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 students using national longitudinal survey data. I examine how factors measured at ages 9 and 13 predict Maths scores in the Irish college entrance exam. Using Oaxaca-Blinder decompositions, I separate the gender gap into two parts: differences in measurable skills and traits (endowments) and differences in how those skills are rewarded (coefficients). Boys score 4.4 to 5.2 points higher than girls in Maths on average. When using age 9 predictors, most of the gap comes from differences in returns to skills. By age 13, actual differences in cognitive skills explain most of the gap. Early differences in treatment turn into real skill gaps by the teenage years. Family structure directly affects achievement. Students with absent fathers score lower on average, exactly 13.6 points for boys and 15.2 points for girls. For boys, this comes from both weaker skills and lower returns to family resources. For girls, lower Maths scores link more strongly to mother's education and household income. 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 improvement in educational attainment across countries, persistent disparities in Maths performance remain a key 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 in high-paying fields), 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). This gap is attributable in part to persistent gender differences in Maths, which emerge early and vary significantly across different cultural and institutional contexts (Fryer & Levitt, 2010; Guiso et al., 2008; Nollenberger et al., 2016). 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). In addition, evidence from Whitcomb et al. (2020) suggests that women experience gaps in self-efficacy despite similar or higher academic performance, potentially further discouraging them from persisting in STEM careers. This under-representation 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 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.

Such 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 versus differences in the returns to those skills?

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 frame these questions, I draw on models of skill formation (Cunha & Heckman, 2007), which emphasise that early investments in cognitive and socioemotional skills have dynamic effects over time. Early differences in how children are treated can accumulate into real differences in skills as they grow older. Guided by this framework, I use Oaxaca–Blinder decomposition techniques to separate the gender gap into parts due to differences in observable traits (endowments) and differences in how those traits are rewarded (coefficients). This approach shows not just which traits matter, but also when and whether they matter differently for boys and girls.

This theoretical framework is particularly relevant when applied to the Irish educational context, where I situate my empirical analysis. The Irish educational system shares many features with other OECD countries, including a strong focus on standardised examinations and relatively small gender gaps in early academic achievement. However, Ireland shows a persistent underrepresentation of women in STEM fields, suggesting that even modest school-age differences in Maths can have amplified effects over time. Compared to countries like the United States or Germany, Ireland's gender gaps in Maths during adolescence are relatively modest (Hyde & Mertz, 2009; Lindberg et al., 2010), but the labour market implications remain substantial.

To investigate these dynamics in the Irish context, I draw on data from the Growing Up in Ireland study, a nationally representative longitudinal dataset following children from age 9 into early adulthood. Using this rich dataset, 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, which allows me to examine whether gender gaps and father absence penalties are mainly due to differences in observed characteristics 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 is Leaving Certificate Maths score, harmonised across cohorts to ensure comparability. Cognitive skills are measured using standardised logit scores from verbal, numerical, and reasoning assessments collected at ages 9 and 13. Socioemotional traits are assessed 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 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).

Given the data structure and variables considered, 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).

This study builds on economic models of skill development, especially Cunha and Heckman (2007)'s idea that early skills lay the groundwork for later ones. Their framework shows that investments at different ages lead to different returns, and that strong early skills make later learning easier. The timing I see in the formation of gender gaps fits this pattern: in childhood, the gap comes from how boys' and girls' skills are rewarded differently, but by adolescence, it shows up as real differences in their skill levels. Early educational experiences create advantages or disadvantages that build up over time. This reflects dynamic complementarity (i.e., early gains boost later ones), so small differences early on can quickly grow, depending on how boys' and girls' skills are shaped and assessed.

This study makes three main contributions to the literature on educational inequality. First, I provide new evidence on when gender gaps in Maths take shape and change. The results show a clear shift between ages 9 and 13: what starts as a gap in how boys' and girls' skills are rewarded becomes a gap in actual skill levels. While earlier research has shown that these gaps exist, I pinpoint when this transition happens and how it unfolds. Second, I look at gender and family structure together, showing how these two sources of inequality interact and build on each other. This approach gives a fuller picture than looking at either one on its own, especially when it comes to understanding which students are most at risk of falling behind. Third, by comparing patterns at ages 9 and 13, I show that early adolescence is a key period when gender-based skill gaps start to solidify. By age 13, numeracy becomes the main driver of the gap. Taken together, these findings help explain not just that educational inequalities exist, but when they begin to take hold and through which pathways they develop during key stages in childhood.

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). To complement the mean-based Oaxaca-Blinder decompositions, I also provide DiNardo-Fortin-Lemieux decomposition analysis in Appendix K, which examines how gender gaps in Maths achievement vary across the entire distribution of scores rather than just at the mean. In this distributional analysis we see that the gender gap is dramatically concentrated at the median (25 points), with smaller gaps at lower and upper quantiles. Observable characteristics explain varying proportions of the gap across the distribution, with age 13 predictors generally having greater explanatory power than age 9 predictors, particularly at the median where up to 40% of the gap can be attributed to differences in endowments.

