has weight in the parent's utility function. The derivative is then given by

$$\frac{\partial G}{\partial \sigma_1} = \gamma_1 U_1 f_{12}^2 + \gamma_1^2 f_1^1 f_2^1 U_{11}. \tag{D.3}$$

The sign of this derivative is primarily determined by the first term, as the second term is of second order and generally small. The first term is strictly positive, reflecting that when child 1 enters school later, the parent will increase investments in that child beforehand to maximize the benefits of late school entry. Since the parent faces a budget constraint, investments in child 2 will decrease as a result.

The same conclusion can be drawn by evaluating the derivative in eq. D.2 at symmetry, i.e., where $f^i(\cdot) = f(\cdot)$. In this case,

$$\left.\frac{\partial G}{\partial \sigma_1}\right|_{sym} = sign(\gamma_1 - \gamma_2). \tag{D.4}$$

Thus, at symmetry, increasing child 1's school starting age will increase parental investment in them while reducing investment in child 2 if parental preferences are biased toward child 1.

More generally, however, the sign of $\partial G/\partial \sigma_1$ (and consequently $\partial I_1^*/\partial \sigma_1$) can also depend on technological differences in the production functions $f^1(\cdot)$ and $f^2(\cdot)$, even if parental preferences are neutral (i.e., $\gamma_1 = \gamma_2$). For example, even if $\gamma_1 = \gamma_2$, the derivative in eq. (D.1) can be positive if there are strong complementarities between child 1's school starting age and parental investments in them (f_{12}^1 significantly larger than f_{12}^2).