The Timing of Educational Inequality: Early Mechanisms Behind Gender Gaps in Maths Achievement

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Abstract

This study examines the development of gender gaps in Maths achievement among Irish secondary school students using data from the Growing Up in Ireland study. I use Oaxaca-Blinder decompositions at two stages, age 9 and age 13, to separate differences in observed characteristics (endowments) from differences in returns to these characteristics (coefficients). Boys outperform girls by approximately 4.4 to 5.2 points in Leaving Certificate Maths scores. Decomposition results show that at age 9, differences in returns explain a larger share of the gap, while by age 13, differences in cognitive skills, particularly numerical ability, account for most of the observed gap. Family background also matters. Students with absent fathers experience substantial penalties in Maths achievement, with gaps of 13.6 points for boys and 15.2 points for girls. For boys, the penalty is driven by both skill differences and lower returns. For girls, maternal education and socioeconomic factors play a stronger role. These findings point to the need for early interventions to reduce gender disparities in Maths achievement and to address the compounding effects of family disadvantage on educational outcomes.

Keywords: Gender gap; Maths achievement; Oaxaca-Blinder decomposition; Father absence; Cognitive skills; Socioeconomic background

JEL Codes: I21, I24, J12, J16

1 Introduction

Despite significant progress in educational attainment across genders, persistent disparities in Maths performance remain a critical pathway through which educational inequalities translate into broader economic ones. These inequalities are visible both at the intensive margin (subject-specific gaps such as in Maths) and the extensive margin (college graduation rates), with long-term implications for individual careers and broader societal outcomes. Women are still under-represented in STEM fields, limiting their access to high-paying jobs and advancement opportunities (Becker, 1964; Card, 1999). Fryer and Levitt (2010) show that gender gaps in Maths emerge early and vary widely across countries, suggesting that cultural and institutional factors play an important role. Guiso et al. (2008) find that these gaps tend to be smaller in countries with greater gender equality, while Nollenberger et al. (2016) link cross-country differences to culturally transmitted gender norms passed from parents to children. Evidence shows that women earn over 20 per cent less than men in STEM fields during the first year after graduation, with gaps particularly pronounced among Maths graduates (Zajac et al., 2025). Moreover, studies highlight that self-efficacy gaps, despite equivalent or higher academic performance, may contribute to lower persistence among women in STEM careers (Whitcomb et al., 2020). This underrepresentation may not solely reflect differences in preferences but also stem from early differences in opportunities, levels of encouragement, and patterns of skill development throughout childhood (Ceci & Williams, 2014; Xie & Shauman, 2003).

The reversal of the gender gap in higher education, with women now surpassing men in college graduation rates across most OECD countries, has further sparked debate about the role of early-life environments and noncognitive skill formation. Lundberg (2017) finds that boys are more vulnerable to family disadvantage and father absence, exhibiting greater behavioural problems and lower educational aspirations in adolescence. This pattern raises important questions about how boys and girls develop differently, and whether cognitive and socioemotional skills help explain these achievement gaps.

These educational inequalities are intricately linked to broader economic disparities, including imbalances in labour market participation, wage gaps, and career progression (Blau & Kahn, 2000; Mincer & Polachek, 1974). By leveraging longitudinal data, I trace the contribution of key early-life traits and environments to the gender gap, identifying when these factors become most influential. This provides insights for designing targeted policies that address disparities at their source rather than attempting to remediate them after they have solidified.

I examine the gender gap in Maths achievement at age 17/18 through four interconnected research questions:

1. To what extent is the gender difference in Maths achievement at age 17/18 driven by differences in observable skills (endowments) versus differences in the returns to those skills (coefficients)?

2. How does the composition of the gender gap change when comparing predictors measured at ages 9 and 13?

3. How do family background factors, particularly paternal involvement, and school environments contribute to shaping gendered achievement patterns?

4. Does consistent paternal non-response, as a proxy for disengagement, differentially affect boys' and girls' Maths achievement?

To investigate these questions, I use Oaxaca-Blinder decomposition techniques to separate the gender gap into components due to differences in endowments and differences in returns. This approach shows not just which traits matter, but also when and whether they matter differently for boys and girls. Using data from the Growing Up in Ireland study, a nationally representative longitudinal dataset following children from age 9 into early adulthood, I estimate separate decompositions using predictors measured at age 9 (Wave 1) and age 13 (Wave 2), comparing models with and without controls for paternal education. This approach allows me to examine whether gender gaps and father absence penalties are mainly due to differences in observed characteristics (such as prior cognitive ability or socio-emotional skills) or to differences in how these characteristics are rewarded. The analysis sample consists of 4,333 participants who completed the Wave 4 interview and provided valid information on Leaving Certificate Maths achievement, cognitive assessments, socioemotional measures, and key demographic controls. Attrition relative to the original sample (5,190 participants at Wave 4) is mainly due to item-level missingness rather than full-wave nonresponse.

The primary outcome, Leaving Certificate Maths score, is harmonised across cohorts to ensure comparability across grading systems. Cognitive skills are measured using standardised logit scores on verbal, numerical, and reasoning assessments collected at ages 9 and 13. Socioemotional traits are measured using four Strengths and Difficulties Questionnaire (SDQ) scales: Emotional Symptoms, Conduct Problems, Hyperactivity/Inattention, and Peer-relationship Problems. Parental education, family income, and school type are also included as key background variables. Father absence is proxied by consistent missingness of paternal education data across Waves 1 and 2, capturing sustained disengagement throughout childhood and early adolescence (see Table 2 for full sample characteristics).

With the data structure and variables established, I next present the main decomposition results.

I find distinct patterns in both gender gaps and father absence effects. For gender differences, the Maths achievement gap favouring boys (4.4–5.2 points) is explained by a combination of endowment effects, particularly boys' higher prior maths ability, and coefficient effects, which suggest that the same traits are rewarded differently by gender (see Figure 1). The composition of the gap changes between waves, with coefficients playing a larger role in earlier years and endowments becoming more important by age 13. For father absence, substantial penalties exist for both boys (13.6 points) and girls (15.2 points), but with different factors at play. Both endowments and coefficients contribute to the father absence penalty, but maternal education shows stronger effects for girls, while fee-paying school status matters more for boys. These results show that the gender gap in Maths achievement changes over time: what begins as differences in how boys and girls are treated becomes differences in actual skills by adolescence (Cimpian et al., 2016; Legewie & DiPrete, 2014). Early adolescence seems to be a key period when gender differences in skill formation become stronger, consistent with Hyde and Mertz (2009). This change from early differences in treatment to real differences in measured skills suggests that early inequalities do not just continue but grow as children move through the education system (Endendijk et al., 2016; Penner, 2008).

To make the results easier to follow, the main text focuses on two key Oaxaca-Blinder decomposition plots summarising gender gaps and father absence effects on Maths achievement at the Leaving Certificate (Figures 1 and 2). Detailed decomposition tables for Leaving Certificate Maths are provided in Appendices E (gender gaps) and F (father absence effects), based on models estimated with and without controls for father's education. Full OLS regression results underlying these decompositions are reported in Appendix B.

Supplementary results for Junior Certificate Maths and English are included in Appendices I and J, but are not emphasised in the main analysis due to concerns about reporting accuracy and comparability. Additional decomposition analyses for Leaving Certificate English are presented in Appendices G (gender gaps) and H (father absence effects).

Finally, changes in family structure between survey waves, which inform the construction of the father absence variable, are described in Appendix D.

The supplementary decomposition analyses in the appendices are consistent with the main results. For Junior Certificate outcomes, the Maths gender gap favouring boys and the father absence penalties are similar to those found at the Leaving Certificate stage, although slightly smaller. English achievement shows a reversed gender gap, with girls outperforming boys, mainly due to differences in returns to traits rather than differences in observed characteristics. Father absence also has a negative effect on English achievement, although the main factors shift more toward early cognitive skills and family background. These results give additional support to the patterns seen in the main analysis and show that these patterns are present across different stages of schooling.

2 Related Literature

A growing body of research looks at how early skill development, family environments, and school contexts affect academic achievement and later labour market outcomes. Within this broader literature, several areas are particularly relevant for understanding persistent gender gaps in Maths performance.

Gender gaps in educational achievement, especially in Maths, have been widely documented across different countries. Boys tend to show higher rates of behavioural problems and lower levels of school engagement, but also tend to perform better than girls in Maths assessments. This pattern has important implications for later entry into STEM fields. Family disadvantage seems to make these gaps worse: boys from disadvantaged backgrounds face larger educational penalties than girls, both in terms of behaviour (Bertrand & Pan, 2013) and long-term educational outcomes (Autor et al., 2019). Brenøe and Lundberg (2018) find that father absence affects girls' long-run educational outcomes more strongly than boys', largely through reduced parental inputs and monitoring. Cross-national research shows that the size and even the direction of gender gaps in Maths varies a lot depending on the social and educational context (Hyde & Mertz, 2009; Lindberg et al., 2010).

Research on cognitive and socioemotional development helps explain how early skills contribute to these gaps. Early cognitive skills, particularly numeracy and verbal reasoning, are strong predictors of later academic success even after taking socioemotional factors into account (Duncan et al., 2007). The economics of skill formation shows how cognitive and socioemotional traits build on each other, with early investments paying off more over time (Cunha & Heckman, 2007; Heckman et al., 2006). Empirical studies also show that traits like self-regulation and perseverance are strong predictors of academic achievement, sometimes even more important than IQ (Duckworth & Seligman, 2005). However, there is still relatively little research on how these early traits predict subject-specific outcomes like Maths, and how their importance changes as children get older.

Socioeconomic background remains one of the strongest predictors of academic achievement. It shapes both cognitive and socioemotional development through factors such as access to resources, parenting practices, and exposure to stress (Bradley & Corwyn, 2002; Sirin, 2005). These effects also change over time: children from disadvantaged families tend to fall further behind as they grow older, reflecting cumulative disadvantages (Caro et al., 2009). Family structure plays a role as well, with maternal education having particularly strong effects in single-parent households (Augustine, 2014).

Research on family structure also shows that father absence is linked to lower educational attainment and higher rates of behavioural problems, even after controlling for background characteristics (McLanahan et al., 2013). Family instability increases these risks, especially for boys, who seem to be more affected by changes in household composition (Fomby & Cherlin, 2007; Lee & McLanahan, 2015). School environments also matter. Lavy and Sand (2018) document that teacher gender biases can affect both students' academic achievement and their later course selection. Carlana (2019) shows that teachers' implicit stereotypes widen the gender gap in Maths performance and lower students' self-confidence, particularly among girls. Paternal involvement is associated with better cognitive and behavioural outcomes, although the amount of time fathers spend with children often differs depending on the child's gender (Baker & Milligan, 2016; Sarkadi et al., 2008).

Overall, the literature shows that gender differences in academic achievement come from a mix of early skill differences, family resources, and school environments. These factors tend to matter most at certain stages of development. My analysis builds on this work by breaking down the gender gap in Maths achievement into parts explained by differences in skills and family background, and by comparing how these factors matter at different ages. I show that differences in numerical ability become a more important part of the gender gap as students get older, and that the effects of father absence and school environment also change by gender over time.

2.1 The Growing Up in Ireland Longitudinal Study

This study uses data from the *Growing Up in Ireland* (GUI) project, the first large national longitudinal survey of children in the Republic of Ireland. GUI was launched in 2006 to study the factors that influence children's well-being and development, with the goal of informing policymaking. It follows two cohorts: an infant cohort (Cohort '08) and a child cohort (Cohort '98), the latter of which is used in this study.

Cohort '98 includes 8,568 children born between 1 November 1997 and 31 October 1998, selected through a sample of the primary school system. Participants were first interviewed at age 9 (Wave 1, 2007–2008), and later at ages 13 (Wave 2, 2011–2012), 17–18 (Wave 3, 2015–2016), and 20 (Wave 4, 2018–2019). Retention remained high across waves, with 7,525 interviews at age 13, 6,216 at age 17/18, and 5,190 at age 20.[1] Data collection combined in-home interviews, parent and teacher questionnaires, and cognitive and behavioural assessments.

The GUI design offers several advantages. It provides repeated measures of cognitive and socioemotional skills from childhood into adulthood. It also collects detailed information on parental education, household income, school environment, and family structure. Its school-based sampling allows for analysis of peer effects and school contexts. Finally, the high retention rates make longitudinal analysis more reliable.

Table 1 shows the timing of data collection, participant ages, and key variables used in this study.

The GUI sample was selected through schools, leading to natural clustering within local areas. Original household IDs were based on Area and Household identifiers, where "Area" corresponded to a school. New anonymized IDs were later created to protect privacy.

The main outcome in this study is Leaving Certificate Maths performance, measured using self-reported point scores at Wave 4 (age 20).[2] Because of inconsistencies in reporting bonus points across cohorts, two variables were constructed: a raw score and an adjusted version. The

[1]At Wave 4, 20-year-olds became the main respondents, but parents often completed supplementary questionnaires. This wave collected retrospective information on education, work, and time use.

[2]At Wave 3, only 713 participants had already sat the Leaving Cert. Most were still in school and planned to sit it later.

Event	Date	Age (in years)	Variables of interest
Study-child is born	Nov/97 - Oct/98	0	-
Wave 1 data collection	Aug/07 - May/08	9	2 Cognitive variables (Reading and Maths logit scores), 4 SDQ scales, Parental Education (mother and father's), Income quintiles, 1 School Indicator (CoEd)
Wave 2 data collection	Aug/11 - Mar/12	13	3 Cognitive variables (Verbal and Numerical logit scores, BAS Matrices), 4 SDQ scales, Parental Education (mother and father's), Income quintiles, 4 School Indicators (DEIS, CoEd, Fee-paying, Religious Ethos)
Study-child sits the Junior Cert	Jun/13 - Jun/15	15–16	-
Wave 3 data collection	Apr/15 - Aug/16	17–18	Most participants had *not yet sat* the Leaving Cert
Study-child sits the Leaving Cert	Jun/16 - Jun/17	17–18	-
Wave 4 data collection	Aug/18 - Jun/19	20	Leaving Cert points in Maths scores

Table 1: Timeline of Events - Growing Up in Ireland '98 Cohort

adjusted score caps bonus points at 100 and treats invalid entries as missing. This adjusted score is used throughout the main analysis.[3]

A dummy variable identifies which grading system applied to each participant. Before 2017, the grading system used A1–D3 bands mapped to a non-linear points scale. From 2017 onward, grades were simplified into H1–H8 (Higher Level) and O1–O8 (Ordinary Level), with a more uniform points structure. A 25-point bonus was awarded for passing Higher Level Maths, starting in 2012. Because some students mistakenly reported bonus-inflated scores, and because only the best six subjects counted for CAO entry, bonus inflation and score misreporting created challenges. Subtracting 25 points where needed and capping scores at 100 ensures comparability across years.

To measure prior academic achievement, Junior Certificate Maths and English scores were derived from reported grades, mapped to a 12-point scale similar to CAO points. However, due to limited variation and self-reporting concerns, Junior Cert results are used only in supplementary analyses.

The cognitive ability measures are chosen to allow comparison over time. In Wave 1, children completed the Drumcondra Reading and Maths tests (logit scores). In Wave 2, cognitive skills were measured using the Drumcondra Verbal and Numerical Reasoning tests and the British Ability Scales Matrices test. Logit scores adjust for item difficulty and are more comparable across versions than raw percentages, making them better suited for longitudinal analysis.

The Primary Caregiver was identified based on who reported providing the most care. In most cases, this was the mother. In a small number of cases (less than 1%), the father was the

[3]Before 2017, bonus points were only awarded for Higher Level Maths grades above 40%, but the reform introduced broader grade bands. Without adjustments, raw scores are not comparable across cohorts.

Primary Caregiver even when the mother was present.

Parental education was recorded based on the highest completed level. Education levels were grouped into broader categories: Lower Secondary, Higher Secondary/Technical, Non-Degree Third Level, and Degree or Postgraduate. Two dummies were created for each parent: one for Higher Secondary/Technical education and another for Degree or Postgraduate education. No imputation was performed when father's education was missing.

Household income was equivalised based on household composition, using weights of 1 for the first adult, 0.66 for each additional adult, and 0.33 for each child under 14. Disposable income was calculated after taxes and social insurance. Income quintiles and deciles are provided.

In Wave 1, children took group tests at school: the Vocabulary section of the Drumcondra Reading Test and Part 1 of the Drumcondra Maths Test. Depending on grade, they completed Level 2, 3, or 4. These newly revised tests had not been used in schools before GUI. Only the first part of each test was administered to reduce school burden.

In Wave 2, cognitive tests were administered at home. These included the Drumcondra Verbal and Numerical Reasoning tests and the BAS Matrices test. Drumcondra logit scores adjust for item difficulty. The BAS Matrices test measures non-verbal reasoning and provides a total and age-equivalent score.

Socioemotional traits were measured using the Strengths and Difficulties Questionnaire (SDQ), answered by the primary caregiver and, in Wave 1, also by teachers. The SDQ includes five subscales: Emotional Symptoms, Conduct Problems, Hyperactivity/Inattention, Peer Problems, and Prosocial Behaviour. For this study, only the four difficulties subscales are used.

School-level variables such as DEIS, fee-paying status, and religious ethos were collected only in Wave 2. In 2007–2008, DEIS schools were still a new initiative, and fee-paying schools made up a small share of the system. School type (CoEd or single-sex) was available in both waves. These school-level characteristics become more relevant once students enter secondary school, helping explain later achievement differences.

3 What are the relative contributions of gender and family background to the gender gap in Maths achievement at ages 17/18?

To establish a baseline understanding of how cognitive, noncognitive, socioeconomic, and school-related factors predict Maths performance, I estimate OLS regressions using predictors from age 9 (Wave 1) and age 13 (Wave 2). Full regression tables and model diagnostics are provided in Appendix B. Models using Wave 2 predictors explain a greater share of the variance in Maths scores (adjusted $R^2 \approx 0.39$–0.40) than those using Wave 1 predictors (adjusted $R^2 \approx 0.30$), suggesting that factors measured closer to the time of the Leaving Certificate have stronger predictive power. Consistent and statistically significant predictors include numerical ability, reading ability, hyperactivity, and parental education. Moreover, missing father's education information (capturing unobserved aspects of paternal disengagement) is associated with lower achievement. These baseline models serve as the foundation for the decomposition analyses that follow, which quantify the share of the gender gap attributable to differences in endowments versus differences in returns.