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 (Husain & Millimet, 2009), 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.

The remainder of this paper is structured as follows: Section II describes the Growing Up in Ireland longitudinal study, including data collection procedures, cognitive and socioemotional assessment tools, and family background measures used in this research. Section III outlines the empirical strategy, focusing on the Oaxaca-Blinder decomposition approach used to analyse gender gaps and father absence effects on educational outcomes. Section IV presents the main findings on gender differences in Maths achievement, showing how the composition of these gaps evolves between ages 9 and 13. This section also examines how father absence differentially affects boys' and girls' academic performance through both endowment and coefficient effects. Section V concludes with a discussion of the theoretical and policy implications of these findings, and discusses how interventions could better target early adolescence. Supplementary analyses examining Junior Certificate outcomes, English achievement, and distributional patterns are provided in the appendices.

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. While many studies have documented that gender gaps exist, fewer have traced how these gaps change across stages of childhood and adolescence. My study helps to fill this gap by showing when and how differences in skills and treatment emerge.

Across countries, boys and girls follow different patterns in school. Boys tend to show more behavioural problems and lower levels of school engagement, yet they often outperform girls in Maths assessments. These differences matter for later decisions around entering STEM fields. Maths achievement plays a particularly critical role because it is often a gateway to STEM careers, where wage premiums are higher and gender disparities persist (Card, 1999; Zajac et al., 2025). Family disadvantage seems to amplify these gaps. Boys from disadvantaged backgrounds face larger penalties, both in terms of behaviour (Bertrand & Pan, 2013) and long-term educational outcomes (Autor et al., 2019). At the same time, other work shows that father absence has stronger long-run effects on girls' education, often due to reduced parental inputs and monitoring (Brenøe & Lundberg, 2018). Cross-national research also finds that the size—and even the direction—of gender gaps in Maths varies significantly depending on social and educational contexts (Hyde & Mertz, 2009; Lindberg et al., 2010).

Work on cognitive and socioemotional development helps explain how these early differences emerge. Skills like numeracy and verbal reasoning are strong predictors of later academic success, even after accounting for behavioural traits (Duncan et al., 2007). Characteristics such as self-regulation and perseverance also matter, in some cases more than IQ (Duckworth & Seligman, 2005). However, there is still relatively limited research on how early traits relate to subject-specific outcomes like Maths, or how their importance shifts as children grow older.

The economics of skill formation provides a useful framework for understanding how these gaps evolve. Cunha and Heckman (2007) highlight two core ideas: self-productivity, where early skills reinforce later ones, and dynamic complementarity, where early gains increase the returns to later investments. In my analysis, I break down the gender gap into differences in skills (endowments) and differences in how those skills are rewarded (coefficients). The results align with this framework. At age 9, the gap is mostly driven by how boys' and girls' skills are treated differently. By age 13, the gap reflects actual differences in skill levels. This shift suggests that early differences in treatment accumulate into real differences in achievement over time.

The fact that coefficient effects dominate at age 9 fits with the idea of statistical discrimination. If teachers or parents assume boys are better at Maths, they may give them more attention or encouragement—even when boys and girls have similar abilities (Carlana, 2019; Lavy & Sand, 2018). Over time, these differences in treatment can shape students' learning paths. By age 13, what began as a difference in how skills were evaluated becomes a difference in actual performance.

While family environments shape early skills, school contexts further reinforce or narrow early differences as children age. Socioeconomic status remains one of the strongest predictors of academic achievement. It influences both cognitive and socioemotional development through access to resources, parenting practices, and exposure to stress (Bradley & Corwyn, 2002; Sirin, 2005). These effects tend to build over time—children from disadvantaged backgrounds often fall further behind as they age (Caro et al., 2009). Family structure plays an important role as well. Maternal education, for instance, tends to have stronger effects in single-parent households (Augustine, 2014).

Evidence also shows that father absence is associated with lower educational attainment and more behavioural issues, even after accounting for background characteristics (McLanahan et al., 2013). These risks appear to be larger for boys, who may be more affected by household instability (Fomby & Cherlin, 2007; Lee & McLanahan, 2015). Becker's household production model offers a useful way to think about this. In this model, families are both producers and investors in children's skills. When a father is absent, this can impact Maths achievement through several channels: reduced income, less time spent on schoolwork, and less efficient use of resources. My findings show that father absence affects boys and girls differently, suggesting that fathers may contribute in gender-specific ways to skill development.