3.1 Empirical Strategy

To decompose the gender gap in Maths achievement, I employ the Oaxaca-Blinder decomposition method (Blinder, 1973; Oaxaca, 1973). This technique decomposes mean differences in outcomes between two groups into explained components (differences in observable characteristics) and unexplained components (differences in returns to those characteristics). The decomposition takes the following form:

$$\bar{Y}_B - \bar{Y}_G = \underbrace{(\bar{\mathbf{X}}_B - \bar{\mathbf{X}}_G) \cdot \beta_G}_{\text{Endowments}} + \underbrace{\bar{\mathbf{X}}_G \cdot (\beta_B - \beta_G)}_{\text{Coefficients}} + \underbrace{(\bar{\mathbf{X}}_B - \bar{\mathbf{X}}_G) \cdot (\beta_B - \beta_G)}_{\text{Interaction}} \tag{3.1}$$

Where $\bar{Y}_B$ and $\bar{Y}_G$ are the mean Maths scores for boys and girls, $\bar{\mathbf{X}}_B$ and $\bar{\mathbf{X}}_G$ are vectors of mean values of predictors, and β_B and β_G are the estimated coefficients from separate regressions for each gender. The endowments component reflects how much of the gap stems from differences in observable characteristics between boys and girls. The coefficients component captures differences in returns to those same characteristics. The interaction term accounts for the simultaneous effect of differences in both endowments and coefficients.

The analysis is conducted separately using predictors measured at age 9 (Wave 1) and age 13 (Wave 2), allowing for an examination of how the gender gap evolves over time. For each wave, I estimate two models: one excluding paternal education variables and one including them. This approach is not driven by missing data but instead reflects two analytical strategies: first, controlling only for maternal education and other key factors; second, explicitly accounting for paternal education to assess its contribution to the gender gap.

After analysing gender differences, I extend the Oaxaca-Blinder decomposition to investigate the role of father absence. In this second set of decompositions, students are compared based on whether their fathers consistently failed to participate in the study's parental surveys at both Wave 1 and Wave 2. Separate decompositions by gender capture potential differences in how boys and girls are affected by paternal absence.

3.2 Decomposition of Gender Differences

I first apply the Oaxaca-Blinder decomposition to the gender gap in Leaving Certificate Maths achievement. Using predictors from age 9 (Wave 1) and age 13 (Wave 2), the gap is separated into components explained by differences in skills and family background (endowments) and components driven by differences in returns to these traits (coefficients).

Each decomposition is estimated twice: once excluding paternal education, and once including it for comparability. The results, presented in Figure 1, illustrate how the sources of the gender gap shift over the course of development.

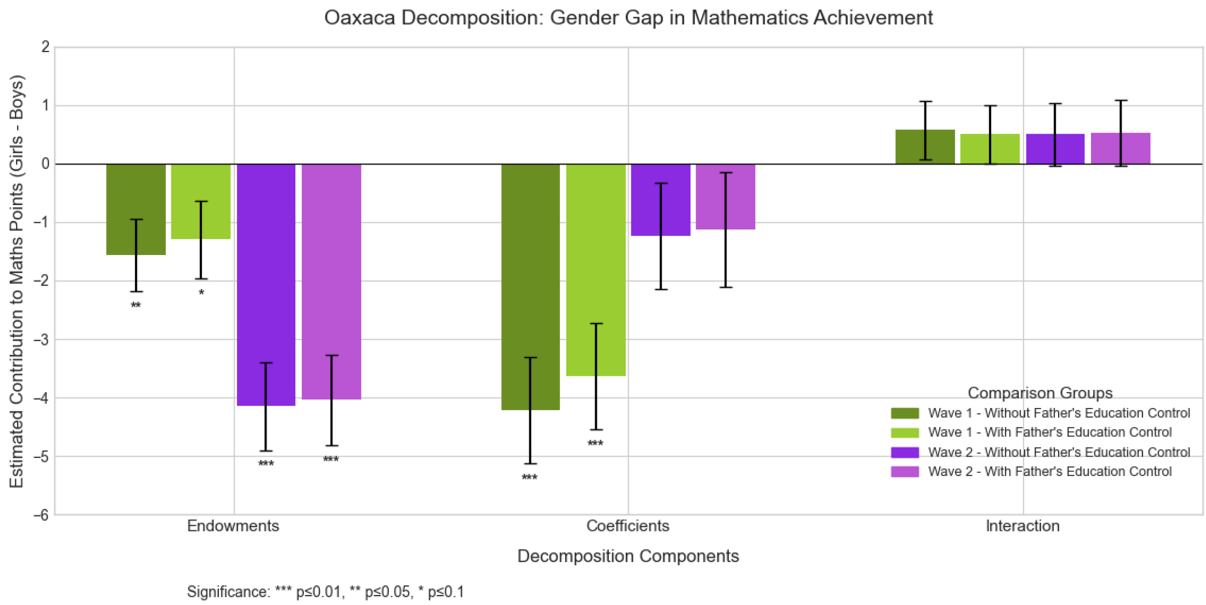

Figure 1: Oaxaca-Blinder Decomposition of Gender Differences in Leaving Certificate Maths Scores Using Predictors from Age 9 (Wave 1) and Age 13 (Wave 2). The figure shows the contribution of endowments (differences in characteristics), coefficients (differences in returns to characteristics), and their interaction to the overall gender gap. Negative values indicate components that contribute to boys' advantage over girls. The endowments component reflects gender differences in observed characteristics (e.g., prior achievement, socio-emotional skills), while the coefficients component captures differences in how these characteristics translate into Maths performance for boys versus girls. Average Maths scores show consistent gender gaps: Wave 1 without father's education control (Girls: 52.83, Boys: 58.04, gap: 5.21 points, n=3,690), Wave 1 with father's education control (Girls: 54.75, Boys: 59.18, gap: 4.43 points, n=3,241), Wave 2 without father's education control (Girls: 54.21, Boys: 59.09, gap: 4.88 points, n=3,401), and Wave 2 with father's education control (Girls: 56.27, Boys: 60.91, gap: 4.63 points, n=2,777). Results demonstrate a shift in the composition of the gender gap between waves, with the coefficients effect dominating in Wave 1 and the endowments effect becoming more pronounced in Wave 2. Models that control for father's education show slightly smaller gender gaps. Bootstrap standard errors based on 100 replications are represented by error bars. Significance: $***p \leq 0.01, **p \leq 0.05, *p \leq 0.1$.

Having established how the gender gap in Maths achievement evolves over time, I now turn to examining the role of father absence.

3.3 Decomposition of Father Absence Effects

I next examine how father absence affects Maths achievement, distinguishing effects by student gender. Father absence is defined as consistent non-response to the father's questionnaire at both Wave 1 and Wave 2, capturing sustained patterns of paternal disengagement. Approximately 80% of these cases correspond to households without a resident father figure, while 20% involve fathers who were physically present but did not participate in data collection. This measure captures a continuum of paternal disengagement, from physical absence to sustained non-involvement.

Separate Oaxaca-Blinder decompositions are estimated for boys and girls, comparing students with and without fathers present. Figure 2 shows the role of family structure in shaping gendered differences in academic achievement.

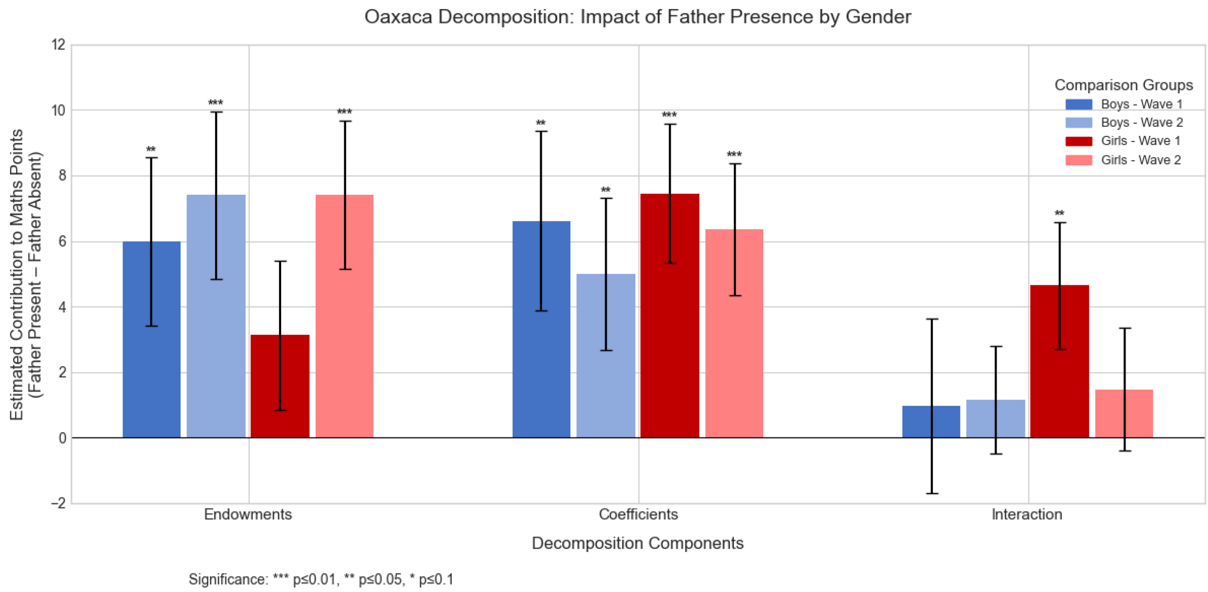

Figure 2: Oaxaca-Blinder Decomposition of the Impact of Father Absence on Leaving Certificate Maths Scores by Gender and Wave. The figure shows the contribution of endowments (differences in characteristics), coefficients (differences in returns to characteristics), and their interaction to the overall score gap between students with and without fathers present. Positive values indicate advantages associated with father presence. The endowments component reflects differences in observed characteristics between children with and without fathers present, while the coefficients component captures differences in how these characteristics translate into Maths performance. Average Maths scores reveal substantial gaps: Boys (Father present: 60.83, Father absent: 47.27, gap: 13.56 points, n=1,314 with 1,188 father-present and 126 father-absent) and Girls (Father present: 55.80, Father absent: 40.57, gap: 15.23 points, n=1,292 with 1,142 father-present and 150 father-absent). For boys, both endowments and coefficients contribute substantially to the advantage of father presence across both waves. For girls, the coefficients effect is particularly strong in Wave 1, while in Wave 2, both endowments and coefficients show significant contributions. The interaction effect is notable for girls in Wave 1 but diminishes by Wave 2. Bootstrap standard errors based on 100 replications are represented by error bars. Significance: $***p \leq 0.01, **p \leq 0.05, *p \leq 0.1$.

3.4 Discussion

Figures 1 and 2 show the main findings from the Oaxaca–Blinder decompositions. Figure 1 shows that boys consistently score higher than girls in Maths by about 4.5–5.2 points. However, the reasons behind this gap change over time. At age 9 (Wave 1), most of the gap comes from differences in how boys' and girls' skills are rewarded (coefficients effect: –4.21 points, $p<0.01$). By age 13 (Wave 2), the gap is mainly explained by real differences in skills (endowments effect: –4.15 points, $p<0.01$). As shown in Appendix E, Maths ability at age 9 and Numerical Ability at age 13 are the strongest contributors to the skill gap (–1.89 and –3.66 points, both $p<0.01$).

Figure 2 looks at differences between students with and without a father present. The Maths gap is large for both boys and girls: 13.56 points for boys and 15.23 points for girls. For boys, both skill differences and differences in returns explain the penalty across both waves. For girls, the penalty is mainly due to differences in returns in Wave 1 (coefficients effect: 7.46 points, $p<0.01$; interaction: 4.65 points, $p<0.05$) and a mix of skills and returns by Wave 2. Appendix F shows that maternal education plays an important role for girls: those whose mothers completed higher secondary education score 8.43 points higher on average ($p<0.01$).

These patterns show that educational inequality grows as students get older. Early on, it is less about differences in skills and more about how those skills are treated by the system, which matches concerns about teacher bias and unequal expectations for boys and girls (Carlana, 2019; Lavy & Sand, 2018). As students move into adolescence, real skill gaps take over, which is consistent with research on how early differences grow over time (Cunha & Heckman, 2007; Heckman et al., 2006).

The results on father absence fit closely with other research. Boys from homes without an engaged father show large penalties in Maths achievement, with both lower skills and lower returns contributing. This is consistent with findings that boys are more sensitive to family instability during key developmental stages (Autor et al., 2019; Lundberg, 2017). Girls also lose out when fathers are absent, but for them, differences seem to be driven more by family resources and maternal education, in line with Brenøe and Lundberg (2018) who shows that father absence lowers parental investment in girls' education.

Importantly, the effects of family structure are not the same for boys and girls. Father absence worsens existing inequalities for both, but the ways it matters differ. For boys, it is a mix of lower skills and fewer rewards. For girls, family support and resources make a bigger difference.

While the Oaxaca-Blinder decompositions provide useful information about where the gaps come from, they do not prove causality. The analysis shows which traits and background factors are associated with achievement gaps but cannot fully separate cause from correlation. Some early differences in skills or behaviour might be shaped by factors not captured here, like early teacher experiences or unmeasured parenting practices. Future research using experimental or quasi-experimental designs could build on these results and better identify the channels that drive these differences.

4 Conclusion

This study looks at when and how gender gaps in Maths achievement open up and grow during adolescence. Using data from the Growing Up in Ireland study, I show that early cognitive skills, socioemotional traits, family background, and school factors all shape these gaps. By applying Oaxaca-Blinder decomposition at ages 9 and 13, I find that what matters changes over time: early on, differences in how skills are rewarded (coefficients) matter more, but by early adolescence, real skill differences (endowments) explain a bigger share of the gap.

The Maths gap favouring boys (about 4.4 to 5.2 points) comes from a mix of boys' early advantage in numerical ability and the way skills are rewarded differently across genders. By age 13, real differences in ability become the main driver. Socioemotional traits, parental education, and school characteristics also play a role, but their effects are smaller compared to cognitive skills.

The results on father absence show a similar pattern. Both boys and girls lose out when fathers are absent, but for different reasons. For boys, the penalty comes from both lower skills and lower returns to family background. For girls, lower family resources and maternal education matter more. These patterns match other research showing that boys are more sensitive to family instability during key stages of development (Autor et al., 2019; Lundberg, 2017).

The supplementary analyses in the Appendices — including Junior Certificate results, English scores, and different model setups, confirm that the main patterns hold. Across all outcomes, the same story repeats: early gaps are mostly about differences in returns, but later gaps are about real differences in skills.

This work speaks to three areas of research. First, it shows that gender gaps in academic achievement are not fixed but grow as children get older, which is consistent with theories of cumulative advantage and skill building (Cunha & Heckman, 2007; Heckman et al., 2006). Second, it shows that early adolescence is a key turning point when inequalities deepen, strengthening the case for early intervention (Eccles & Roeser, 2011; Hyde & Mertz, 2009). Third, it shows that family background matters for gender gaps too, with disadvantaged groups facing even bigger challenges. Recent studies show that targeted educational programs, even short ones, can help close gaps. For example, classroom programs that build skills like patience and risk-taking have helped reduce gender differences in competitiveness (Alan & Ertac, 2018), and growth mindset interventions have improved achievement during important school transitions (Yeager et al., 2019).

While the decomposition results provide strong insights into where the gender gap comes from, it is important to remember that these findings are descriptive, not causal. Oaxaca-Blinder decompositions show how differences in characteristics and how they are rewarded relate to gaps, but they do not prove why these differences exist. Some traits, like early cognitive skills or socioemotional traits, may themselves be shaped by earlier experiences not fully captured in the models.

Overall, the results point to the need for early action. Since initial gaps come from differences in how boys' and girls' skills are rewarded, long before big skill differences appear, interventions need to focus on both building strong cognitive skills and making sure those skills are valued equally. Addressing teacher expectations and assessment practices early on could help reduce the gaps seen by age 9. At the same time, the large penalties linked to father absence show how important family support policies are, especially for disadvantaged students who are at the highest risk of falling behind.

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Appendices

This appendix section presents additional information supporting the empirical analysis. Appendix A describes the construction of key variables. Appendices B through F report supplementary descriptive statistics and robustness checks. Appendices G through J present extended Blinder–Oaxaca decompositions, including analyses by subject (Maths and English), gender, and family background. These materials complement the main text by providing further detail on data preparation, model specification, and subgroup analyses.

A Appendix A. Summary Statistics

Table 2 presents descriptive statistics for the main variables used in the analysis, drawn from the Growing Up in Ireland Child Cohort ('98 Cohort).

Maths LC Points (Adjusted) represent Leaving Certificate Maths scores with bonus points harmonized and capped at 100 to ensure comparability across grading systems. Cognitive measures are standardized logit scores, adjusting for item difficulty and discrimination. SDQ scales (range 0–10) capture socioemotional difficulties, with higher scores indicating greater problems. Parental education is categorized based on completion of Upper Secondary (Leaving Certificate or equivalent) or Third-Level qualifications. "Father Consistently Absent" indicates missing father's education data across both Wave 1 and Wave 2.

The final analytical sample consists of 4,333 participants. Although 5,190 cohort members completed the Wave 4 interview, the working sample is restricted to individuals with complete data on cognitive assessments, socioemotional measures, Leaving Certificate Maths outcomes, and key demographic controls. Attrition relative to the original sample is thus primarily attributable to item-level missingness on predictor variables rather than full-wave nonresponse.

Table 2: Summary Statistics for the GUI Child Cohort (Cohort '98)

Variable	N	Mean	Std. Dev.	Min	Max
Panel A: Leaving Certificate Performance					
Maths LC Points (Self-reported)	4,333	60.93	32.84	0.00	125.00
Maths LC Points (Harmonized)	4,333	56.03	27.43	0.00	100.00
New Grading System (post-2017)	4,333	0.39	0.49	0.00	1.00
Panel B: Cognitive Skills					
Wave 1 (Age 9)					
Reading Ability (logit)	4,264	0.35	0.66	-3.36	2.87
Maths Ability (logit)	4,306	-0.48	0.61	-3.62	1.90
Wave 2 (Age 13)					
Verbal Reasoning (logit)	4,105	0.15	0.64	-2.37	1.78
Numerical Ability (logit)	4,093	0.14	0.64	-2.36	2.11
BAS Matrix Reasoning (score)	3,939	119.40	9.48	10.00	161.00
Panel C: Non-Cognitive Skills (SDQ Scales)					
Wave 1 (Age 9)					
Emotional Symptoms	4,330	1.94	1.48	0.00	10.00
Conduct Problems	4,328	1.11	0.99	0.00	9.00
Hyperactivity	4,325	2.73	1.49	0.00	10.00
Peer-relationship Problems	4,322	1.07	0.99	0.00	9.00
Wave 2 (Age 13)					
Emotional Symptoms	4,252	1.65	1.48	0.00	10.00
Conduct Problems	4,252	0.95	0.97	0.00	10.00
Hyperactivity	4,252	2.29	0.98	0.00	10.00
Peer-relationship Problems	4,252	1.01	0.98	0.00	10.00
Panel D: Demographic and Family Characteristics					
Male	4,333	0.48	0.50	0.00	1.00
Wave 1 (Age 9)					
PCG Education: Upper Secondary	4,333	0.56	0.50	0.00	1.00
PCG Education: Third Level	4,333	0.32	0.47	0.00	1.00
SCG Education: Upper Secondary	3,808	0.46	0.50	0.00	1.00
SCG Education: Third Level	3,808	0.32	0.47	0.00	1.00
Income Quintile	4,033	3.50	1.47	1.00	5.00
Mixed School	4,051	0.76	0.43	0.00	1.00
Father Missing	4,333	0.12	0.33	0.00	1.00
Wave 2 (Age 13)					
PCG Education: Upper Secondary	4,253	0.56	0.50	0.00	1.00
PCG Education: Third Level	4,253	0.36	0.48	0.00	1.00
SCG Education: Upper Secondary	3,435	0.49	0.50	0.00	1.00
SCG Education: Third Level	3,435	0.36	0.48	0.00	1.00
Income Quintile	3,960	3.42	1.47	1.00	5.00
Fee-Paying School	4,124	0.11	0.31	0.00	1.00
DEIS School	4,124	0.11	0.31	0.00	1.00
Mixed School	4,023	0.53	0.50	0.00	1.00
Religious School	4,333	0.67	0.47	0.00	1.00
Father Missing	4,333	0.21	0.41	0.00	1.00
Father Consistently Absent	3,700	0.11	0.31	0.00	1.00

B Appendix B. OLS Regressions for Leaving Certificate Maths

B.1 How do early cognitive, socioemotional, and socioeconomic factors affect later Maths achievement at ages 17-18?

To investigate this, I first examine the relationship between cognitive, socioemotional, and socioeconomic factors measured at age 9 and later Maths achievement at 17–18 years. Cognitive skills include Numerical Ability and Reading Ability, socioemotional traits are captured through Conduct Problems and Hyperactivity, and socioeconomic factors include parental education and household income.

Regression results reveal that early cognitive skills are strong predictors of later Maths performance, with maternal education and income also exerting significant effects. These findings align with dynamic skill formation theories which propose that early cognitive and noncognitive skills form a foundation for subsequent learning and development.

Following developmental systems theory, I simultaneously examine cognitive, socioemotional, and socioeconomic domains, acknowledging their combined influence on achievement trajectories (Duncan et al., 2007; Watts et al., 2014). Consistent with prior research, early mathematical skills emerge as particularly important (Duncan et al., 2007).

Socioemotional traits, particularly behavioural regulation and executive function, are also critical for academic outcomes. Hyperactivity and conduct problems measured here capture aspects of self-regulation that have been shown to significantly affect learning (Blair & Razza, 2007; McClelland et al., 2007). Self-discipline, in particular, often surpasses IQ as a predictor of academic success (Duckworth & Seligman, 2005).

The observed socioeconomic gradients are consistent with a large body of evidence documenting links between family background and educational achievement (Bradley & Corwyn, 2002; Sirin, 2005). These effects operate through multiple mechanisms, including resource access, parental involvement, and neighborhood conditions.

Building on this, I incorporate predictors from age 13 to capture how factors evolve across a critical educational transition (Eccles & Roeser, 2011). The inclusion of Wave 2 variables allows for an examination of whether the predictive power of early influences remains stable or shifts over time.

Finally, following models of dynamic development (Caro et al., 2009; Deary et al., 2007), I consider both direct effects of early skills and potential cumulative pathways through intermediate outcomes such as engagement, academic self-concept, and school choice.

This developmental perspective underscores that achievement at any stage reflects the accumulation of prior experiences (Cunha & Heckman, 2007) and that critical periods for intervention may vary (Knudsen et al., 2006). By tracing predictors from childhood to adolescence, this analysis highlights how cognitive, socioemotional, and socioeconomic factors jointly shape educational outcomes—and points to policy approaches that target multiple domains across development.

B.2 Empirical Strategy

B.2.1 Regression Models

I estimate a series of regression models to examine how cognitive, socioemotional, socioeconomic, and school-related factors at different developmental stages predict Maths achievement. The general model specification is:

$$\text{Maths Points}_i = \beta_0 + \sum_k \beta_k \cdot \text{Cog}_{k,i,w} + \sum_l \beta_l \cdot \text{SocioEmotional}_{l,i,w} + \sum_n \beta_n \cdot \text{SES}_{n,i,w} + \sum_x \beta_x \cdot \text{School}_{x,i,w} + \varepsilon_i \tag{B.1}$$

Where Maths Points$_i$ represents the Leaving Certificate Maths score for individual i, Cog$_{k,i,w}$ denotes cognitive skills, SocioEmotional$_{l,i,w}$ captures socioemotional traits, SES$_{n,i,w}$ includes socioeconomic status indicators, and School$_{x,i,w}$ represents school-related factors, all measured at wave w (where $w = 1$ corresponds to age 9 and $w = 2$ corresponds to age 13).

I estimate four main model specifications, systematically varying the included variables to examine both developmental patterns and the role of father's involvement. Table 3 summarizes the variables included in each model.

B.2.2 Models Using Wave 1 Predictors (Age 9)

Models 1 and 2 examine how early childhood factors (measured at age 9) predict later Maths achievement. The key difference between these specifications is the treatment of father's education data.

Model 1 includes a dummy variable for missing father's education data to account for cases where the father did not complete the questionnaire:

$$\begin{aligned}
\text{Maths Points}_i = \beta_0 &+ \beta_1 \cdot \text{Numerical Ability}_{W1,i} + \beta_2 \cdot \text{Reading Ability}_{W1,i} \\
&+ \beta_3 \cdot \text{Emotional Symptoms}_{W1,i} + \beta_4 \cdot \text{Conduct Problems}_{W1,i} \\
&+ \beta_5 \cdot \text{Hyperactivity}_{W1,i} + \beta_6 \cdot \text{Peer-Relationship Problems}_{W1,i} \\
&+ \beta_7 \cdot \text{Mother's Education (Higher Secondary/Technical)}_{W1,i} \\
&+ \beta_8 \cdot \text{Mother's Education (Bachelor's/Postgrad)}_{W1,i} \\
&+ \beta_9 \cdot \text{Income Quintile}_{W1,i} + \beta_{10} \cdot \text{Male}_i \\
&+ \beta_{11} \cdot \text{CoEd}_{W1,i} + \beta_{12} \cdot \text{Father's Education Missing}_{W1,i} + \varepsilon_i
\end{aligned}$$

Table 3: Variables Included in Regression Models

Variable Group	Model 1	Model 2	Model 3	Model 4
Wave	1 (Age 9)	1 (Age 9)	2 (Age 13)	2 (Age 13)
Cognitive Skills				
Numerical Ability	✓	✓	✓	✓
Reading Ability/Verbal Reasoning	✓	✓	✓	✓
BAS Matrices			✓	✓
Socioemotional Traits				
Emotional Symptoms	✓	✓	✓	✓
Conduct Problems	✓	✓	✓	✓
Hyperactivity	✓	✓	✓	✓
Peer-Relationship Problems	✓	✓	✓	✓
Socioeconomic Status				
Mother's Education	✓	✓	✓	✓
Father's Education		✓		✓
Father's Education Missing	✓		✓	
Income Quintile	✓	✓	✓	✓
Individual & School Factors				
Male	✓	✓	✓	✓
CoEd School	✓	✓	✓	✓
Fee Paying School			✓	✓
DEIS School			✓	✓
Religious School			✓	✓

Model 2 excludes cases with missing father's education data and instead directly includes father's education variables:

$$
\begin{aligned}
\text{Maths Points}_i = \beta_0 &+ \beta_1 \cdot \text{Numerical Ability}_{W1,i} + \beta_2 \cdot \text{Reading Ability}_{W1,i} \\
&+ \beta_3 \cdot \text{Emotional Symptoms}_{W1,i} + \beta_4 \cdot \text{Conduct Problems}_{W1,i} \\
&+ \beta_5 \cdot \text{Hyperactivity}_{W1,i} + \beta_6 \cdot \text{Peer-Relationship Problems}_{W1,i} \\
&+ \beta_7 \cdot \text{Mother's Education (Higher Secondary/Technical)}_{W1,i} \\
&+ \beta_8 \cdot \text{Mother's Education (Bachelor's/Postgrad)}_{W1,i} \\
&+ \beta_9 \cdot \text{Father's Education (Higher Secondary/Technical)}_{W1,i} \\
&+ \beta_{10} \cdot \text{Father's Education (Bachelor's/Postgrad)}_{W1,i} \\
&+ \beta_{11} \cdot \text{Income Quintile}_{W1,i} + \beta_{12} \cdot \text{Male}_i \\
&+ \beta_{13} \cdot \text{CoEd}_{W1,i} + \varepsilon_i
\end{aligned}
$$

Comparing these two specifications allows me to assess whether paternal non-response—potentially indicating disengagement—has differential effects on Maths achievement beyond what can be explained by observable paternal characteristics.

B.2.3 Models Using Wave 2 Predictors (Age 13)

Models 3 and 4 focus on factors measured at age 13, during the transition to secondary education. These models include an expanded set of cognitive measures and school environment variables unavailable in Wave 1.

Model 3 includes a dummy for missing father's education data:

$$\begin{aligned}
\text{Maths Points}_i = \beta_0 &+ \beta_1 \cdot \text{Numerical Ability}_{W2,i} + \beta_2 \cdot \text{Verbal Reasoning}_{W2,i} \\
&+ \beta_3 \cdot \text{BAS Matrices}_{W2,i} \\
&+ \beta_4 \cdot \text{Emotional Symptoms}_{W2,i} + \beta_5 \cdot \text{Conduct Problems}_{W2,i} \\
&+ \beta_6 \cdot \text{Hyperactivity}_{W2,i} + \beta_7 \cdot \text{Peer-Relationship Problems}_{W2,i} \\
&+ \beta_8 \cdot \text{Mother's Education (Higher Secondary/Technical)}_{W2,i} \\
&+ \beta_9 \cdot \text{Mother's Education (Bachelor's/Postgrad)}_{W2,i} \\
&+ \beta_{10} \cdot \text{Income Quintile}_{W2,i} + \beta_{11} \cdot \text{Male}_i \\
&+ \beta_{12} \cdot \text{Fee Paying}_{W2,i} + \beta_{13} \cdot \text{DEIS}_{W2,i} \\
&+ \beta_{14} \cdot \text{Religious School}_{W2,i} + \beta_{15} \cdot \text{CoEd}_{W2,i} \\
&+ \beta_{16} \cdot \text{Father's Education Missing}_{W2,i} + \varepsilon_i
\end{aligned}$$

Model 4 includes father's education variables directly:

$$\begin{aligned}
\text{Maths Points}_i = \beta_0 &+ \beta_1 \cdot \text{Numerical Ability}_{W2,i} + \beta_2 \cdot \text{Verbal Reasoning}_{W2,i} \\
&+ \beta_3 \cdot \text{BAS Matrices}_{W2,i} \\
&+ \beta_4 \cdot \text{Emotional Symptoms}_{W2,i} + \beta_5 \cdot \text{Conduct Problems}_{W2,i} \\
&+ \beta_6 \cdot \text{Hyperactivity}_{W2,i} + \beta_7 \cdot \text{Peer-Relationship Problems}_{W2,i} \\
&+ \beta_8 \cdot \text{Mother's Education (Higher Secondary/Technical)}_{W2,i} \\
&+ \beta_9 \cdot \text{Mother's Education (Bachelor's/Postgrad)}_{W2,i} \\
&+ \beta_{10} \cdot \text{Father's Education (Higher Secondary/Technical)}_{W2,i} \\
&+ \beta_{11} \cdot \text{Father's Education (Bachelor's/Postgrad)}_{W2,i} \\
&+ \beta_{12} \cdot \text{Income Quintile}_{W2,i} + \beta_{13} \cdot \text{Male}_i \\
&+ \beta_{14} \cdot \text{Fee Paying}_{W2,i} + \beta_{15} \cdot \text{DEIS}_{W2,i} \\
&+ \beta_{16} \cdot \text{Religious School}_{W2,i} + \beta_{17} \cdot \text{CoEd}_{W2,i} + \varepsilon_i
\end{aligned}$$

All models are estimated with heteroskedasticity-robust standard errors. The initial sample includes 8,568 children at age 9, with final analytical samples ranging from 4,210 to 5,918 due to attrition and missing data. Results are reported in Table 4 (Wave 1 predictors) and Table 5

(Wave 2 predictors).

These four specifications allow me to examine: (1) how early versus later factors predict Maths achievement; (2) how the importance of different predictors changes over development; (3) the relationship between paternal involvement and educational outcomes; and (4) gender differences in these patterns. Subsequent sections build on these baseline models to explore gender-specific pathways through interaction terms and decomposition analyses.

B.3 Results

Regression results in Tables 4 and 5 reveal consistent patterns regarding the predictors of Maths achievement. Models using age 13 predictors (Wave 2) explain substantially more variance (adjusted $R^2 \approx 0.39$–0.40) than those using age 9 predictors (adjusted $R^2 \approx 0.30$), suggesting that factors measured closer in time to the outcome have greater predictive power.

B.3.1 Cognitive Skills

Numerical ability emerges as the strongest predictor across all models. At age 9, a one standard deviation increase in numerical ability is associated with approximately 9.6 points higher Maths scores, strengthening to around 11.7 points at age 13 ($p < 0.001$). Reading ability and verbal reasoning show consistent, more modest effects (approximately 3.6–4.7 points, all $p < 0.001$). The BAS Matrices measure at age 13 also has a small but highly significant effect ($\beta \approx 0.19$, $p < 0.001$).

The relative importance of numerical versus verbal skills remains consistent, aligning with Duncan et al. (2007).

B.3.2 Socioemotional Traits

Hyperactivity shows the most robust negative association with Maths achievement, strengthening slightly between ages 9 and 13 ($\beta \approx -1.5$ to -1.8, $p < 0.001$). Conduct problems are significant only at age 9. Emotional symptoms show a marginal effect at age 9 that strengthens by age 13. Peer relationship problems are not significant predictors.

These findings reinforce the critical role of attention-related regulation skills for learning (McClelland et al., 2007).

B.3.3 Socioeconomic Factors

Parental education shows strong graded effects across models. Mother's higher education yields the largest benefits at age 9 ($\beta \approx 10$–12.8), while father's education has comparable effects ($\beta \approx 9.9$ at age 9; 5.7 at age 13, both $p < 0.001$).

Table 4: Predictors of Leaving Certificate Maths Performance: OLS Regression Results Using Age 9 (Wave 1) Variables.

Variable	Model 1	Model 2
(Intercept)	47.153***	45.770***
	(1.972)	(2.149)
Numerical Ability	9.637***	9.568***
	(0.587)	(0.621)
Reading Ability	4.125***	3.612***
	(0.555)	(0.588)
Emotional Symptoms	-0.441†	-0.595*
	(0.242)	(0.257)
Conduct Problems	-0.964**	-1.044**
	(0.349)	(0.371)
Hyperactivity	-1.508***	-1.566***
	(0.202)	(0.214)
Peer-relationship Problems	-0.096	0.055
	(0.332)	(0.353)
Mother's Education (Higher Secondary/Technical)	5.887***	4.739**
	(1.352)	(1.507)
Mother's Education (Bachelor's/Postgrad)	12.808***	10.011***
	(1.524)	(1.723)
Father's Education (Higher Secondary/Technical)	–	5.886***
		(1.167)
Father's Education (Bachelor's/Postgrad)	–	9.917***
		(1.396)
Income (quintiles, equivalized)	2.459***	1.885***
	(0.352)	(0.385)
Male	3.881***	3.350***
	(0.863)	(0.907)
CoEd	0.957	0.956
	(0.992)	(1.041)
Father's Education Missing	-6.350***	–
	(1.303)	
Observations	3,690	3,241
Residual Std. Error	25.28	24.90
Adjusted R^2	0.297	0.299
F-statistic	130.6***	107.1***

Notes: Standard errors are in parentheses. Significance levels: $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Parental education is captured via dummy variables indicating (1) completion of Higher Secondary or Non-Degree Third-Level education, and (2) attainment of a Bachelor's Degree or Postgraduate qualification. The omitted category is parents with at most Lower Secondary education. *Estimates are based on corrected Leaving Certificate Maths scores that account for bonus point overreporting and restrict the maximum to 100. Coefficient magnitudes are slightly attenuated relative to earlier specifications, but key patterns and statistical significance remain consistent. Results are robust to controlling for grading system effects.*

Household income is positively associated with achievement, though slightly weaker at age 13. Father's education missing is linked to lower achievement in both waves, highlighting potential effects of paternal disengagement.

B.3.4 School Factors

School-related predictors become salient at age 13. Fee-paying schools are associated with higher Maths scores ($\beta \approx 4.2$–4.3, $p < 0.01$), while DEIS schools predict lower scores ($\beta \approx -3.3$ to -4.8). Mixed schools show a negative association only in one model; religious ethos is unrelated.

B.3.5 Gender Differences

At age 9, boys outperform girls by approximately 3.4–3.9 points ($p < 0.001$). By age 13, this advantage attenuates and becomes non-significant, suggesting that gender gaps may be shaped by intervening factors during adolescence (Fryer & Levitt, 2010).

B.3.6 Comparing Wave 1 and Wave 2 Predictors

While the overall pattern of significant predictors is stable across waves, some shifts emerge. Cognitive predictors strengthen over time, while the effects of mother's education weaken slightly. School environment factors grow more predictive at age 13, and the penalty associated with missing father's education decreases.

These trends are consistent with developmental cascade models (Masten et al., 2005), in which early abilities and environments influence later achievement through evolving pathways.

Table 5: Predictors of Leaving Certificate Maths Performance: OLS Regression Results Using Age 13 (Wave 2) Variables.