School environments matter as well. Lavy and Sand (2018) document that teacher gender biases influence both student performance and later subject choices. Carlana (2019) finds that teachers' implicit stereotypes widen gender gaps in Maths and lower girls' confidence. Research also shows that paternal involvement is linked to better cognitive and behavioural outcomes, although the time fathers spend with their children often varies depending on the child's gender (Baker & Milligan, 2016; Sarkadi et al., 2008).

Taken together, these studies show that gender differences in achievement emerge from a combination of early skill gaps, family dynamics, and school factors. These influences change over time. My analysis builds on this work by unpacking how the gender gap in Maths develops across different ages. I show that numeracy becomes a more important driver of the gap as students get older, and that the role of father absence and school context also shifts by gender.

These early gaps carry long-term consequences. Lower Maths scores reduce the likelihood of entering STEM tracks, which limits future educational and labour market opportunities (Card, 1999). My distributional analysis in Appendix K shows that not all students are affected equally: those facing both gender and family structure disadvantages often experience the steepest barriers. Weaker Maths skills make it harder to access higher-return education pathways, which constrains upward mobility later in life.

2.1 The Growing Up in Ireland Longitudinal Study

This section describes the Growing Up in Ireland (GUI) study design, sample structure, and key measures used in the analysis. I outline the data collection timeline, cognitive and socioemotional assessments, and background variables such as parental education, income, and school characteristics. These details provide important context for interpreting the results on gender gaps and family influences in educational achievement.

The Growing Up in Ireland project is 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. Cognitive skills were measured using standardised logit scores, which adjust for item difficulty and allow for comparison over time. In Wave 1, children completed group tests at school: the Vocabulary section of the Drumcondra Reading Test and Part 1 of the Drumcondra Maths Test, using Level 2, 3, or 4 depending on school grade. In Wave 2, cognitive tests were administered at home and included the Drumcondra Verbal and Numerical Reasoning tests and the British Ability Scales (BAS) Matrices test, measuring non-verbal reasoning. These assessments offer repeated measures of cognitive ability across childhood and adolescence.

The GUI design offers several advantages. It provides repeated measures of cognitive and socioemotional skills, detailed information on parental education, household income, school environment, and family structure, and allows for analysis of peer effects through its school-based sampling. High retention rates across waves also make longitudinal analysis more reliable.

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

[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.

study.

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

Below, I describe the sample structure and key measurement choices in more detail.

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 anonymised 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 bonus point reporting across cohorts, two variables were constructed: a raw score and an adjusted score. Bonus points were subtracted where incorrectly reported, and scores were capped at 100 to ensure comparability across years. The adjusted score is used throughout the main analysis.[3]

A dummy variable identifies which grading system applied to each participant. Before 2017, the 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.

Prior academic achievement was measured using Junior Certificate Maths and English grades, mapped to a 12-point scale similar to CAO points. However, due to concerns about variation and self-reporting reliability, Junior Certificate results are used only in supplementary analyses.

Socioemotional traits were assessed through the Strengths and Difficulties Questionnaire (SDQ), completed by the primary caregiver at both Waves 1 and 2, and by teachers at Wave 1.

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

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

The SDQ includes five subscales: Emotional Symptoms, Conduct Problems, Hyperactivity/Inattention, Peer Problems, and Prosocial Behaviour. This study uses only the four difficulties subscales.

Parental education was recorded based on the highest completed qualification. Education was grouped into 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 one for Degree or Postgraduate education. No imputation was performed when father's education was missing.

Household income was equivalised based on composition, using weights of 1 for the first adult, 0.66 for additional adults, and 0.33 for children under 14. Disposable income was calculated after taxes and social insurance contributions. Both income quintiles and deciles are available in the dataset.

School-level variables such as DEIS status, fee-paying status, and religious ethos were collected only at Wave 2. In 2007–2008, DEIS schools were still a relatively new programme, and fee-paying schools represented a small proportion of the system. School type (co-educational or single-sex) was available at both waves. These school-level characteristics become more important once students transition to secondary education.

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 (Group G: Girls, defined as dummy=0; Group B: Boys, defined as dummy=1) into explained components (differences in observable characteristics) and unexplained components (differences in returns to those characteristics). The decomposition of the mean difference ($\bar{Y}_G - \bar{Y}_B$), using girls' coefficients as the reference for the endowment effect and boys' characteristics as the reference for the coefficient effect, takes the following form:

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

In Equation 3.1, $\bar{Y}_G$ and $\bar{Y}_B$ represent the mean Leaving Certificate Maths scores for girls (G) and boys (B) respectively; $\bar{\mathbf{X}}_G$ and $\bar{\mathbf{X}}_B$ are vectors of the mean values of predictor variables for each group; and β_G and β_B are the vectors of estimated coefficients derived from separate linear regressions for girls and boys. The **endowments** component therefore quantifies the extent to which the gap arises from inter-group differences in mean characteristics ($\bar{\mathbf{X}}_G - \bar{\mathbf{X}}_B$), valued at the girls' rates of return (β_G). The **coefficients** component reflects how boys' mean characteristics ($\bar{\mathbf{X}}_B$) would be valued differently if their returns changed from their own (β_B) to those of girls (β_G). The **interaction** term accounts for the portion of the gap attributable to the simultaneous occurrence of differences in both endowments and coefficients.