Variable	Model 3	Model 4
(Intercept)	25.557***	24.032***
	(3.813)	(4.335)
Numerical Ability	11.704***	11.684***
	(0.578)	(0.635)
Verbal Reasoning	4.688***	4.301***
	(0.566)	(0.626)
BAS Matrices Score	0.199***	0.188***
	(0.026)	(0.029)
Emotional Symptoms	-0.446†	-0.706**
	(0.246)	(0.273)
Conduct Problems	-0.249	-0.432
	(0.367)	(0.414)
Hyperactivity	-1.818***	-1.792***
	(0.215)	(0.240)
Peer-relationship Problems	-0.066	-0.114
	(0.317)	(0.352)
Motherś Education (Higher Secondary/Technical)	3.921*	5.003**
	(1.595)	(1.877)
Motherś Education (Bachelor's/Postgrad)	7.371***	7.686***
	(1.722)	(2.031)
Fatherś Education (Higher Secondary/Technical)	–	2.883*
		(1.344)
Fatherś Education (Bachelor's/Postgrad)	–	5.728***
		(1.534)
Income (quintiles, equivalized)	1.823***	1.469***
	(0.324)	(0.372)
Male	0.981	0.834
	(0.837)	(0.916)
Fee-paying School	4.287**	4.228**
	(1.366)	(1.478)
DEIS School	-4.802***	-3.310*
	(1.423)	(1.663)
Religious School	-0.025	0.179
	(1.082)	(1.195)
Mixed School	-2.264*	-1.639
	(0.979)	(1.068)
Father's Education Missing	-2.961**	–
	(1.052)	
Observations	3,401	2,777
Residual Std. Error	23.21	23.01
Adjusted R^2	0.397	0.390
F-statistic	140.7***	105.5***

Notes: Standard errors are in parentheses. Significance levels: $^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Parental education is captured via dummy variables indicating (1) completion of Higher Secondary or Non-Degree Third-Level education, and (2) attainment of a Bachelor's Degree or Postgraduate qualification. The omitted category is parents with at most Lower Secondary education. *Estimates are based on corrected Leaving Certificate Maths scores that account for bonus point overreporting and restrict the maximum to 100. Results remain consistent in sign and significance. Including a dummy for the grading system does not alter the conclusions.*

C Appendix C: OLS Regressions for Junior Certificate Maths

This appendix presents supplementary OLS regression results predicting Maths achievement at age 15–16 (Junior Certificate) using cognitive, socioemotional, and socioeconomic factors measured at ages 9 and 13. Although the main paper focuses on Leaving Certificate outcomes at age 17–18, these results offer additional insight into earlier stages of academic development and the stability of predictors across educational milestones.

C.0.1 Cognitive Skills as Predictors of Maths Achievement

Cognitive skills measured at ages 9 and 13 strongly predict Maths achievement at age 15. In Model 1 (Wave 1), a one standard deviation increase in Numerical Ability is associated with a 0.563-point increase in Maths scores ($p < 0.001$), while Reading Ability is associated with a 0.366-point increase (Table 6). Similar patterns emerge at age 13 (Table 7), with Numerical Ability and Reading Ability remaining significant predictors across Models 3 and 4 ($p < 0.001$ in all cases).

C.0.2 Socioemotional Factors

Socioemotional skills, particularly Conduct Problems and Hyperactivity, also significantly predict Maths achievement. Higher scores on these dimensions are associated with lower Maths scores at both ages 9 and 13. In Wave 1, Conduct Problems ($\beta = -0.092$, $p < 0.001$) and Hyperactivity ($\beta = -0.095$, $p < 0.001$) are negatively associated with achievement. At Wave 2, the effect of Conduct Problems attenuates, but Hyperactivity continues to show a robust negative association. These findings highlight the persistent influence of behavioural regulation on academic outcomes across development.

C.0.3 Socioeconomic Factors

Socioeconomic status consistently predicts Maths performance. In Wave 1, household income (equivalized) shows positive associations ($\beta = 0.156$ and $\beta = 0.121$, both $p < 0.001$ across Models 1 and 2), and while the effect size diminishes slightly after adding school variables in Wave 2, it remains significant. This suggests that socioeconomic status shapes early academic trajectories, even after accounting for school context.

C.0.4 Parental Education

Maternal and paternal education are positively associated with Maths achievement, with maternal education showing stronger effects. In Model 1, mother's completion of a Bachelor's/Postgraduate degree is associated with a 0.882-point increase in Maths scores ($p < 0.001$).

Table 6: OLS Regression Results Predicting Junior Certificate Maths Scores Using Age 9 Predictors

Variable	Model 1	Model 2
(Intercept)	9.118***	8.985***
	(0.088)	(0.095)
Numerical Ability	0.563***	0.551***
	(0.027)	(0.028)
Reading Ability	0.366***	0.332***
	(0.025)	(0.027)
Emotional Symptoms	-0.016	-0.021
	(0.011)	(0.012)
Conduct Problems	-0.092***	-0.083***
	(0.016)	(0.017)
Hyperactivity	-0.095***	-0.104***
	(0.009)	(0.010)
Peer-Relationship Problems	-0.013	-0.007
	(0.015)	(0.016)
Mother's Education (Higher Secondary/Technical)	0.499***	0.437***
	(0.059)	(0.065)
Mother's Education (Bachelor's/Postgrad)	0.882***	0.678***
	(0.068)	(0.076)
Father's Education (Higher Secondary/Technical)	–	0.370***
		(0.052)
Father's Education (Bachelor's/Postgrad)	–	0.627***
		(0.063)
Income (quintiles, equivalized)	0.156***	0.121***
	(0.016)	(0.017)
Male	0.040	0.023
	(0.040)	(0.041)
CoEd	0.057	0.095*
	(0.046)	(0.048)
Father's Education Missing	-0.351***	–
	(0.057)	
Observations	5,030	4,341
Residual Std. Error	1.359	1.321
Adjusted R^2	0.410	0.409
F-statistic	291.9***	231.9***

Notes: Standard errors are in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Parental education is captured through dummy variables for (1) Higher Secondary/Technical education and (2) Bachelor's/Postgraduate degrees. The reference group comprises parents with at most Lower Secondary education.

Including father's education in Model 2 reveals additional positive effects, but also slightly attenuates the estimated maternal effects, suggesting that earlier models partly captured both parents' contributions.

Importantly, missing paternal education data is associated with significantly lower Maths scores. Comparing students with and without recorded father's education reveals a mean difference of 0.87 points ($p < 0.001$), confirming that missing data is not random. Controlling for household income reduces this gap to 0.57 points, suggesting that part of the disparity reflects

Table 7: OLS Regression Results Predicting Junior Certificate Maths Scores Using Age 13 Predictors

Variable	Model 3	Model 4
(Intercept)	7.870***	7.626***
	(0.161)	(0.184)
Numerical Ability	0.723***	0.672***
	(0.026)	(0.028)
Reading Ability	0.343***	0.324***
	(0.025)	(0.028)
BAS Matrices Score	0.012***	0.012***
	(0.001)	(0.001)
Emotional Symptoms	-0.015	-0.030*
	(0.011)	(0.012)
Conduct Problems	-0.056***	-0.058***
	(0.015)	(0.018)
Hyperactivity	-0.096***	-0.098***
	(0.009)	(0.010)
Peer-Relationship Problems	0.003	0.006
	(0.013)	(0.015)
Mother's Education (Higher Secondary/Technical)	0.431***	0.477***
	(0.064)	(0.077)
Mother's Education (Bachelor's/Postgrad)	0.669***	0.646***
	(0.071)	(0.085)
Father's Education (Higher Secondary/Technical)	–	0.312***
		(0.058)
Father's Education (Bachelor's/Postgrad)	–	0.439***
		(0.067)
Income (quintiles, equivalized)	0.108***	0.081***
	(0.014)	(0.016)
Male	-0.149***	-0.115**
	(0.037)	(0.041)
Fee-paying School	0.192**	0.156*
	(0.063)	(0.068)
DEIS School	-0.361***	-0.327***
	(0.060)	(0.070)
Religious School	-0.064	-0.023
	(0.048)	(0.053)
Mixed School	-0.149***	-0.106*
	(0.043)	(0.047)
Father's Education Missing	-0.228***	–
	(0.045)	
Observations	5,030	4,341
Residual Std. Error	1.201	1.177
Adjusted R^2	0.520	0.505
F-statistic	317.1***	221.3***

Notes: Standard errors are in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Parental education is captured through dummy variables for (1) Higher Secondary/Technical education and (2) Bachelor's/Postgraduate degrees. The reference group comprises parents with at most Lower Secondary education.

lower socioeconomic backgrounds among students with missing paternal information. Maternal education further mediates this effect, although a significant penalty persists, highlighting the need to account for selection bias in models using parental education.

C.0.5 Gender Differences

Gender effects differ between waves. In Wave 1, gender is not a significant predictor. However, by Wave 2, being male is associated with significantly lower Maths achievement (Model 3: $\beta = -0.149$, $p < 0.001$; Model 4: $\beta = -0.115$, $p < 0.01$). This emerging gender gap suggests that factors accumulating during adolescence, such as socioemotional development and school environment, may differentially affect boys and girls.

This finding warrants further investigation into how gender interacts with socioemotional and school-level predictors during the transition to secondary education. It also suggests that interventions addressing behavioural regulation and school engagement could be important for mitigating emerging gender disparities.

C.0.6 Summary

In summary, cognitive skills are the strongest predictors of Junior Certificate Maths achievement, followed by socioemotional and socioeconomic factors. Behavioural difficulties, particularly hyperactivity, exert persistent negative effects. Parental education—especially maternal education—remains a robust predictor, with the inclusion of father's education clarifying underlying selection patterns. Socioeconomic status consistently influences achievement, though its effect diminishes when school-level variables are included.

Finally, the gender gap, while absent at age 9, becomes significant by age 13–15, highlighting the dynamic nature of academic inequalities across development. These results reinforce the need for a developmental perspective when designing policies to promote academic success and equity.

D Appendix D. Family Structure Changes Between Waves

This appendix subsection provides detailed information on family structure transitions and secondary caregiver (SCG) participation patterns across the three waves of data collection. In the majority of households, the secondary caregiver is the father, making these transition patterns particularly relevant for understanding paternal involvement and family stability throughout the study period.

Tables 8, 9 and 10 document the changes in partnership status, marital status, and secondary caregiver questionnaire completion between Waves 1-2 and Waves 2-3. These transitions offer valuable context for interpreting the father absence variable used in the main decomposition analysis. The tables highlight several notable patterns: (1) a decline in secondary caregiver questionnaire completion across waves, with a particularly sharp drop between Waves 2 and 3 (from 5.4% to 11.8%); (2) relatively stable partnership and marital dissolution rates between Waves 1-2 and 2-3; and (3) decreasing rates of new partnership formation and marriage among initially single or never-married primary caregivers as the study progressed.

These transition patterns support the use of secondary caregiver non-response as a proxy for paternal disengagement, reflecting not only physical absence but also declining involvement among fathers who remain in the household. The increasing rate of non-completion among present secondary caregivers (from 8.7% in Waves 1-2 to 15.8% in Waves 2-3) suggests that questionnaire participation may capture varying degrees of family involvement even when fathers remain in the household.

Together, these patterns reinforce the interpretation of secondary caregiver non-response as a meaningful indicator of paternal engagement across development and provide important context for the analysis of father absence effects in the main study.

Table 8: Summary of Family Dynamics Transitions Between Wave 1 and Wave 2

Transition Type	**Count**	**Percentage**
Partner Status Transitions		
No partner → No partner	360	85.1% of initially without partner
No partner → Partner	63	14.9% of initially without partner
Partner → Partner	4,141	96.2% of initially with partner
Partner → No partner	165	3.8% of initially with partner
Primary Caregiver Marital Status Transitions		
Married → Married	3,868	95.9% of initially married
Married → Separated	101	2.5% of initially married
Married → Divorced	33	0.8% of initially married
Separated → Separated	118	60.5% of initially separated
Separated → Married	16	8.2% of initially separated
Separated → Divorced	53	27.2% of initially separated
Never married → Never married	291	81.1% of initially never married
Never married → Married	60	16.7% of initially never married
Secondary Caregiver Participation Transitions		
No SCG → No SCG	360	85.1% of initially without SCG
No SCG → SCG (completed)	38	9.0% of initially without SCG
No SCG → SCG (non-completed)	25	5.9% of initially without SCG
SCG (completed) → SCG (completed)	3,619	87.8% of initial SCG completers
SCG (completed) → SCG (non-completed)	359	8.7% of initial SCG completers
SCG (completed) → No SCG	146	3.5% of initial SCG completers
Key Net Changes		
Net partner loss	102	2.4% of initial partnered households
Net increase in separation/divorce	171	4.2% of initial married households
Net decrease in SCG questionnaire completion	223	5.4% of initial SCG completers

Table 9: Summary of Family Dynamics Transitions Between Wave 2 and Wave 3

Transition Type	**Count**	**Percentage**
Partner Status Transitions		
No partner → No partner	480	91.6% of initially without partner
No partner → Partner	44	8.4% of initially without partner
Partner → Partner	3,996	95.5% of initially with partner
Partner → No partner	186	4.5% of initially with partner
Primary Caregiver Marital Status Transitions		
Married → Married	3,771	95.1% of initially married
Married → Separated	114	2.9% of initially married
Married → Divorced	11	0.3% of initially married
Separated → Separated	159	65.1% of initially separated
Separated → Married	9	3.7% of initially separated
Separated → Divorced	55	22.5% of initially separated
Divorced → Divorced	85	56.7% of initially divorced
Divorced → Widowed	53	35.3% of initially divorced
Never married → Never married	267	89.0% of initially never married
Never married → Married	32	10.7% of initially never married
Secondary Caregiver Participation Transitions		
No SCG → No SCG	480	91.6% of initially without SCG
No SCG → SCG (completed)	17	3.2% of initially without SCG
No SCG → SCG (non-completed)	27	5.2% of initially without SCG
SCG (completed) → SCG (completed)	3,009	81.4% of initial SCG completers
SCG (completed) → SCG (non-completed)	584	15.8% of initial SCG completers
SCG (completed) → No SCG	149	4.0% of initial SCG completers
Key Net Changes		
Net partner loss	142	3.4% of initial partnered households
Net increase in separation/divorce	170	4.3% of initial married households
Net decrease in SCG questionnaire completion	436	11.8% of initial SCG completers

Table 10: Comparison of Family Dynamics Transitions Between Waves 1-2 and 2-3

Transition Type	**Wave 1 → Wave 2**	**Wave 2 → Wave 3**
Partner Status Transitions		
No partner → No partner	360 (85.1%)	480 (91.6%)
No partner → Partner	63 (14.9%)	44 (8.4%)
Partner → Partner	4,141 (96.2%)	3,996 (95.5%)
Partner → No partner	165 (3.8%)	186 (4.5%)
Primary Caregiver Marital Status Transitions		
Married → Married	3,868 (95.9%)	3,771 (95.1%)
Married → Separated	101 (2.5%)	114 (2.9%)
Married → Divorced	33 (0.8%)	11 (0.3%)
Separated → Separated	118 (60.5%)	159 (65.1%)
Separated → Married	16 (8.2%)	9 (3.7%)
Separated → Divorced	53 (27.2%)	55 (22.5%)
Never married → Never married	291 (81.1%)	267 (89.0%)
Never married → Married	60 (16.7%)	32 (10.7%)
Secondary Caregiver Participation Transitions		
No SCG → No SCG	360 (85.1%)	480 (91.6%)
No SCG → SCG (completed)	38 (9.0%)	17 (3.2%)
No SCG → SCG (non-completed)	25 (5.9%)	27 (5.2%)
SCG (completed) → SCG (completed)	3,619 (87.8%)	3,009 (81.4%)
SCG (completed) → SCG (non-completed)	359 (8.7%)	584 (15.8%)
SCG (completed) → No SCG	146 (3.5%)	149 (4.0%)
Key Net Changes		
Net partner loss	102 (2.4%)	142 (3.4%)
Net increase in separation/divorce	171 (4.2%)	170 (4.3%)
Net decrease in SCG questionnaire completion	223 (5.4%)	436 (11.8%)

E Appendix E. Oaxaca Decompositions: Gender Gaps in Maths, Leaving Cert

The figures shown in the main text are based on the detailed Blinder-Oaxaca decomposition results reported here. Overall, the results show that differences in cognitive skills, especially numerical ability, explain much of the gender gap in Maths achievement by the end of secondary school. Differences in how skills are rewarded, and how these two effects combine, play a smaller part. This suggests that most of the gap comes from differences in skills rather than from differences in returns to those skills.

Table 11: Decomposition of Gender Differences in Maths Achievement at ages 17/18: Comparing Models With and Without Father's Education Variables (Wave 1)

Statistic	**No Father**	**With Father**
Group 1 (Female)	52.831*** (0.667)	54.749*** (0.727)
Group 2 (Male)	58.043*** (0.722)	59.183*** (0.684)
Difference	-5.212*** (1.046)	-4.434*** (0.992)
Endowments	-1.570** (0.615)	-1.298* (0.667)
Coefficients	-4.215*** (0.909)	-3.641*** (0.905)
Interaction	0.572 (0.506)	0.505 (0.499)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	No Father	**With Father**	**No Father**	**With Father**	**No Father**	**With Father**
Reading Ability	0.021	0.033	0.659*	0.722*	0.014	0.028
	(0.101)	(0.090)	(0.350)	(0.401)	(0.070)	(0.090)
Maths Ability	-1.886***	-1.762***	0.864*	0.809*	0.376*	0.346
	(0.358)	(0.374)	(0.476)	(0.479)	(0.223)	(0.225)
Emotional Symptoms	-0.004	-0.044	-1.343	-1.333	-0.208	-0.191
	(0.109)	(0.096)	(0.856)	(0.902)	(0.151)	(0.143)
Conduct Problems	0.262**	0.327***	1.354	1.595*	-0.194	-0.259
	(0.120)	(0.123)	(0.927)	(0.839)	(0.150)	(0.166)
Hyperactivity	0.784***	0.857***	-1.645	-1.069	0.340	0.224
	(0.195)	(0.191)	(1.298)	(1.331)	(0.275)	(0.287)
Peer-relationship Problems	0.000	0.003	-0.250	-0.320	-0.003	-0.004
	(0.026)	(0.027)	(0.690)	(0.759)	(0.031)	(0.040)
Mother's Educ.	0.007	0.003	0.548	2.069	0.001	0.004
(Higher 2ndary/Tech)	(0.097)	(0.054)	(1.574)	(1.762)	(0.046)	(0.082)
Mother's Educ.	-0.353*	-0.174	0.958	1.211	-0.090	-0.079
(Bachelor's/Postgrad)	(0.194)	(0.133)	(1.106)	(1.320)	(0.133)	(0.115)
Father's Educ.	-	0.058	-	-0.197	-	-0.004
(Higher 2ndary/Tech)	-	(0.098)	-	(0.990)	-	(0.036)
Father's Educ.	-	-0.488***	-	-0.246	-	0.035
(Bachelor's/Postgrad)	-	(0.169)	-	(1.011)	-	(0.149)
Father's Educ. Missing	-0.131*	-	-0.140	-	-0.030	-
	(0.072)	-	(0.303)	-	(0.074)	-
Income Quintile	-0.227*	-0.062	0.629	2.067	-0.017	-0.022
	(0.125)	(0.079)	(2.642)	(2.965)	(0.082)	(0.061)
Mixed School	-0.043	-0.049	2.228*	2.359	0.384	0.426
	(0.150)	(0.159)	(1.332)	(1.520)	(0.235)	(0.278)
Constant	–	–	-8.076*	-11.309**	–	–
			(4.210)	(4.881)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in adjusted Maths Leaving Certificate points at ages 17/18, using predictors measured at age 9 (Wave 1). The "No Father" model includes all observations (3,690; 1,886 females, 1,804 males) and controls for father absence using a missing data dummy. The "With Father" model includes paternal education but is restricted to cases with valid data (3,241 observations; 1,635 females, 1,606 males). Negative "Difference" values indicate that boys outperform girls. Negative endowment effects reflect characteristics more favourable to boys (e.g., Maths ability), while negative coefficients indicate greater returns for boys. Interaction terms represent how differential returns combine with differences in endowments. Bootstrap standard errors based on 100 replications.

Table 12: Decomposition of Gender Differences in Maths Achievement: Comparing Models With and Without Father's Education Variables (Wave 2)

Statistic	**No Father**	**With Father**
Group 1 (Female)	54.209*** (0.696)	56.272*** (0.697)
Group 2 (Male)	59.091*** (0.700)	60.907*** (0.775)
Difference	-4.882*** (1.033)	-4.635*** (1.020)
Endowments	-4.150*** (0.752)	-4.039*** (0.776)
Coefficients	-1.236 (0.913)	-1.128 (0.984)
Interaction	0.504 (0.537)	0.532 (0.562)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	No Father	**With Father**	**No Father**	**With Father**	**No Father**	**With Father**
Verbal Reasoning	-1.034***	-0.803***	-0.389	-0.324	0.275	0.183
	(0.214)	(0.232)	(0.268)	(0.392)	(0.194)	(0.223)
Numerical Ability	-3.658***	-3.546***	-0.151	-0.325	0.146	0.266
	(0.405)	(0.454)	(0.365)	(0.405)	(0.349)	(0.326)
Matrices	-0.186	-0.259	-9.436*	-13.013*	0.061	0.115
	(0.152)	(0.172)	(5.485)	(7.647)	(0.072)	(0.109)
Emotional Symptoms	-0.006	-0.083	-1.130	-1.143	-0.269	-0.299
	(0.124)	(0.161)	(0.692)	(0.797)	(0.182)	(0.237)
Conduct Problems	0.012	0.023	0.316	0.219	-0.009	-0.009
	(0.041)	(0.055)	(0.801)	(0.795)	(0.048)	(0.051)
Hyperactivity	0.970***	0.948***	-1.636	-1.303	0.401	0.322
	(0.229)	(0.222)	(1.280)	(1.189)	(0.323)	(0.296)
Peer-relationship Problems	0.080	0.059	1.124	0.601	-0.144	-0.083
	(0.064)	(0.067)	(0.765)	(0.712)	(0.113)	(0.095)
Mother's Educ.	0.099	0.100	-1.010	1.211	-0.038	0.056
(Higher 2ndary/Tech)	(0.094)	(0.133)	(1.552)	(2.100)	(0.079)	(0.141)
Mother's Educ.	-0.217	-0.179	0.863	1.847	-0.076	-0.151
(Bachelor's/Postgrad)	(0.137)	(0.161)	(1.295)	(1.617)	(0.143)	(0.183)
Father's Educ.	-	0.081	-	0.570	-	0.045
(Higher 2ndary/Tech)	-	(0.093)	-	(1.224)	-	(0.101)
Father's Educ.	-	-0.277*	-	0.485	-	-0.068
(Bachelor's/Postgrad)	-	(0.148)	-	(1.223)	-	(0.183)
Father Educ. Missing	-0.123	-	0.101	-	0.022	-
	(0.082)	-	(0.360)	-	(0.084)	-
Income Quintile	-0.063	-0.002	0.635	1.532	-0.007	-0.001
	(0.088)	(0.065)	(2.018)	(2.601)	(0.034)	(0.044)
Fee Paying School	-0.126	-0.142*	0.048	-0.100	-0.012	0.024
	(0.083)	(0.069)	(0.322)	(0.315)	(0.088)	(0.076)
Other School Variables†	–	–	–	–	–	–
Constant	–	–	10.688	9.830	–	–
			(7.190)	(8.819)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in adjusted Maths Leaving Certificate points at age 15, using predictors measured at age 13 (Wave 2). The "No Father" model uses the full sample (3,401 observations; 1,724 females, 1,677 males) and controls for father absence using a missing data dummy. The "With Father" model includes paternal education but is restricted to cases with valid data (2,777 observations; 1,377 females, 1,400 males). Negative "Difference" values indicate that boys outperform girls. Negative endowment effects reflect characteristics more favourable to boys (e.g., Numerical ability), while negative coefficients indicate greater returns for boys. Bootstrap standard errors based on 100 replications. † Other school variables (DEIS School, Mixed School, Religious School) were included in the model but none showed significant effects.

F Appendix F. Oaxaca Decompositions: Father Absence Effects in Maths, Leaving Cert

The detailed decomposition results underlying the figures on father absence effects in the main text are reported in the tables below.

Table 13: Gender Differences in the Impact of Father Absence on Maths Achievement (Wave 1)

Statistic	**Boys**	**Girls**
Group 1 (Father Present)	60.834*** (0.865)	55.799*** (0.814)
Group 2 (Father Absent)	47.270*** (2.793)	40.573*** (2.266)
Difference	13.564*** (2.986)	15.225*** (2.322)
Endowments	5.984** (2.561)	3.122 (2.263)
Coefficients	6.612** (2.737)	7.456*** (2.123)
Interaction	0.969 (2.659)	4.647** (1.939)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	Boys	**Girls**	**Boys**	**Girls**	**Boys**	**Girls**
Reading Ability	0.842	0.294	-0.285	-0.378	-0.238	-0.058
	(0.790)	(0.572)	(1.078)	(1.033)	(0.771)	(0.303)
Maths Ability	2.807**	1.326	0.193	-1.425	-0.083	0.391
	(1.271)	(0.900)	(2.410)	(2.397)	(1.053)	(0.639)
Emotional Symptoms	-0.929	0.252	-3.883	-2.351	0.837	0.513
	(0.858)	(0.561)	(3.164)	(2.583)	(0.862)	(0.634)
Conduct Problems	-0.379	-0.048	-5.076*	-0.156	0.872	0.037
	(0.557)	(0.537)	(2.925)	(2.316)	(0.744)	(0.562)
Hyperactivity	1.177	0.634	-0.081	-2.602	0.020	0.557
	(1.221)	(0.651)	(4.776)	(3.287)	(1.268)	(0.788)
Peer-relationship Problems	1.049	0.001	3.358	0.528	-1.181	-0.123
	(0.794)	(0.424)	(2.399)	(2.066)	(0.898)	(0.470)
Mother's Educ. (Higher 2ndary/Tech)	0.569	-0.183	-9.889***	5.997*	-0.414	0.527
	(1.041)	(0.358)	(3.570)	(3.074)	(0.771)	(0.625)
Mother's Educ. (Bachelor's/Postgrad)	0.944	1.290	-3.294	-1.028	-0.424	-0.283
	(1.111)	(1.154)	(2.411)	(1.879)	(0.661)	(0.809)
Income Quintile	-0.038	-0.616	6.929	9.781*	1.523	3.180*
	(1.422)	(1.639)	(6.580)	(5.141)	(1.589)	(1.810)
Mixed School	-0.058	0.172	-4.745	-1.262	0.057	-0.092
	(0.407)	(0.292)	(4.288)	(3.969)	(0.423)	(0.306)
Constant	–	–	23.384**	0.352	–	–
			(9.465)	(8.197)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender-specific impact of father absence on adjusted Maths Leaving Certificate points at age 15, using Wave 1 predictors (measured at age 9). The decomposition compares students with fathers present versus absent, separately for boys (n=1,314; 1,188 father present, 126 absent) and girls (n=1,292; 1,142 father present, 150 absent). Results are bootstrapped with 100 replications. The father absence penalty is larger for girls (15.23 points) than for boys (13.56 points). For boys, the gap is driven by both endowments (5.98) and coefficients (6.61), whereas for girls, the interaction term (4.65) is also significant, indicating a stronger role of unobserved heterogeneity or differences in returns to observed traits. Mother's education and Maths ability are key contributors across both groups.

Table 14: Gender Differences in the Impact of Father Absence on Maths Achievement (Wave 2)

Statistic	**Boys**	**Girls**
Group 1 (Father Present)	60.834*** (0.818)	55.799*** (0.826)
Group 2 (Father Absent)	47.270*** (3.172)	40.573*** (2.428)
Difference	13.564*** (3.256)	15.225*** (2.602)
Endowments	7.406*** (2.557)	7.405*** (2.261)
Coefficients	4.992** (2.311)	6.351*** (2.020)
Interaction	1.166 (1.640)	1.469 (1.874)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	Boys	**Girls**	**Boys**	**Girls**	**Boys**	**Girls**
Verbal Reasoning	1.410	1.165*	-0.945	0.169	-0.742	-0.396
	(1.008)	(0.639)	(0.989)	(0.326)	(0.651)	(0.576)
Numerical Ability	2.020	2.940**	0.372	-0.428	1.490	0.511
	(1.552)	(1.266)	(0.710)	(0.941)	(1.330)	(1.114)
BAS Matrices	0.880	0.638	3.991	-7.021	0.151	-0.177
	(0.699)	(0.408)	(18.694)	(13.469)	(0.698)	(0.359)
Emotional Symptoms	-0.608	0.160	-2.156	-2.202	0.593	0.440
	(0.662)	(0.502)	(2.553)	(2.518)	(0.745)	(0.609)
Conduct Problems	-0.046	0.074	-1.420	0.226	0.108	-0.037
	(0.244)	(0.318)	(1.767)	(1.897)	(0.342)	(0.326)
Hyperactivity	1.504	1.458*	-0.336	3.418	0.099	-0.658
	(0.921)	(0.825)	(3.288)	(3.294)	(0.986)	(0.693)
Peer-relationship Problems	0.861	-0.851	3.349	-2.479	-0.767	0.752
	(0.666)	(0.595)	(2.365)	(1.872)	(0.708)	(0.607)
Mother's Educ. (Higher 2ndary/Tech)	0.411	-0.114	-4.969	8.428***	-0.277	0.191
	(0.767)	(0.508)	(3.491)	(3.120)	(0.573)	(0.790)
Mother's Educ. (Bachelor's/Postgrad)	0.235	0.491	0.001	1.454	0.000	0.376
	(0.502)	(0.818)	(3.044)	(2.655)	(0.403)	(0.799)
Income Quintile	0.967	0.151	-3.413	5.468	-0.421	1.183
	(0.706)	(1.047)	(5.682)	(5.425)	(0.702)	(1.126)
Fee Paying School	-1.065*	0.371	1.884**	-0.210	1.246*	-0.176
	(0.619)	(0.756)	(0.769)	(0.519)	(0.695)	(0.740)
Other School Variables†	–	–	–	–	–	–
Constant	–	–	14.486	-2.961	–	–
			(21.513)	(19.086)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents the Blinder-Oaxaca decomposition results for the gendered impact of father absence on Maths performance at age 15 using Wave 2 predictors. The decomposition is conducted separately for boys (n=1,314) and girls (n=1,292), comparing those with father presence versus absence. Standard errors are based on 100 bootstrap replications. While the total gap is substantial for both genders, the decomposition reveals stronger endowment and coefficient effects among girls. Notably, maternal education shows a significant coefficient effect for girls only, while fee-paying school status yields significant returns among boys. The interaction terms are not statistically significant for either group, implying that differences are primarily driven by observable characteristics and their direct effects. †Other school variables (DEIS School, Mixed School, Religious School) were included in the model but none showed significant effects.

G Appendix G. Oaxaca Decompositions: Gender Gaps in English, Leaving Cert

Although the main analysis focuses on Maths achievement, this appendix reports Oaxaca decomposition results for gender gaps in English performance for completeness.

Overall, the decomposition results show that girls score higher than boys in English at the Leaving Certificate, with an average gap of about 3 points across both the Wave 1 and Wave 2 models. Most of this gap comes from differences in coefficients—meaning that, for the same set of skills, girls tend to get better returns than boys. Differences in skill levels themselves explain a smaller part of the gap. This suggests that the gender gap in English is more about how skills are used or rewarded than about differences in skills. The patterns stay similar whether or not paternal education is included in the models.

Table 15: Decomposition of Gender Differences in English Achievement at ages 17/18: Comparing Models With and Without Father's Education Variables (Wave 1)

Statistic	**No Father**	**With Father**
Group 1 (Female)	69.065*** (0.448)	69.875*** (0.401)
Group 2 (Male)	65.986*** (0.517)	66.309*** (0.435)
Difference	3.079*** (0.725)	3.566*** (0.588)
Endowments	0.260 (0.400)	0.456 (0.399)
Coefficients	2.360*** (0.666)	2.821*** (0.542)
Interaction	0.459 (0.311)	0.288 (0.319)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	No Father	**With Father**	**No Father**	**With Father**	**No Father**	**With Father**
Reading Ability	0.079	0.146	0.015	-0.056	0.001	-0.003
	(0.223)	(0.219)	(0.260)	(0.268)	(0.024)	(0.027)
Maths Ability	-0.190*	-0.147	0.173	0.129	0.074	0.053
	(0.112)	(0.101)	(0.315)	(0.291)	(0.132)	(0.122)
Emotional Symptoms	0.034	0.063	0.146	-0.266	0.022	-0.038
	(0.077)	(0.075)	(0.627)	(0.657)	(0.096)	(0.096)
Conduct Problems	0.135**	0.178**	0.290	0.614	-0.044	-0.104
	(0.068)	(0.084)	(0.566)	(0.602)	(0.089)	(0.106)
Hyperactivity	0.688***	0.705***	-0.207	-0.051	0.043	0.011
	(0.158)	(0.173)	(0.853)	(0.946)	(0.178)	(0.208)
Peer-relationship Problems	0.000	-0.001	-0.510	-0.352	-0.010	-0.006
	(0.017)	(0.018)	(0.527)	(0.557)	(0.033)	(0.038)
Mother's Educ.	0.004	0.001	0.947	0.911	0.002	0.000
(Higher 2ndary/Tech)	(0.055)	(0.055)	(1.237)	(1.258)	(0.050)	(0.052)
Mother's Educ.	-0.196*	-0.098	0.703	0.751	-0.065	-0.045
(Bachelor's/Postgrad)	(0.113)	(0.087)	(0.791)	(0.816)	(0.095)	(0.079)
Father's Educ.	-	0.019	-	0.417	-	0.006
(Higher 2ndary/Tech)	-	(0.059)	-	(0.724)	-	(0.037)
Father's Educ.	-	-0.178*	-	0.635	-	-0.087
(Bachelor's/Postgrad)	-	(0.106)	-	(0.664)	-	(0.097)
Father's Educ. Missing	-0.019	-	-0.166	-	-0.043	-
	(0.044)	-	(0.218)	-	(0.062)	-
Income Quintile	-0.070	-0.013	0.803	1.072	-0.024	-0.012
	(0.054)	(0.029)	(1.885)	(1.871)	(0.060)	(0.036)
Mixed School	-0.205*	-0.217**	2.944**	2.803**	0.502***	0.512***
	(0.115)	(0.110)	(0.972)	(0.917)	(0.181)	(0.176)
Constant	–	–	-2.777	-3.785	–	–
			(2.658)	(2.778)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in adjusted English Leaving Certificate points at age 15, using predictors measured at age 9 (Wave 1). The "No Father" model includes all observations (3,679; 1,887 females, 1,792 males) and controls for father absence using a missing data dummy. The "With Father" model includes paternal education but is restricted to cases with valid data (3,233 observations; 1,633 females, 1,600 males). Positive "Difference" values indicate that girls outperform boys. Positive endowment effects reflect characteristics more favourable to girls, while positive coefficients indicate greater returns for girls. Interaction terms represent how differential returns combine with differences in endowments. Bootstrap standard errors based on 100 replications.

Table 16: Decomposition of Gender Differences in English Achievement: Comparing Models With and Without Father's Education Variables (Wave 2)

Statistic	**No Father**	**With Father**
Group 1 (Female)	69.557*** (0.483)	70.585*** (0.466)
Group 2 (Male)	66.650*** (0.442)	67.450*** (0.558)
Difference	2.906*** (0.667)	3.135*** (0.725)
Endowments	-1.588*** (0.412)	-1.123** (0.454)
Coefficients	4.548*** (0.645)	4.396*** (0.759)
Interaction	-0.054 (0.400)	-0.138 (0.416)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	No Father	**With Father**	**No Father**	**With Father**	**No Father**	**With Father**
Verbal Reasoning	-1.655***	-1.363***	-0.411	-0.577*	0.282*	0.312*
	(0.253)	(0.290)	(0.236)	(0.303)	(0.163)	(0.185)
Numerical Ability	-0.553***	-0.420**	0.235	0.420	-0.228	-0.343
	(0.211)	(0.193)	(0.288)	(0.309)	(0.281)	(0.259)
Matrices	-0.026	-0.041	-6.556	-7.606	0.047	0.061
	(0.035)	(0.046)	(4.467)	(5.375)	(0.050)	(0.068)
Emotional Symptoms	-0.013	0.016	-0.289	-0.388	-0.069	-0.105
	(0.089)	(0.110)	(0.421)	(0.537)	(0.103)	(0.149)
Conduct Problems	-0.011	-0.003	-0.693	-0.539	0.022	0.020
	(0.025)	(0.027)	(0.575)	(0.555)	(0.042)	(0.042)
Hyperactivity	0.677***	0.720***	-0.107	0.008	0.026	-0.002
	(0.169)	(0.173)	(0.931)	(0.888)	(0.226)	(0.215)
Peer-relationship Problems	0.043	0.026	-0.115	-0.298	0.014	0.038
	(0.044)	(0.044)	(0.496)	(0.525)	(0.065)	(0.075)
Mother's Educ.	0.082	0.086	-1.196	-0.854	-0.037	-0.036
(Higher 2ndary/Tech)	(0.089)	(0.077)	(1.507)	(1.680)	(0.091)	(0.090)
Mother's Educ.	-0.178	-0.124	-0.614	-0.240	0.052	0.018
(Bachelor's/Postgrad)	(0.119)	(0.096)	(1.136)	(1.313)	(0.115)	(0.115)
Father's Educ.	—	0.048	—	1.001	—	0.082
(Higher 2ndary/Tech)	—	(0.056)	—	(0.910)	—	(0.095)
Father's Educ.	—	-0.111	—	1.051	—	-0.153
(Bachelor's/Postgrad)	—	(0.089)	—	(0.900)	—	(0.136)
Father Educ. Missing	-0.053	—	0.121	—	0.030	—
	(0.053)	—	(0.246)	—	(0.061)	—
Income Quintile	-0.027	-0.002	1.928	2.205	-0.022	-0.003
	(0.042)	(0.024)	(1.470)	(2.148)	(0.035)	(0.049)
Mixed School	0.136*	0.075	1.406*	0.828	-0.159	-0.076
	(0.071)	(0.064)	(0.737)	(0.819)	(0.102)	(0.085)
Constant	—	—	9.425	8.364	—	—
			(5.933)	(6.727)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in adjusted English Leaving Certificate points at age 15, using predictors measured at age 13 (Wave 2). The "No Father" model uses the full sample (3,375 observations; 1,719 females, 1,656 males) and controls for father absence using a missing data dummy. The "With Father" model includes paternal education but is restricted to cases with valid data (2,756 observations; 1,370 females, 1,386 males). Positive "Difference" values indicate that girls outperform boys. Significant school variables are reported; non-significant ones (e.g., DEIS, Fee-paying, Religious School) are excluded. Bootstrap standard errors based on 100 replications.