Several important considerations pertain to the interpretation of B-O decomposition results. Firstly, the "coefficients" (or "unexplained") component, while often a focus in studies of inequality, is a residual term. It captures not only potential differential treatment or returns but also the effects of any unobserved variables correlated with group membership and the outcome, differences in the quality of measured endowments (e.g., years of schooling versus quality of schooling), and potential model misspecification (Fortin et al., 2011; Jann, 2008). Therefore, it should not be interpreted solely as a direct measure of "disadvantage" in how characteristics translate to outcomes. Secondly, the precise magnitudes of the decomposed components can be sensitive to the choice of the reference group's coefficient vector (the "index number problem"). The formulation in Equation 3.1 uses girls' coefficients (β_G) as the reference for valuing the difference in endowments, and boys' characteristics ($\bar{\mathbf{X}}_B$) as the reference for valuing the difference in coefficients; other specifications exist, though the fundamental insights often remain consistent (Yun, 2004). Finally, while the threefold decomposition explicitly identifies the interaction term, its interpretation can be complex, representing compounding or offsetting effects of endowment and coefficient differences (Jones & Kelley, 1984). For these reasons, while I present the full threefold decomposition, we should be cautious when interpreting the coefficients component.

To examine how the composition of the gender gap changes over development, I conduct separate decompositions using predictors measured at two different ages — age 9 (Wave 1) and age 13 (Wave 2) — while consistently examining the same outcome: Leaving Certificate Maths scores at age 17/18. This approach allows me to determine whether the relative importance of endowments versus coefficients changes as children progress from middle childhood to early adolescence. If coefficient effects dominate using age 9 predictors but endowment effects become more important using age 13 predictors, this would suggest that early differential treatment eventually manifests as measurable skill differences by adolescence.

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.

By comparing results across waves, between genders, and by father presence, this analytical approach allows me to address all four research questions: (1) the extent to which gender differences reflect endowments versus coefficients, (2) how this composition changes between ages 9 and 13, (3) the role of family and school factors, and (4) differential effects of father absence by gender.

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. Detailed tables containing all the variables used in the decomposition can be found in Appendix E, Tables 12 for Wave 1 and 13 for Wave 2.

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

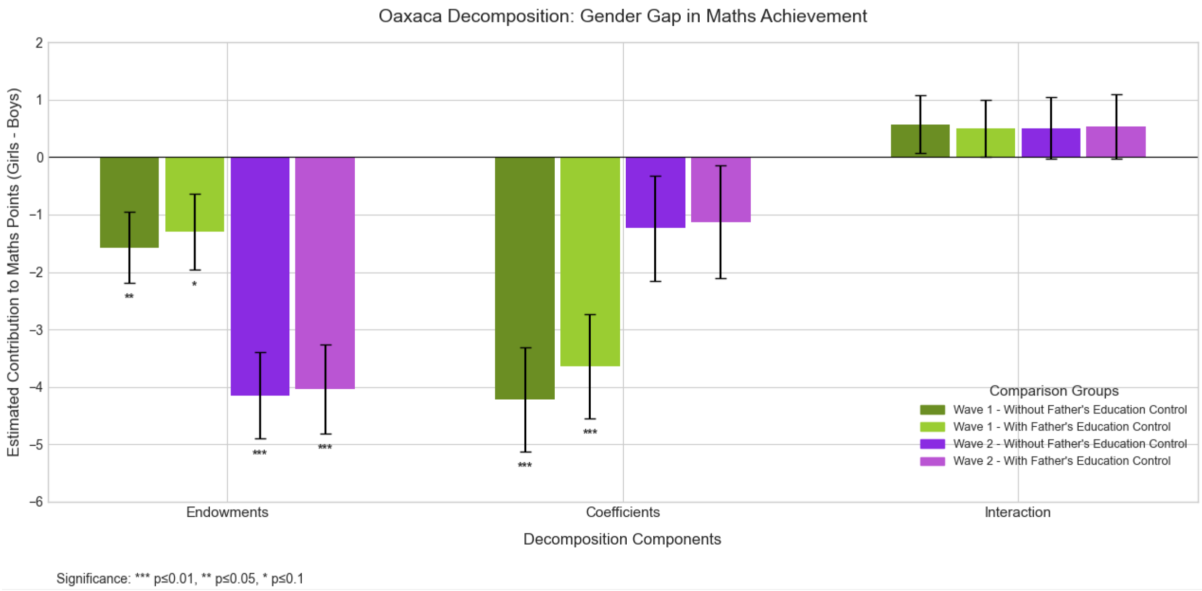

Figure 1: Oaxaca-Blinder Decomposition of Gender Differences in Leaving Certificate Maths Scores Using Predictors from Age 9 (Wave 1) and Age 13 (Wave 2). The figure shows the contribution of endowments (differences in characteristics), coefficients (differences in returns to characteristics), and their 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 500 replications are represented by error bars. Significance: $***p \leq 0.01, **p \leq 0.05, *p \leq 0.1$.