H Appendix H. Oaxaca Decompositions: Father Absence Effects in English, Leaving Cert

This appendix presents supplementary Blinder-Oaxaca decomposition results for English Leaving Certificate achievement, examining the impact of father absence separately for boys and girls. While the primary analysis focuses on Maths outcomes, the patterns observed for English provide additional support for the broader interpretation that family structure and early-life characteristics shape academic performance. Consistent with the findings for Maths, the results show that father absence is associated with lower achievement in English for both genders, with endowment differences explaining a substantial share of the gap.

Father absence is associated with significant reductions in English achievement for both boys and girls, with slightly larger penalties observed among boys. Across both waves, differences in endowments—particularly cognitive skills such as verbal reasoning—account for a substantial share of the gap, especially among girls. While coefficient effects contribute to the gap among boys, interaction terms remain insignificant for both genders. These findings suggest that observed differences in skill endowments, rather than differential returns or unobserved heterogeneity, largely drive the English achievement penalties linked to father absence.

Table 17: Gender Differences in the Impact of Father Absence on English Achievement (Wave 1)

Statistic	Boys	Girls
Group 1 (Father Present)	66.911*** (0.563)	70.569*** (0.530)
Group 2 (Father Absent)	61.238*** (2.198)	66.391*** (1.761)
Difference	5.673** (2.281)	4.179** (1.830)
Endowments	3.323 (2.038)	2.980** (1.428)
Coefficients	1.930 (1.900)	0.742 (1.588)
Interaction	0.420 (1.642)	0.457 (1.054)

Variable	Endowments		Coefficients		Interactions	
	Boys	Girls	Boys	Girls	Boys	Girls
Reading Ability	1.670	0.622	-0.278	-0.198	-0.243	-0.049
	(1.067)	(0.700)	(0.490)	(0.616)	(0.592)	(0.223)
Maths Ability	0.222	0.131	0.273	0.002	-0.110	-0.000
	(0.597)	(0.354)	(1.403)	(1.361)	(0.613)	(0.387)
Emotional Symptoms	0.115	-0.457	0.833	-2.162	-0.181	0.486
	(0.528)	(0.460)	(2.463)	(2.219)	(0.560)	(0.517)
Conduct Problems	-0.266	0.015	-2.634	0.732	0.484	-0.167
	(0.384)	(0.393)	(1.730)	(1.799)	(0.466)	(0.437)
Hyperactivity	0.707	0.729	-1.826	-1.135	0.465	0.235
	(0.810)	(0.490)	(3.087)	(2.232)	(0.814)	(0.544)
Peer-relationship Problems	-0.192	0.335	-0.795	0.794	0.282	-0.197
	(0.614)	(0.348)	(1.746)	(1.438)	(0.651)	(0.360)
Mother's Educ.	0.263	0.044	-2.557	2.145	-0.140	0.139
(Higher 2ndary/Tech)	(0.585)	(0.280)	(3.364)	(2.431)	(0.493)	(0.315)
Mother's Educ.	0.833	0.222	-4.867**	1.362	-0.598	0.398
(Bachelor's/Postgrad)	(1.065)	(0.366)	(2.302)	(1.270)	(0.820)	(0.477)
Income Quintile	-0.073	1.148	2.067	-0.758	0.457	-0.256
	(0.985)	(0.939)	(4.838)	(2.900)	(1.060)	(0.951)
Mixed School	0.044	0.192	-0.126	-2.134	0.005	-0.131
	(0.218)	(0.250)	(3.290)	(3.107)	(0.220)	(0.253)
Constant	–	–	11.839	2.095	–	–
			(7.898)	(6.873)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender-specific impact of father absence on adjusted English Leaving Certificate points at age 15, using Wave 1 predictors (measured at age 9). The decomposition compares students with fathers present versus absent, separately for boys (n=1,300; 1,178 father present, 122 absent) and girls (n=1,289; 1,138 father present, 151 absent). Results are bootstrapped with 100 replications. For boys, the gap is driven by endowments (3.32 points), while for girls, endowments (2.98 points) also explain a substantial share. None of the individual predictors significantly explain the gap, but mother's education and reading ability are among the key contributors.

Table 18: Gender Differences in the Impact of Father Absence on English Achievement (Wave 2)

Statistic	Boys	Girls
Group 1 (Father Present)	66.911*** (0.575)	70.569*** (0.502)
Group 2 (Father Absent)	61.238*** (2.148)	66.391*** (1.813)
Difference	5.673** (2.234)	4.179** (1.888)
Endowments	4.112** (2.036)	4.376*** (1.519)
Coefficients	1.975 (1.936)	-0.684 (1.713)
Interaction	-0.413 (1.527)	0.487 (1.453)

Variable	Endowments		Coefficients		Interactions	
	Boys	Girls	Boys	Girls	Boys	Girls
Verbal Reasoning	1.450	1.918***	-0.925	0.207	-0.534	-0.524
	(1.212)	(0.706)	(0.800)	(0.251)	(0.616)	(0.430)
Numerical Ability	-1.031	1.056	0.451	0.257	1.330	-0.308
	(0.935)	(0.709)	(0.500)	(0.538)	(0.951)	(0.647)
BAS Matrices	0.488	-0.108	-6.891	0.384	-0.231	0.012
	(0.504)	(0.468)	(11.437)	(13.959)	(0.466)	(0.469)
Emotional Symptoms	0.169	0.209	0.839	0.534	-0.248	-0.095
	(0.515)	(0.455)	(1.898)	(2.185)	(0.572)	(0.453)
Conduct Problems	-0.107	-0.010	-0.822	-0.126	0.104	0.018
	(0.367)	(0.242)	(2.007)	(1.454)	(0.373)	(0.249)
Hyperactivity	1.218	0.435	-0.627	-0.225	0.191	0.039
	(0.892)	(0.516)	(2.953)	(2.693)	(0.903)	(0.519)
Peer-relationship Problems	-0.199	-0.035	-1.076	-0.793	0.251	0.237
	(0.304)	(0.592)	(1.360)	(1.935)	(0.355)	(0.653)
Mother's Educ. (Higher 2ndary/Tech)	0.142	-0.031	-0.221	4.278	-0.012	0.056
	(0.410)	(0.257)	(3.385)	(3.095)	(0.355)	(0.359)
Mother's Educ. (Bachelor's/Postgrad)	0.385	-0.338	-2.110	2.766*	-0.199	0.768
	(0.718)	(0.562)	(2.641)	(1.526)	(0.550)	(0.764)
Income Quintile	0.138	0.673	-0.096	0.408	-0.011	0.085
	(0.405)	(0.733)	(3.818)	(3.301)	(0.468)	(0.707)
Fee Paying School	-0.201	0.073	0.342	-0.047	0.213	-0.038
	(0.451)	(0.370)	(0.663)	(0.239)	(0.463)	(0.380)
DEIS School	1.665**	0.735	2.334*	0.205	-1.299*	-0.102
	(0.806)	(0.552)	(1.246)	(0.913)	(0.765)	(0.476)
Mixed School	0.045	0.041	-0.227	0.661	0.013	-0.061
	(0.223)	(0.273)	(2.581)	(2.080)	(0.244)	(0.273)
Religious School	-0.049	-0.243	0.781	2.423	0.020	0.399
	(0.240)	(0.671)	(3.206)	(3.130)	(0.238)	(0.717)
Constant	–	–	10.223	-11.616	–	–
			(14.736)	(18.561)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents the Blinder-Oaxaca decomposition results for the gendered impact of father absence on adjusted English Leaving Certificate points at age 15 using Wave 2 predictors. The decomposition is conducted separately for boys (n=1,300; 1,178 father present, 122 absent) and girls (n=1,289; 1,138 father present, 151 absent). Bootstrap standard errors based on 100 replications. The total gap is statistically significant for both genders. Among girls, endowments explain the majority of the gap. Significant predictors include verbal reasoning (girls) and DEIS school status (boys). No significant interaction effects were found.

I Appendix I. Supplementary Decompositions: Gaps in Junior Cert Maths

This appendix presents supplementary Blinder–Oaxaca decomposition results examining how gender and family background contribute to Maths achievement gaps at age 15. I first isolate the male–female differential in Maths scores (Part I), then compare children with present versus absent fathers (Part II). All decompositions split the total gap into endowments (differences in skills/resources), coefficients (differences in returns to those endowments), and interaction components. Predictors come from age 9 (Wave 1) and age 13 (Wave 2), allowing us to trace developmental changes. Throughout, "No Father" models omit paternal education, while "With Father" models include it—each reported in the tables below.

I.1 Part I: Decomposition Results by Gender - Waves 1 and 2 - Maths Junior Certificate

I.2 Part II: Decomposition Results by Father Absence - Waves 1 and 2 - Maths Junior Cert

This section presents Blinder–Oaxaca decompositions comparing Maths achievement between children with present and absent fathers, using predictors from Wave 1 and Wave 2.

I.3 Discussion

The Blinder–Oaxaca decompositions show that both gender and father-absence gaps in Junior Certificate Maths at age 15 are substantial and change clearly between middle childhood and early adolescence. Children with absent fathers face about a 1-point disadvantage on the 12-point OPS scale, which is roughly equivalent to a full grade. At age 9, the gap is split between differences in skills and differences in how skills are rewarded, but by age 13, it is mainly due to skill differences. This timing matches developmental windows when numerical and abstract reasoning skills grow quickly (Casey et al., 2005; Luna et al., 2010).

Gender differences follow a similar pattern. Boys score about 0.13 points higher than girls at age 15. In earlier years, the gap reflects both skill differences and how those skills are rewarded, but by adolescence, it is mostly about differences in cognitive abilities. Having a father present boosts how much girls can make use of their numerical skills (β = 0.154, p<0.01), pointing to the role of paternal support during adolescence (Eccles et al., 1990).

Across both sets of decompositions, numerical ability is the strongest contributor. At Wave 2, it explains 0.359 out of the 0.676 gap for father absence, and 0.234 out of the 0.269

gender gap. Maternal education helps soften the father-absence penalty, especially for girls (Black & Devereux, 2011). Behavioural traits such as conduct problems and hyperactivity, and school factors like mixed-gender environments, fee-paying status, and DEIS classification, also influence outcomes (Downey, 1995; Evans & Schamberg, 2009; Pianta & Stuhlman, 2004; Raver, 2002).

Table 19: Gender Differences in Junior Certificate Maths Achievement at Age 15 (Wave 1 Predictors)

Statistic	**No Father**	**With Father**
Group 1 (Female)	9.541*** (0.036)	9.664*** (0.040)
Group 2 (Male)	9.671*** (0.039)	9.781*** (0.039)
Difference	-0.130** (0.053)	-0.116** (0.055)
Endowments	-0.098** (0.038)	-0.085** (0.038)
Coefficients	-0.082* (0.044)	-0.087* (0.047)
Interaction	0.050** (0.023)	0.055** (0.023)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	No Father	**With Father**	**No Father**	**With Father**	**No Father**	**With Father**
Reading Ability	0.005	0.006	0.027*	0.033**	0.002	0.003
	(0.009)	(0.008)	(0.016)	(0.017)	(0.004)	(0.005)
Maths Ability	-0.116***	-0.104***	0.050*	0.047*	0.020*	0.019*
	(0.020)	(0.020)	(0.026)	(0.025)	(0.011)	(0.011)
Emotional Symptoms	-0.001	-0.001	-0.066	-0.054	-0.010	-0.008
	(0.005)	(0.005)	(0.044)	(0.043)	(0.008)	(0.007)
Conduct Problems	0.012**	0.014**	-0.020	-0.025	0.003	0.004
	(0.005)	(0.006)	(0.045)	(0.045)	(0.006)	(0.007)
Hyperactivity	0.043***	0.046***	-0.084	-0.062	0.015	0.011
	(0.010)	(0.010)	(0.061)	(0.070)	(0.011)	(0.013)
Peer Problems	0.000	-0.000	-0.002	-0.024	0.000	0.000
	(0.001)	(0.001)	(0.036)	(0.038)	(0.002)	(0.002)
Mother's Educ.	-0.001	0.001	-0.056	-0.023	0.000	-0.000
(Higher 2ndary/Tech)	(0.009)	(0.008)	(0.082)	(0.092)	(0.003)	(0.003)
Mother's Educ.	-0.033**	-0.023*	-0.036	-0.020	0.004	0.002
(Bachelor's/Postgrad)	(0.015)	(0.012)	(0.050)	(0.059)	(0.006)	(0.007)
Father's Educ.	-	0.004	-	0.012	-	0.000
(Higher 2ndary/Tech)	-	(0.005)	-	(0.053)	-	(0.003)
Father's Educ.	-	-0.028***	-	-0.014	-	0.002
(Bachelor's/Postgrad)	-	(0.010)	-	(0.044)	-	(0.007)
Income Quintile	-0.010	-0.002	0.078	0.146	-0.002	-0.001
	(0.007)	(0.004)	(0.127)	(0.139)	(0.003)	(0.003)
Mixed School	0.002	0.003	0.114	0.141*	0.019	0.023*
	(0.007)	(0.008)	(0.070)	(0.078)	(0.012)	(0.013)
Constant	–	–	-0.088	-0.244	–	–
			(0.217)	(0.236)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in Maths achievement at age 15, using predictors measured at age 9 (Wave 1). The "No Father" model uses the full sample (4,040 observations; 2,039 females, 2,001 males) and excludes paternal education variables. The "With Father" model includes paternal education but has a smaller sample size (3,489 observations; 1,746 females, 1,743 males) due to non-response from some fathers. The negative "Difference" indicates that boys score higher than girls on average. Negative values in the "Endowments" section indicate characteristics where boys have an advantage (e.g., Maths ability), while positive values indicate girls' advantages (e.g., behaviour). The negative "Coefficients" component suggests that boys receive better returns to their characteristics, though this flips to positive in Wave 2. The significant positive "Interaction" term indicates an intricate interplay between gender differences in characteristics and returns that partially offsets boys' advantage. Bootstrap procedure with 500 replications was used to estimate standard errors.

Table 20: Gender Differences in Junior Certificate Maths Achievement at Age 15 (Wave 2 Predictors)

Statistic	No Father	With Father
Group 1 (Female)	9.541*** (0.038)	9.695*** (0.044)
Group 2 (Male)	9.671*** (0.037)	9.828*** (0.038)
Difference	-0.130** (0.055)	-0.132** (0.058)
Endowments	-0.269*** (0.042)	-0.248*** (0.044)
Coefficients	0.110*** (0.041)	0.093** (0.047)
Interaction	0.028 (0.025)	0.024 (0.029)

Variable	Endowments		Coefficients		Interactions	
	No Father	With Father	No Father	With Father	No Father	With Father
Verbal Reasoning	-0.059***	-0.049***	-0.000	0.002	0.000	-0.002
	(0.012)	(0.012)	(0.009)	(0.013)	(0.010)	(0.011)
Numerical Ability	-0.234***	-0.211***	-0.007	-0.016	0.011	0.019
	(0.023)	(0.024)	(0.012)	(0.016)	(0.017)	(0.019)
BAS Matrices	-0.009	-0.012	0.214	0.419	-0.001	-0.004
	(0.007)	(0.008)	(0.289)	(0.339)	(0.002)	(0.004)
Emotional Symptoms	-0.006	-0.007	-0.011	-0.032	-0.003	-0.010
	(0.007)	(0.009)	(0.035)	(0.037)	(0.009)	(0.012)
Conduct Problems	0.001	0.002	-0.074**	-0.075*	0.004	0.004
	(0.002)	(0.002)	(0.037)	(0.042)	(0.004)	(0.005)
Hyperactivity	0.058***	0.055***	-0.077	-0.084	0.017	0.019
	(0.011)	(0.011)	(0.055)	(0.064)	(0.013)	(0.015)
Peer Problems	0.001	0.000	0.050	0.052	-0.005	-0.006
	(0.002)	(0.003)	(0.032)	(0.035)	(0.004)	(0.005)
Mother's Educ.	0.010	0.010	0.006	0.132	0.000	0.006
(Higher 2ndary/Tech)	(0.008)	(0.008)	(0.086)	(0.100)	(0.004)	(0.007)
Mother's Educ.	-0.028**	-0.023**	0.027	0.077	-0.003	-0.008
(Bachelor's/Postgrad)	(0.011)	(0.011)	(0.060)	(0.072)	(0.008)	(0.009)
Father's Educ.	-	0.004	-	0.066	-	0.002
(Higher 2ndary/Tech)	-	(0.005)	-	(0.066)	-	(0.004)
Father's Educ.	-	-0.018**	-	0.033	-	-0.004
(Bachelor's/Postgrad)	-	(0.008)	-	(0.057)	-	(0.008)
Income Quintile	-0.003	-0.000	0.059	0.034	-0.001	-0.000
	(0.005)	(0.004)	(0.102)	(0.120)	(0.002)	(0.002)
Mixed School	0.002	-0.000	-0.100*	-0.107*	0.009	0.008
	(0.003)	(0.003)	(0.053)	(0.056)	(0.005)	(0.006)
Fee Paying School	-0.005	-0.003	-0.006	-0.002	0.001	0.000
	(0.003)	(0.003)	(0.013)	(0.015)	(0.002)	(0.003)
DEIS School	0.003	0.003	0.001	0.004	-0.000	-0.000
	(0.004)	(0.003)	(0.017)	(0.017)	(0.002)	(0.002)
Religious School	-0.000	0.001	-0.055	-0.059	-0.001	-0.002
	(0.001)	(0.002)	(0.073)	(0.083)	(0.002)	(0.003)
Constant	–	–	0.084	-0.351	–	–
			(0.348)	(0.406)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in Maths achievement at age 15, using predictors measured at age 13 (Wave 2). The ”No Father” model uses the full sample (4,040 observations; 2,039 females, 2,001 males) and excludes paternal education variables. The ”With Father” model includes paternal education but has a smaller sample size (3,206 observations; 1,576 females, 1,630 males) due to non-response from some fathers. Bootstrap procedure with 500 replications was used to estimate standard errors.