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 throughout childhood and early adolescence. Approximately 80% of these cases involve households without a resident father, while about 20% involve fathers who were physically present but not actively engaged in the study. This measure thus captures a continuum of paternal disengagement, from physical absence to limited involvement. It reflects both structural absence and psychological disengagement, which may have distinct effects on children's development.

Supporting this definition, Wave 3 data show that among students classified as father-absent in Waves 1 and 2, 41% lived with no partner in the household, 11% had a partner who did not complete the Secondary Caregiver Questionnaire, and only 5% lived with an engaged father figure. In contrast, 66% of students with father presence continued to live with an engaged father figure at Wave 3.[4]

Father absence is not randomly distributed. Students classified as father-absent come from households with lower parental education, reduced income, weaker cognitive test performance, and more socioemotional difficulties. These students are also significantly less likely to attend fee-paying or religious schools. These observed patterns validate the importance of decomposing the gap: we are not simply asking whether there is a difference in academic achievement, but why such a difference exists. The observed group differences, particularly in cognitive scores (Drumcondra and BAS), SDQ subscales, and SES, provide strong explanatory power for the achievement gap estimated in the Oaxaca-Blinder decomposition. Summary statistics can be found in Appendix A, Table 3.

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. Detailed tables containing all the variables used in the decomposition can be found in Appendix F, Tables 14 for Wave 1 and 15 for Wave 2.

3.4 Discussion

Figures 1 and 2 show the main findings from the Oaxaca–Blinder decompositions. Figure 1 indicates that boys consistently score higher than girls in Maths by about 4.5–5.2 points on the Leaving Certificate (representing a negative Girls-Boys difference). However, the underlying reasons for this gap evolve. When using predictors from age 9 (Wave 1), the majority of the gap is attributed to differences in how boys' and girls' skills are rewarded (coefficients effect: –4.215 points in the "No Father" model, p<0.01; see Table 12). While boys' higher average Maths ability at age 9 explains a significant portion of the endowment difference (contributing –1.886 points, p<0.01, to boys' advantage in the "No Father" model), this is partly counterbalanced by girls' advantages in certain noncognitive endowments, such as lower reported Hyperactivity (contributing +0.784 points, p<0.01) and fewer Conduct Problems (contributing +0.262 points, p<0.05), both effectively reducing the raw gap. The substantial negative constant term within the overall coefficients effect in Wave 1 (–8.076 points, p<0.1, in the "No Father" model) further points to unobserved factors or baseline differences in returns favouring boys at this early stage.

By age 13 (Wave 2), a notable shift occurs, and the gap is then primarily explained by differences in observed endowments (endowments effect: –4.150 points in the "No Father"

[4] An additional 44% of father-absent cases and 17% of father-present cases had missing Wave 3 partner data. Attrition analysis shows that students with absent fathers were significantly more likely to drop out before Wave 4: only 36% had valid Leaving Certificate Maths scores, compared to 64% among those with present fathers ($\chi^2 = 320.52, p < 0.001$). This differential attrition suggests that the effects of father absence reported in this study are likely conservative.

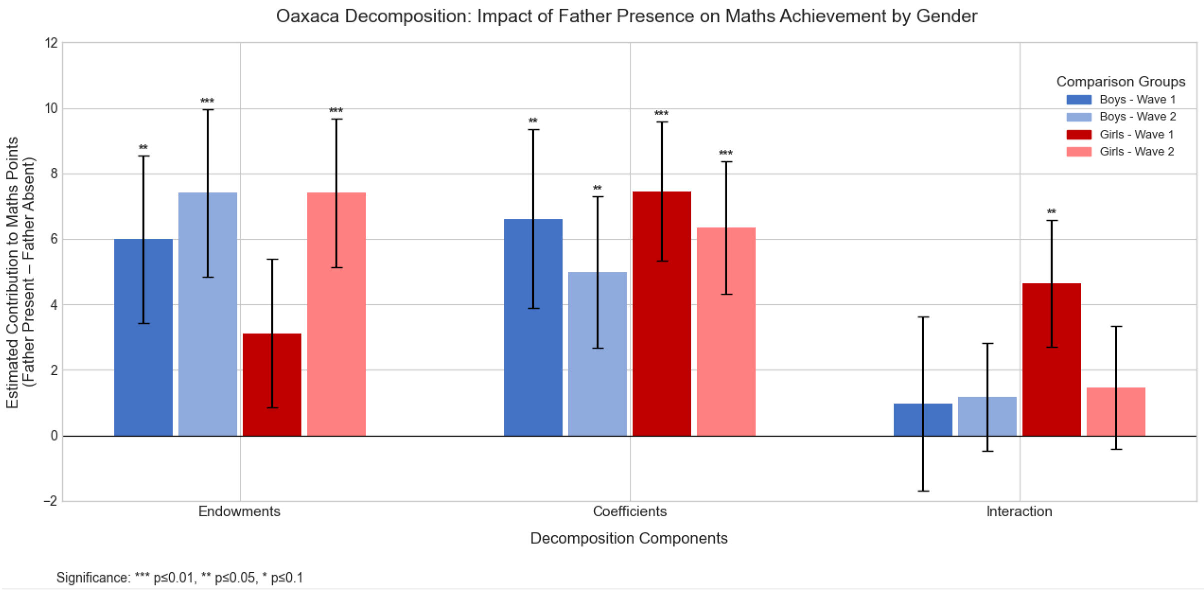

Figure 2: Oaxaca-Blinder Decomposition of the Impact of Father Absence on Leaving Certificate Maths Scores by Gender and Wave. The figure shows the contribution of endowments (differences in characteristics), coefficients (differences in returns to characteristics), and their interaction to the overall 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 (Wave 1/age 9 and Wave 2/age 13). For girls, the coefficients effect is particularly strong in Wave 1 (age 9), while in Wave 2 (age 13), 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 500 replications are represented by error bars. Significance: $***p \leq 0.01, **p \leq 0.05, *p \leq 0.1$.

model, p<0.01; see Table 13). As detailed in Appendix E, boys' higher average Numerical Ability at age 13 emerges as the overwhelmingly strongest contributor to this endowment gap (–3.658 points, p<0.01, in the "No Father" model), with their advantage in Verbal Reasoning also playing an important role (contributing –1.034 points, p<0.01). Although the overall coefficients component is smaller (–1.236 points) and not statistically significant at Wave 2, it is noteworthy that boys appear to gain substantially higher returns from BAS Matrices reasoning skills at this stage (contributing –9.436 points, p<0.1, to the coefficients part in the "No Father" model).

Figure 2 details the substantial Maths achievement advantage associated with father presence, amounting to an average of 13.564 points for boys and 15.225 points for girls on the Leaving Certificate. For boys, this advantage stems from both more favourable endowments and higher returns to those endowments across both assessment waves. At age 9 (Wave 1 predictors,

Table 14), father-present boys' higher average Maths ability contributes +2.807 points ($p<0.05$) to their endowment advantage. Their higher achievement is also explained by differential returns, notably higher returns to household income (contributing +6.929 points, $p<0.1$) and a large positive constant term in the coefficients component (+23.384 points, $p<0.05$), indicating significant baseline advantages in how their characteristics are rewarded. By age 13 (Wave 2 predictors, Table 15), important endowment advantages for father-present boys include higher Numerical Ability (+2.020 points), Verbal Reasoning (+1.410 points), and lower reported Hyperactivity (+1.504 points). At this later stage, they also particularly benefit from higher returns if their mother has completed higher secondary or technical education (contributing +8.428 points, $p<0.01$, via the coefficient effect).

For girls, the structure of the father presence advantage also shows developmental shifts. At Wave 1 (Table 14), the 15.225-point advantage for father-present girls is largely driven by differences in returns (coefficients effect: +7.456 points, $p<0.01$) and a significant interaction effect (+4.647 points, $p<0.05$). Specifically, father-present girls appear to benefit from higher returns if their mother completed higher secondary education (contributing +5.997 points, $p<0.1$, to the coefficient effect), and the significant positive interaction for income quintile (+3.180 points, $p<0.1$) suggests an amplified benefit from father presence in higher-income households. By Wave 2 (Table 15), while the overall advantage remains, it is explained by a mix of endowments and coefficients. Father-present girls' higher average Numerical Ability is a key endowment factor (contributing +2.940 points, $p<0.05$). The coefficients component continues to favour father-present girls, partly through the aforementioned higher returns to maternal education (Higher Secondary/Technical, contributing +8.428 points, $p<0.01$), although intriguingly, they exhibit significantly lower returns to BAS Matrices skills (a contribution of –7.021 points to the coefficient difference) compared to their father-absent counterparts at this stage.

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 educational system or wider social environment, 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.