Table 21: Impact of Father Absence on Junior Certificate Maths Achievement (Wave 1 Predictors)

Statistic	Value
Group 1 (Father Present)	9.782*** (0.030)
Group 2 (Father Absent)	8.763*** (0.084)
Difference	1.020*** (0.086)
Endowments	0.470*** (0.075)
Coefficients	0.426*** (0.077)
Interaction	0.124** (0.059)

Variable	Endowments	Coefficients	Interactions
Reading Ability	0.078***	0.000	0.001
	(0.027)	(0.010)	(0.026)
Maths Ability	0.197***	0.044	-0.017
	(0.039)	(0.082)	(0.032)
Emotional Symptoms	-0.007	-0.099	0.026
	(0.028)	(0.107)	(0.029)
Conduct Problems	0.017	-0.054	0.012
	(0.017)	(0.075)	(0.017)
Hyperactivity	0.031	-0.170	0.035
	(0.022)	(0.109)	(0.023)
Peer Problems	0.020	0.084	-0.027
	(0.027)	(0.084)	(0.027)
Mother's Educ. (Higher 2ndary/Tech)	0.002	0.247**	0.008
	(0.005)	(0.117)	(0.014)
Mother's Educ. (Bachelor's/Postgrad)	0.088***	-0.011	-0.004
	(0.029)	(0.054)	(0.022)
Income Quintile	0.049	0.243	0.081
	(0.056)	(0.185)	(0.061)
Mixed School	0.002	0.011	0.000
	(0.005)	(0.127)	(0.006)
Male	-0.007	0.096	0.010
	(0.009)	(0.077)	(0.010)
Constant	–	0.034	–
		(0.264)	

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results comparing Maths achievement between children with present fathers and those with absent fathers, using predictors measured at age 9 (Wave 1). Father absence is defined as non-response to the father questionnaire in both waves, which may indicate either physical absence or non-participation. This approach maximizes sample size while capturing paternal disengagement. The large positive difference (1.020***) indicates a substantial achievement advantage for children with present fathers. The decomposition shows that 46% of this gap is explained by differences in endowments, particularly cognitive skills (Reading and Maths Ability) and maternal education level. The significant coefficients component (0.426***) suggests father presence also alters the returns to these characteristics. Bootstrap procedure with 100 replications was used to estimate standard errors for the decomposition analysis of 3,523 total observations (3,089 with father present, 434 with father absent).

Table 22: Gender Differences in the Impact of Father Absence on Junior Certificate Maths Achievement (Wave 1 Predictors)

Statistic	**Boys**	**Girls**
Group 1 (Father Present)	9.835*** (0.040)	9.728*** (0.045)
Group 2 (Father Absent)	8.725*** (0.111)	8.795*** (0.121)
Difference	1.110*** (0.119)	0.934*** (0.129)
Endowments	0.468*** (0.115)	0.459*** (0.100)
Coefficients	0.597*** (0.112)	0.274** (0.122)
Interaction	0.045 (0.107)	0.200*** (0.073)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	Boys	**Girls**	**Boys**	**Girls**	**Boys**	**Girls**
Reading Ability	0.061	0.090**	0.001	-0.000	0.009	-0.001
	(0.048)	(0.044)	(0.018)	(0.016)	(0.049)	(0.041)
Maths Ability	0.222***	0.162***	0.075	0.007	-0.032	-0.002
	(0.064)	(0.045)	(0.113)	(0.128)	(0.047)	(0.046)
Emotional Symptoms	-0.037	0.010	-0.137	-0.099	0.035	0.026
	(0.034)	(0.032)	(0.130)	(0.132)	(0.034)	(0.035)
Conduct Problems	0.022	0.020	-0.030	-0.045	0.006	0.012
	(0.034)	(0.027)	(0.140)	(0.104)	(0.032)	(0.028)
Hyperactivity	0.007	0.048	-0.284	-0.088	0.061	0.019
	(0.043)	(0.032)	(0.210)	(0.148)	(0.051)	(0.031)
Peer Problems	0.043	0.008	0.176	0.023	-0.064	-0.007
	(0.047)	(0.024)	(0.136)	(0.088)	(0.052)	(0.024)
Mother's Educ. (Higher 2ndary/Tech)	0.002	-0.002	0.058	0.381***	0.001	0.019
	(0.018)	(0.010)	(0.184)	(0.145)	(0.013)	(0.028)
Mother's Educ. (Bachelor's/Postgrad)	0.102*	0.082*	-0.053	-0.005	-0.019	-0.002
	(0.052)	(0.044)	(0.088)	(0.079)	(0.037)	(0.038)
Income Quintile	0.040	0.041	0.197	0.340*	0.055	0.130*
	(0.074)	(0.069)	(0.262)	(0.185)	(0.077)	(0.075)
Mixed School	0.005	0.001	-0.115	0.176	-0.006	0.006
	(0.012)	(0.007)	(0.168)	(0.184)	(0.012)	(0.010)
Constant	–	–	0.710**	-0.416	–	–
			(0.345)	(0.404)		

Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. The output shows a bootstrap procedure with 500 replications used to estimate standard errors for the Blinder-Oaxaca decomposition. The decomposition analyzes differences in Maths scores between children with father present versus absent, separately for boys (n=1,772; 1,572 with father present, 200 with father absent) and girls (n=1,751; 1,517 with father present, 234 with father absent). Father absence is defined as non-response to the father questionnaire in both waves. The total gap is larger for boys (1.110) than for girls (0.934), suggesting that boys may be more adversely affected by father absence. For boys, the coefficients effect (0.597) is larger than the endowments effect (0.468), while for girls the endowments and coefficients effects are more similar (0.459 and 0.274). The interaction term is significant only for girls (0.200***), indicating that for girls, a complex interplay between characteristics and returns partially offsets the negative impact of father absence. Notable gender differences include: higher Maths ability endowment effect for boys, significant reading ability endowment effect only for girls, and significant maternal education coefficient effect only for girls.

Table 23: Impact of Father Absence on Maths Achievement: Blinder-Oaxaca Decomposition Results (Wave 2)

Statistic	**Value**
Group 1 (Father Present)	9.782*** (0.029)
Group 2 (Father Absent)	8.763*** (0.089)
Difference	1.020*** (0.097)
Endowments	0.676*** (0.085)
Coefficients	0.348*** (0.068)
Interaction	-0.004 (0.043)

Variable	**Endowments**	**Coefficients**	**Interactions**
Verbal Reasoning	0.108***	0.012	-0.022
	(0.028)	(0.012)	(0.021)
Numerical Ability	0.359***	0.073***	-0.106***
	(0.059)	(0.026)	(0.036)
BAS Matrices	0.059***	0.072	0.003
	(0.018)	(0.384)	(0.017)
Emotional Symptoms	0.009	-0.028	0.007
	(0.017)	(0.069)	(0.016)
Conduct Problems	0.011	-0.030	0.007
	(0.015)	(0.067)	(0.016)
Hyperactivity	0.053**	-0.091	0.023
	(0.024)	(0.091)	(0.023)
Peer Problems	0.005	0.036	-0.009
	(0.013)	(0.058)	(0.014)
Mother's Educ. (Higher 2ndary/Tech)	-0.001	0.212*	-0.001
	(0.006)	(0.114)	(0.012)
Mother's Educ. (Bachelor's/Postgrad)	0.039	0.099	0.033
	(0.024)	(0.063)	(0.025)
Income Quintile	0.008	0.257*	0.051*
	(0.027)	(0.151)	(0.030)
Fee Paying School	0.011	-0.001	-0.001
	(0.015)	(0.015)	(0.016)
DEIS School	0.028	0.000	-0.000
	(0.020)	(0.037)	(0.019)
Mixed School	0.025*	0.190*	-0.020
	(0.015)	(0.098)	(0.014)
Religious School	-0.018	0.100	0.018
	(0.019)	(0.119)	(0.021)
Male	-0.019*	0.133**	0.014
	(0.012)	(0.065)	(0.010)
Constant	–	-0.685	–
		(0.537)	

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Blinder-Oaxaca decomposition comparing Maths achievement between children with present and absent fathers, using Wave 2 (age 13) predictors. Father absence defined as non-response in both waves. The endowments effect increases from Wave 1 (0.676 vs. 0.470), with Numerical Ability (0.359) being the strongest predictor. The coefficients effect decreases (0.348 vs. 0.426) and interaction becomes non-significant, suggesting the gap increasingly reflects differences in characteristics rather than returns. Numerical Ability shows significant coefficient (0.073***) and interaction (-0.106***) effects. Sample: 3,523 observations (3,089 father present, 434 absent). Bootstrap: 500 replications.

Table 24: Gender Differences in the Impact of Father Absence on Junior Certificate Maths Achievement (Wave 2 Predictors)

Statistic	**Boys**	**Girls**
Group 1 (Father Present)	9.835*** (0.044)	9.728*** (0.044)
Group 2 (Father Absent)	8.725*** (0.134)	8.795*** (0.112)
Difference	1.110*** (0.140)	0.934*** (0.117)
Endowments	0.644*** (0.119)	0.697*** (0.122)
Coefficients	0.481*** (0.097)	0.235*** (0.090)
Interaction	-0.016 (0.078)	0.002 (0.079)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	Boys	**Girls**	**Boys**	**Girls**	**Boys**	**Girls**
Verbal Reasoning	0.121***	0.097**	0.002	-0.001	-0.054*	0.001
	(0.043)	(0.041)	(0.019)	(0.026)	(0.032)	(0.030)
Numerical Ability	0.295***	0.373***	0.010	0.154***	-0.038	-0.143***
	(0.081)	(0.080)	(0.021)	(0.058)	(0.056)	(0.055)
BAS Matrices	0.085***	0.043**	-0.489	0.460	-0.024	0.016
	(0.033)	(0.022)	(0.629)	(0.566)	(0.031)	(0.022)
Emotional Symptoms	0.005	0.002	-0.004	-0.088	0.001	0.018
	(0.037)	(0.016)	(0.133)	(0.098)	(0.038)	(0.022)
Conduct Problems	0.024	0.004	0.062	-0.110	-0.014	0.027
	(0.027)	(0.022)	(0.110)	(0.098)	(0.027)	(0.025)
Hyperactivity	0.021	0.071***	-0.246	0.003	0.069	-0.001
	(0.045)	(0.027)	(0.158)	(0.115)	(0.046)	(0.026)
Peer Problems	0.024	-0.006	0.099	0.038	-0.021	-0.011
	(0.022)	(0.022)	(0.086)	(0.080)	(0.022)	(0.024)
Mother's Educ. (Higher 2ndary/Tech)	0.003	-0.001	0.000	0.389**	0.000	-0.008
	(0.017)	(0.008)	(0.179)	(0.162)	(0.013)	(0.023)
Mother's Educ. (Bachelor's/Postgrad)	0.026	0.052*	0.103	0.091	0.025	0.037
	(0.032)	(0.030)	(0.110)	(0.081)	(0.032)	(0.034)
Income Quintile	-0.009	0.019	0.329	0.234	0.051	0.056
	(0.032)	(0.041)	(0.215)	(0.195)	(0.035)	(0.047)
Other School Variables†	–	–	–	–	–	–
Constant	–	–	0.286	-1.167	–	–
			(0.813)	(0.767)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. The output shows a bootstrap procedure with 500 replications used to estimate standard errors for the Blinder-Oaxaca decomposition. The decomposition analyzes differences in Maths scores between children with father present versus absent, separately for boys (n=1,772; 1,572 with father present, 200 with father absent) and girls (n=1,751; 1,517 with father present, 234 with father absent). Father absence is defined as non-response to the father questionnaire in both waves. As in Wave 1, the total gap remains larger for boys (1.110) than for girls (0.934). The endowments effect increases for both genders from Wave 1 to Wave 2, but more substantially for girls (from 0.459 to 0.697). For boys, the coefficients effect decreases (from 0.597 to 0.481), while for girls it remains similar (0.235 vs. 0.274). The interaction term becomes non-significant for both genders, suggesting that as children age, the father absence gap increasingly reflects differences in endowments. Numerical ability shows a particularly strong endowment effect for both genders, but the coefficient effect is significant only for girls (0.154***), indicating that father absence uniquely affects how numerical skills translate into Maths achievement for girls. †Other school variables (DEIS School, Mixed School, Religious School) were included in the model but none showed significant effects.

J Appendix J. Supplementary Decompositions: Gender Gaps in Junior Cert English

This appendix examines how gender and family background contribute to the English achievement gap at age 15, using Blinder–Oaxaca decompositions. I first isolate the male–female differential in English scores (Part I), then compare children with present versus absent fathers (Part II). All decompositions split the total gap into endowments (differences in skills/resources), coefficients (differences in returns to those endowments), and interaction components. Predictors come from age 9 (Wave 1) and age 13 (Wave 2), allowing us to trace developmental changes. Throughout, "No Father" models omit paternal education, while "With Father" models include it—each reported in the tables below.

J.1 Part I: Decomposition Results by Gender - Waves 1 and 2 - English Junior Certificate

J.2 Part II: Decomposition Results by Father Absence - Waves 1 and 2 - English Junior Cert

Discussion

The English decompositions reveal a markedly different pattern from Maths. As Tables 25 and 26 show, girls outperform boys by about 0.31 points at age 15, a gap driven almost entirely by coefficients rather than by raw skill differences. In Wave 1, the endowments component is effectively zero (–0.01, n.s.), while coefficients account for 0.27–0.32 points and a small positive interaction (0.044, $p<.05$) further offsets boys' slight advantage in cognitive and behavioural predictors. By Wave 2, endowments actually work against girls (–0.12, $p<.01$), reflecting boys' superior Verbal Reasoning and Numerical Ability at age 13, yet girls still gain 0.43–0.44 points from coefficients, and interaction is negligible (–0.002, n.s.). Thus, unlike in Maths where skill gaps loom large by adolescence, the English gender gap owes almost everything to girls' greater productivity in translating their endowments into higher English marks.

Girls' lower Hyperactivity and Conduct Problems confer modest endowment advantages, but the lion's share arises from school context (especially CoEd schooling), which yields large positive coefficients and interaction effects in both waves. This echoes findings that co-educational environments can boost girls' literacy confidence and achievement through social emulation and reduced stereotype threat (Eccles et al., 1990; Raver, 2002).

Turning to family background (Tables 27 and 28), father presence confers a 0.68 point English advantage at both ages, which is smaller than the Maths penalty. In Wave 1, 53% of this gap is endowment-based (primarily Reading Ability and maternal education), with the remainder in coefficients; by Wave 2, endowments rise to 63% (led by Verbal Reasoning) and coefficients shrink to 0.308 points, while interaction remains non-significant. Unlike in Maths, where father absence increasingly undermines skill acquisition, the English penalty remains partially rooted in early cognitive endowments, suggesting that paternal involvement bolsters foundational literacy skills and enriches the home language environment (Yeung et al., 2002).

Gender-specific father-absence decompositions (Tables 29–30) reveal that girls suffer a larger absence penalty (0.75 points) than boys (0.63 points), and that both endowments and coefficients contribute more for girls. For girls, Conduct Problems and maternal education exert particularly strong coefficient effects, suggesting that fathers' presence may interact with maternal support and child behaviour to enhance girls' literacy outcomes.

Overall, the English results underscore subject-specific mechanisms:

- Returns to skills dominate gender gaps, pointing to girls' superior engagement, motivation, and perhaps teacher expectations in language subjects (Durlak et al., 2011).
- Early cognitive endowments drive father-absence gaps, highlighting the importance of paternal language interactions and literacy activities in middle childhood (Downey, 1995; Evans & Schamberg, 2009).
- School context remains central, with mixed-gender settings amplifying girls' English returns, suggesting that peer modelling and classroom dynamics differ by subject.

Literacy-focused family interventions, such as encouraging fathers to engage in reading and storytelling with their children, could help mitigate early skill deficits. School-based programmes that leverage mixed-gender peer support and target boys' literacy engagement (e.g. boys' reading groups, male mentor volunteers) may help close both gender and father-absence gaps in English.

Table 25: Decomposition of Gender Differences in English Achievement: Comparing Models With and Without Father's Education Variables (Wave 1)

Statistic	**No Father**	**With Father**
Group 1 (Female)	10.299*** (0.027)	10.398*** (0.029)
Group 2 (Male)	9.992*** (0.027)	10.045*** (0.036)
Difference	0.307*** (0.039)	0.353*** (0.046)
Endowments	-0.010 (0.026)	0.004 (0.028)
Coefficients	0.273*** (0.035)	0.317*** (0.035)
Interaction	0.044** (0.018)	0.031 (0.021)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	No Father	**With Father**	**No Father**	**With Father**	**No Father**	**With Father**
Reading Ability	0.008	0.011	0.012	0.009	0.001	0.001
	(0.013)	(0.015)	(0.014)	(0.013)	(0.002)	(0.002)
Maths Ability	-0.038***	-0.034***	0.033	0.030	0.013	0.012
	(0.008)	(0.009)	(0.022)	(0.020)	(0.009)	(0.009)
Emotional Symptoms	-0.001	-0.000	-0.043	-0.047	-0.007	-0.007
	(0.005)	(0.005)	(0.035)	(0.041)	(0.006)	(0.006)
Conduct Problems	0.008*	0.010**	0.013	0.058	-0.002	-0.008
	(0.004)	(0.004)	(0.035)	(0.042)	(0.005)	(0.007)
Hyperactivity	0.043***	0.043***	-0.013	-0.014	0.002	0.003
	(0.008)	(0.009)	(0.050)	(0.055)	(0.009)	(0.010)
Peer Problems	-0.000	-0.000	-0.023	-0.011	0.000	0.000
	(0.001)	(0.001)	(0.030)	(0.028)	(0.001)	(0.001)
Mother's Educ.	-0.001	0.001	-0.076	-0.043	0.000	-0.000
(Higher 2ndary/Tech)	(0.006)	(0.005)	(0.075)	(0.077)	(0.003)	(0.002)
Mother's Educ.	-0.018**	-0.011	-0.030	-0.007	0.003	0.001
(Bachelor's/Postgrad)	(0.009)	(0.007)	(0.049)	(0.049)	(0.007)	(0.005)
Father's Educ.	-	0.002	-	0.029	-	0.001
(Higher 2ndary/Tech)	-	(0.003)	-	(0.046)	-	(0.002)
Father's Educ.	-	-0.012*	-	0.022	-	-0.003
(Bachelor's/Postgrad)	-	(0.006)	-	(0.034)	-	(0.006)
Income Quintile	-0.006	-0.001	0.085	0.018	-0.002	-0.000
	(0.004)	(0.003)	(0.100)	(0.108)	(0.003)	(0.002)
Mixed School	-0.005	-0.004	0.208***	0.204***	0.035***	0.033***
	(0.008)	(0.006)	(0.063)	(0.061)	(0.011)	(0.011)
Constant	–	–	0.105	0.070	–	–
			(0.180)	(0.193)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in English achievement at age 15, using predictors measured at age 9 (Wave 1). The "No Father" model uses the full sample (4,040 observations; 2,039 females, 2,001 males) and excludes paternal education variables. The "With Father" model includes paternal education but has a smaller sample size (3,489 observations; 1,746 females, 1,743 males) due to non-response from some fathers. The positive "Difference" indicates that girls score higher than boys on average in English, in contrast to the Maths results where boys outperformed girls. Negative values in the "Endowments" section indicate characteristics where boys have an advantage (e.g., Maths ability), while positive values indicate girls' advantages (e.g., behaviour). The positive "Coefficients" component suggests that girls receive better returns to their characteristics in English. The "Interaction" term is significant in the No Father model but not in the With Father model. Mixed schools appear to have a significant influence on the gender gap in English achievement. Bootstrap procedure with 100 replications was used to estimate standard errors.