The finding that numerical skills become increasingly important by early adolescence aligns closely with research from developmental psychology and neuroscience, which emphasize that early adolescence is a critical period for numerical cognition development (Dehaene, 2011). Neuroscience studies suggest that this period is marked by rapid maturation of brain regions involved in numerical processing and executive function, making it particularly sensitive to cognitive skill-building (Ansari, 2008). Sociologically, gendered expectations and stereotype threats around Maths can shape how effectively boys and girls convert their abilities into academic outcomes (Spencer et al., 1999). Boys might experience fewer psychological barriers and higher perceived self-efficacy in Maths, potentially explaining their greater productivity in converting numerical skills into achievement (Bandura et al., 1996). Additionally, father absence could introduce stress and instability, negatively affecting brain development associated with mathematical reasoning (Lupien et al., 2009; Shonkoff et al., 2012). Thus, these interdisciplinary perspectives offer robust explanations for the timing and nature of gender gaps in Maths observed in this study.

While the Oaxaca-Blinder decompositions provide useful information about where the gaps come from, they do not prove causality, and the 'coefficients' component, in particular, includes unobserved heterogeneity beyond differential treatment. 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 longitudinal data from the Growing Up in Ireland study, I show that early cognitive skills, socioemotional traits, family background, and school factors jointly shape the emergence and growth of 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 matter more, but by early adolescence, real skill differences 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. Several overlapping mechanisms likely explain how small early differences in treatment develop into real skill gaps by adolescence.

First, teacher expectations and implicit biases may affect how boys' and girls' skills are recognised and supported early in schooling. Teachers may, often without realising it, see boys as stronger in Maths, which can lead to differences in feedback, encouragement, and the kinds of challenges offered (Carlana, 2019; Lavy & Sand, 2018). Even small early differences in how skills are treated can add up over time, leading to real gaps in achievement.

Second, peer dynamics and stereotype threat can reinforce these early differences. As students move into adolescence, comparisons with classmates become more important. Girls may start to internalise stereotypes that boys are naturally better at Maths. Research shows that stereotype threat can lower girls' confidence and reduce their engagement with Maths at critical stages (Cimpian et al., 2016; Spencer et al., 1999).

Third, self-efficacy plays an important role. Even when boys and girls perform similarly, girls often report lower confidence in their Maths ability (Whitcomb et al., 2020). Over time, lower self-efficacy can affect subject choices, persistence, and effort, widening gaps in both achievement and later educational pathways.

These mechanisms are not separate. Early differences in treatment may shape peer environments and self-beliefs, starting a cumulative process where small gaps in how skills are valued or reinforced grow into real differences in measured ability by early adolescence.

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).

The gender and family structure gaps in Maths achievement discussed in this paper have important implications for wider economic inequality. These early differences in how students are treated and how their skills develop help shape who ends up in higher-paying jobs later on. The gender gap in Maths, which starts with differences in treatment and becomes a real skill gap by age 13, helps explain why women remain underrepresented in STEM fields where wage returns are high. Card and Payne (2021) estimate that closing the gender gap in Maths could reduce the gender wage gap by 8 to 10 percentage points by increasing women's participation in these areas.

The penalties linked to father absence add to this problem. They mostly affect students from disadvantaged backgrounds, creating a double disadvantage that can limit social mobility. Chetty et al. (2020) show that Maths achievement is a strong predictor of both college entry and adult income, with a one standard deviation increase in Maths scores linked to a 12% increase in earnings. The distributional patterns I report in the appendices show that these effects are not evenly spread: students in the middle of the Maths performance distribution seem to face the steepest barriers to moving into higher-return educational and career paths.

At the national level, these gaps represent a loss in potential. Hsieh et al. (2019) estimate that better use of talent (especially through removing barriers for women in STEM) accounted for between 20% and 40% of U.S. economic growth from 1960 to 2010. Reducing the early Maths gaps identified in this paper could therefore have large long-term payoffs, not only for individual students but for the economy as a whole.

There are several limitations that should be kept in mind when interpreting these results. While the Oaxaca-Blinder decomposition is useful for separating differences in skill levels from differences in how those skills are rewarded, it also has some important drawbacks. First, it focuses on average differences, which means it can miss patterns that happen at different points in the achievement distribution. To address this, I include a DiNardo-Fortin-Lemieux analysis in Appendix K. The results from the quantile distribution show that gender gaps and the effects of father absence vary across the distribution, with the biggest gaps appearing around the middle.

Second, decomposition methods assume that the relationship between predictors and outcomes is both linear and additive, which means they may miss more complex interactions between skills, behaviours, and environments.

Third, the results should be interpreted as descriptive associations rather than causal effects. Students who differ by gender or experience father absence may also differ on unobserved characteristics (e.g., early parental investment, academic self-concept, or exposure to stereotype threats) that are not fully captured in the models. As such, selection bias remains a potential concern in both the gender and family structure analyses.