Table 26: Decomposition of Gender Differences in English Achievement: Comparing Models With and Without Father's Education Variables (Wave 2)

Statistic	**No Father**	**With Father**
Group 1 (Female)	10.299*** (0.028)	10.407*** (0.031)
Group 2 (Male)	9.992*** (0.032)	10.082*** (0.029)
Difference	0.307*** (0.044)	0.325*** (0.043)
Endowments	-0.123*** (0.031)	-0.108*** (0.030)
Coefficients	0.431*** (0.036)	0.441*** (0.038)
Interaction	-0.002 (0.022)	-0.008 (0.024)

Variable	**Endowments**		**Coefficients**		**Interactions**	
	No Father	**With Father**	**No Father**	**With Father**	**No Father**	**With Father**
Verbal Reasoning	-0.086***	-0.071***	-0.005	-0.002	0.006	0.001
	(0.015)	(0.014)	(0.007)	(0.009)	(0.007)	(0.008)
Numerical Ability	-0.087***	-0.084***	-0.003	-0.009	0.005	0.010
	(0.013)	(0.015)	(0.010)	(0.014)	(0.015)	(0.016)
BAS Matrices	-0.004	-0.004	-0.095	0.088	0.001	-0.001
	(0.003)	(0.003)	(0.212)	(0.309)	(0.002)	(0.004)
Emotional Symptoms	0.000	-0.003	0.004	0.009	0.001	0.003
	(0.006)	(0.007)	(0.035)	(0.031)	(0.009)	(0.010)
Conduct Problems	-0.000	-0.001	-0.034	-0.024	0.002	0.001
	(0.001)	(0.002)	(0.030)	(0.036)	(0.002)	(0.002)
Hyperactivity	0.055***	0.053***	0.047	0.079	-0.011	-0.018
	(0.009)	(0.010)	(0.051)	(0.050)	(0.012)	(0.012)
Peer Problems	0.004	0.005	-0.005	-0.008	0.001	0.001
	(0.003)	(0.003)	(0.028)	(0.031)	(0.003)	(0.004)
Mother's Educ.	0.006	0.005	-0.026	0.010	-0.001	0.000
(Higher 2ndary/Tech)	(0.005)	(0.005)	(0.079)	(0.081)	(0.004)	(0.005)
Mother's Educ.	-0.015**	-0.011*	0.004	0.019	-0.000	-0.002
(Bachelor's/Postgrad)	(0.007)	(0.006)	(0.052)	(0.054)	(0.006)	(0.007)
Father's Educ.	-	0.003	-	-0.039	-	-0.001
(Higher 2ndary/Tech)	-	(0.003)	-	(0.064)	-	(0.004)
Father's Educ.	-	-0.006	-	0.003	-	-0.000
(Bachelor's/Postgrad)	-	(0.005)	-	(0.047)	-	(0.007)
Income Quintile	-0.002	-0.000	0.108	0.038	-0.001	-0.000
	(0.002)	(0.003)	(0.086)	(0.100)	(0.002)	(0.001)
Other School Variables†	–	–	–	–	–	–
Constant	–	–	0.490*	0.317	–	–
			(0.281)	(0.393)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results for the gender gap in English achievement at age 15, using predictors measured at age 13 (Wave 2). The "No Father" model uses the full available sample and excludes paternal education variables. The "With Father" model includes paternal education but has a smaller sample size due to non-response from some fathers. The positive "Difference" indicates that girls score higher than boys on average in English, in contrast to the Maths results where boys outperformed girls. The negative "Endowments" component suggests that boys have certain characteristics that should advantage them, particularly cognitive abilities (Verbal Reasoning and Numerical Ability), yet girls still outperform them in English. The strong positive "Coefficients" component indicates that girls receive substantially better returns to their characteristics for English achievement. Unlike the Maths results, the "Interaction" term is not significant for English. Bootstrap procedure with 100 replications was used to estimate standard errors. †Other school variables (DEIS School, Mixed School, Religious School) were included in the model but none showed significant effects.

Table 27: Impact of Father Absence on English Achievement: Blinder-Oaxaca Decomposition Results (Wave 1)

Statistic	**Value**
Group 1 (Father Present)	10.249*** (0.021)
Group 2 (Father Absent)	9.567*** (0.072)
Difference	0.682*** (0.075)
Endowments	0.360*** (0.070)
Coefficients	0.334*** (0.066)
Interaction	-0.013 (0.049)

Variable	**Endowments**	**Coefficients**	**Interactions**
Reading Ability	0.133***	-0.007	-0.026
	(0.038)	(0.009)	(0.022)
Maths Ability	0.024	-0.071	0.028
	(0.029)	(0.071)	(0.028)
Emotional Symptoms	-0.004	-0.056	0.015
	(0.024)	(0.093)	(0.025)
Conduct Problems	0.030*	0.093	-0.021
	(0.016)	(0.065)	(0.016)
Hyperactivity	0.036	-0.093	0.019
	(0.023)	(0.113)	(0.023)
Peer Problems	-0.001	-0.001	0.000
	(0.019)	(0.063)	(0.020)
Mother's Educ. (Higher 2ndary/Tech)	0.003	0.103	0.003
	(0.007)	(0.095)	(0.007)
Mother's Educ. (Bachelor's/Postgrad)	0.067***	-0.064	-0.026
	(0.023)	(0.040)	(0.017)
Income Quintile	0.083**	-0.008	-0.003
	(0.040)	(0.130)	(0.042)
Mixed School	-0.001	0.086	0.003
	(0.005)	(0.122)	(0.005)
Gender Binary	-0.011	-0.052	-0.005
	(0.010)	(0.061)	(0.010)
Constant	–	0.404	–
		(0.246)	

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. This table presents Blinder-Oaxaca decomposition results comparing English achievement between children with present fathers and those with absent fathers, using predictors measured at age 9 (Wave 1). Father absence is defined as non-response to the father questionnaire in both waves, which may indicate either physical absence or non-participation. The positive difference (0.682***) indicates a substantial achievement advantage for children with present fathers, though smaller than the gap observed in Maths (1.020***). The decomposition shows that 53% of this gap is explained by differences in endowments, primarily Reading Ability (rather than Maths Ability which was more important for Maths achievement), mother's education level, and household income. The significant coefficients component (0.334***) suggests father presence also alters the returns to these characteristics, though none of the individual variables show significant differences in returns. Unlike Maths, the interaction component is not statistically significant for English. Bootstrap procedure with 100 replications was used to estimate standard errors for the decomposition analysis of 3,523 total observations (3,089 with father present, 434 with father absent).

Table 28: Impact of Father Absence on English Achievement: Blinder-Oaxaca Decomposition Results (Wave 2)

Statistic	**Value**
Group 1 (Father Present)	10.249*** (0.020)
Group 2 (Father Absent)	9.567*** (0.068)
Difference	0.682*** (0.074)
Endowments	0.432*** (0.059)
Coefficients	0.308*** (0.065)
Interaction	-0.058 (0.043)

Variable	**Endowments**	**Coefficients**	**Interactions**
Verbal Reasoning	0.147***	0.017	-0.032
	(0.034)	(0.015)	(0.026)
Numerical Ability	0.092**	-0.005	0.007
	(0.039)	(0.026)	(0.038)
BAS Matrices	0.025	-0.108	-0.005
	(0.018)	(0.438)	(0.019)
Emotional Symptoms	-0.025	-0.103	0.025
	(0.018)	(0.077)	(0.020)
Conduct Problems	0.016	0.073	-0.017
	(0.018)	(0.077)	(0.019)
Hyperactivity	0.050**	-0.022	0.005
	(0.024)	(0.103)	(0.025)
Peer Problems	0.004	-0.045	0.011
	(0.015)	(0.059)	(0.016)
Mother's Educ. (Higher 2ndary/Tech)	-0.001	0.011	-0.000
	(0.008)	(0.121)	(0.005)
Mother's Educ. (Bachelor's/Postgrad)	0.042*	-0.037	-0.012
	(0.022)	(0.065)	(0.021)
Income Quintile	0.049*	-0.071	-0.014
	(0.028)	(0.151)	(0.029)
Fee Paying School	0.000	-0.003	-0.003
	(0.011)	(0.012)	(0.011)
DEIS School	0.047**	0.033	-0.017
	(0.020)	(0.041)	(0.020)
Mixed School	0.002	0.029	-0.003
	(0.011)	(0.104)	(0.011)
Religious School	0.002	-0.002	-0.000
	(0.020)	(0.114)	(0.020)
Male	-0.019	-0.028	-0.003
	(0.012)	(0.055)	(0.006)
Constant	–	0.570	–
		(0.616)	

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Blinder-Oaxaca decomposition comparing English achievement between children with present and absent fathers, using Wave 2 (age 13) predictors. Father absence defined as non-response in both waves. The endowments effect increases from Wave 1 (0.432 vs. 0.360), with Verbal Reasoning (0.147***) being the strongest predictor, followed by Numerical Ability (0.092**), unlike Maths where Numerical Ability dominated. The endowments component explains a larger portion of the gap (63% vs. 53% in Wave 1). Unlike Maths, there are no significant coefficient effects for individual variables, though the overall coefficients component remains significant (0.308***). Notably, DEIS school attendance (0.047**) and Hyperactivity (0.050**) significantly contribute to the endowments effect. The gender coefficient (male) is negative but not significant, reflecting girls' advantage in English. Sample: 3,523 observations (3,089 father present, 434 absent). Bootstrap: 100 replications.

Table 29: Gender Differences in the Impact of Father Absence on English Achievement (Wave 1)

Statistic	Boys	Girls
Group 1 (Father Present)	10.074*** (0.035)	10.429*** (0.027)
Group 2 (Father Absent)	9.440*** (0.091)	9.675*** (0.105)
Difference	0.634*** (0.099)	0.754*** (0.107)
Endowments	0.342*** (0.093)	0.375*** (0.090)
Coefficients	0.280*** (0.094)	0.382*** (0.103)
Interaction	0.013 (0.074)	-0.003 (0.080)

Variable	Endowments		Coefficients		Interactions	
	Boys	Girls	Boys	Girls	Boys	Girls
Reading Ability	0.112**	0.157***	-0.000	-0.021	-0.001	-0.050
	(0.046)	(0.053)	(0.015)	(0.018)	(0.031)	(0.030)
Maths Ability	0.052*	-0.013	-0.019	-0.153	0.008	0.053
	(0.030)	(0.043)	(0.077)	(0.117)	(0.032)	(0.043)
Emotional Symptoms	0.006	-0.015	0.033	-0.150	-0.008	0.039
	(0.027)	(0.031)	(0.118)	(0.126)	(0.030)	(0.036)
Conduct Problems	-0.001	0.070**	-0.083	0.265***	0.017	-0.069**
	(0.022)	(0.028)	(0.114)	(0.095)	(0.025)	(0.029)
Hyperactivity	0.038	0.036	-0.097	-0.083	0.021	0.018
	(0.043)	(0.027)	(0.207)	(0.128)	(0.048)	(0.028)
Peer Problems	-0.009	0.010	-0.024	0.042	0.009	-0.012
	(0.031)	(0.025)	(0.088)	(0.093)	(0.033)	(0.026)
Mother's Educ. (Higher 2ndary/Tech)	0.003	-0.005	-0.091	0.275**	-0.001	0.014
	(0.021)	(0.013)	(0.163)	(0.137)	(0.012)	(0.022)
Mother's Educ. (Bachelor's/Postgrad)	0.105**	0.037	-0.182**	0.011	-0.067*	0.005
	(0.045)	(0.030)	(0.082)	(0.063)	(0.038)	(0.028)
Income Quintile	0.045	0.092	0.100	-0.003	0.028	-0.001
	(0.062)	(0.074)	(0.226)	(0.193)	(0.066)	(0.074)
Mixed School	-0.010	0.006	0.138	0.040	0.008	0.001
	(0.013)	(0.008)	(0.127)	(0.186)	(0.012)	(0.009)
Constant	–	–	0.504	0.161	–	–
			(0.350)	(0.318)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. The output shows a bootstrap procedure with 100 replications used to estimate standard errors for the Blinder-Oaxaca decomposition. The decomposition analyzes differences in English scores between children with father present versus absent, separately for boys (n=1,772; 1,572 with father present, 200 with father absent) and girls (n=1,751; 1,517 with father present, 234 with father absent). Father absence is defined as non-response to the father questionnaire in both waves. While both genders show significant advantages with father presence, the gap is larger for girls (0.754) than for boys (0.634), contrasting with Maths where boys showed a larger father absence penalty. For both genders, endowments and coefficients effects contribute significantly to the gap, but with important differences. Reading ability is a significant endowment contributor for both genders, whereas Maths ability is only significant for boys. Conduct problems show significant endowment effects for girls but not boys. For coefficients, maternal education shows opposite patterns: for boys, higher maternal education (Bachelor's/Postgrad) has a significant negative effect (-0.182**), while for girls, intermediate maternal education (Higher 2ndary/Tech) has a significant positive effect (0.275**). Conduct problems show a significant positive coefficient effect for girls (0.265***) with a corresponding negative interaction effect (-0.069**), suggesting complex relationships between behavioural factors and father absence for girls' English achievement.

Table 30: Gender Differences in the Impact of Father Absence on English Achievement (Wave 2)

Statistic	Boys	Girls
Group 1 (Father Present)	10.074*** (0.033)	10.429*** (0.033)
Group 2 (Father Absent)	9.440*** (0.099)	9.675*** (0.107)
Difference	0.634*** (0.100)	0.754*** (0.108)
Endowments	0.410*** (0.097)	0.468*** (0.094)
Coefficients	0.246*** (0.079)	0.359*** (0.093)
Interaction	-0.022 (0.071)	-0.073 (0.071)

Variable	Endowments		Coefficients		Interactions	
	Boys	Girls	Boys	Girls	Boys	Girls
Verbal Reasoning	0.149***	0.144***	0.002	0.013	-0.057*	-0.016
	(0.044)	(0.040)	(0.016)	(0.028)	(0.030)	(0.034)
Numerical Ability	0.042	0.109*	-0.017	0.025	0.062	-0.023
	(0.042)	(0.056)	(0.016)	(0.057)	(0.044)	(0.052)
BAS Matrices	0.063**	0.004	-0.852	0.405	-0.042	0.014
	(0.030)	(0.018)	(0.543)	(0.498)	(0.028)	(0.021)
Emotional Symptoms	-0.028	-0.026	-0.116	-0.123	0.033	0.025
	(0.029)	(0.030)	(0.094)	(0.137)	(0.030)	(0.031)
Conduct Problems	-0.001	0.038	0.012	0.149	-0.003	-0.036
	(0.020)	(0.027)	(0.091)	(0.105)	(0.020)	(0.028)
Hyperactivity	0.053	0.036	-0.110	0.005	0.031	-0.001
	(0.037)	(0.026)	(0.150)	(0.117)	(0.043)	(0.027)
Peer Problems	0.014	0.006	0.011	-0.050	-0.002	0.015
	(0.020)	(0.025)	(0.081)	(0.087)	(0.018)	(0.026)
Mother's Educ. (Higher 2ndary/Tech)	0.004	0.000	-0.122	0.163	-0.002	-0.003
	(0.016)	(0.012)	(0.149)	(0.220)	(0.012)	(0.016)
Mother's Educ. (Bachelor's/Postgrad)	0.045*	0.033	-0.091	0.004	-0.022	0.002
	(0.027)	(0.035)	(0.075)	(0.092)	(0.023)	(0.037)
Income Quintile	0.020	0.085*	0.032	-0.164	0.005	-0.039
	(0.030)	(0.053)	(0.189)	(0.225)	(0.032)	(0.055)
Other School Variables†	–	–	–	–	–	–
Constant	–	–	1.476**	-0.199	–	–
			(0.658)	(0.832)		

Significance levels: * p<0.1, ** p<0.05, *** p<0.01. The output shows a bootstrap procedure with 100 replications used to estimate standard errors for the Blinder-Oaxaca decomposition. The decomposition analyzes differences in English scores between children with father present versus absent, separately for boys (n=1,772; 1,572 with father present, 200 with father absent) and girls (n=1,751; 1,517 with father present, 234 with father absent). Father absence is defined as non-response to the father questionnaire in both waves. As in Wave 1, the total gap remains larger for girls (0.754) than for boys (0.634), contrasting with Maths where boys showed a larger father absence penalty. The endowments effect increases for both genders from Wave 1 to Wave 2 (boys: from 0.342 to 0.410; girls: from 0.375 to 0.468), a pattern similar to that observed in Maths, suggesting that the influence of measurable characteristics on achievement gaps strengthens with age. Verbal Reasoning is the strongest contributor to the endowments effect for both genders, unlike in Maths where Numerical Ability dominated. For boys, BAS Matrices (0.063**) also contributes significantly to the endowments effect, while for girls, Numerical Ability (0.109*) and Income Quintile (0.085*) are marginally significant. The constant term is significant and large for boys (1.476**), suggesting substantial unexplained advantages for father presence that aren't captured by measured variables. †Other school variables (DEIS School, Mixed School, Religious School) were included in the model but none showed significant effects.