Fourth, the way father absence is measured (through non-response to the father questionnaire) is not a perfect indicator of disengagement. As shown in Appendix D, about 80% of these cases involve households without a resident father, while the other 20% include fathers who are physically present but not actively involved. This measure captures a range of family situations, ranging from structural absence to psychological disengagement. Although Wave 3 data validate this classification to some extent, heterogeneity within this group cannot be fully disentangled.

Fifth, attrition is not random. Students classified as father-absent were significantly more likely to drop out of the study before Wave 4. Only 36% of these students provided valid Leaving Certificate Maths scores, compared to 64% of those with present fathers. This differential attrition likely results in conservative estimates of the effects of father absence, as the most disadvantaged students are underrepresented in the analysis. While these limitations mean the results should not be interpreted as causal, the fact that similar patterns appear across different outcomes, models, and methods gives more confidence in the overall trends. Future research could use inverse probability weighting or matching methods to better address selective attrition.

Overall, the results point to the need for early action. Since initial gender gaps in Maths come from differences in how boys' and girls' skills are rewarded (well before large skill differences appear) interventions should focus both on building strong cognitive foundations and making sure those skills are recognised and supported equally. Teacher expectations and assessment practices matter. Training teachers to notice and reduce gender bias, along with small changes (e.g., anonymised grading or more structured assessments) could help reduce the gaps already seen by age 9. These are low-cost measures that can have long-lasting effects if put in place early.

As children move into early adolescence, the gap becomes more about actual skill levels. By age 13, differences in numerical ability are the main reason why boys and girls perform differently in Maths. This means that middle childhood is a key time for support. Enrichment programs that encourage girls to take part in Maths, along with growth mindset interventions, can help close this gap. These approaches work best when they focus on confidence-building and give students the tools to stay engaged as the subject becomes more demanding.

Family support is very important. Father absence is linked to lower Maths performance, but it affects boys and girls in different ways. Boys tend to show larger drops in skill development, while girls are more affected by the loss of support and guidance at home. This points to the need for different strategies. Father-son activities focused on Maths may help boys, while better educational support for mothers may be more helpful for girls. Schools can also step in by giving extra resources to single-parent households and building stronger links between home and school.

Not all students are affected in the same way. In Appendix K I show that gender gaps are widest around the middle of the achievement distribution, so general classroom-level support aimed at average-performing students could lead to the biggest improvements. Still, students facing both gender and family disadvantages often fall behind across the full distribution. These students need broader support to catch up and stay on track.

The timing of support also matters. Intervening early, when the gap is still about how children are treated, is likely to be more effective than trying to fix skill gaps later on. A small investment in fairer treatment at age 9 could prevent the need for much bigger efforts at age 13. Helping all students receive fair recognition and support from an early age reduces the risk that minor initial differences grow into lasting educational and economic inequalities.

Future research could explore more precise measures of parental engagement, such as time-use data or direct observations of father–child interactions, to better distinguish between physical absence and psychological disengagement. Studies using administrative records could also help address selection and attrition biases more rigorously. In addition, cross-national comparisons would allow for a better understanding of how institutional settings and cultural norms shape the development of gender and family structure gaps in educational achievement.

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Appendices

This section provides additional material supporting the main analysis. Appendix A presents summary statistics for key variables. Appendix B shows OLS regression results predicting Leaving Certificate Maths scores using early cognitive, socioemotional, and socioeconomic factors, with separate models for age 9 and age 13 predictors. Appendix C reports OLS results for Junior Certificate Maths, focusing on the role of early skills, parental background, and gender differences.

Appendix D tracks changes in family structure across survey waves, including the identification of father absence. Appendix E reports Oaxaca-Blinder decompositions of gender gaps in Leaving Certificate Maths. Appendix F presents decompositions of father absence effects on the same outcome.

Appendices G and H repeat these analyses for English scores: Appendix G covers gender gaps, while Appendix H focuses on the effects of father absence. Appendix I contains supplementary decompositions for Junior Certificate Maths, disaggregated by gender and family structure. Appendix J presents similar breakdowns for Junior Certificate English.

Appendix K provides distributional decompositions of gender gaps in Leaving Certificate Maths, showing how these gaps vary across the performance distribution.

A Appendix A. Summary Statistics

Table 2 presents descriptive statistics for the key variables used in the analysis, based on the Growing Up in Ireland Child Cohort ('98 Cohort).

Leaving Certificate (LC) Maths Points (Adjusted) represent self-reported scores, harmonized across grading systems and capped at 100 to remove bonus-related inflation. Cognitive skills are measured using standardized logit scores, while socioemotional development is captured via SDQ subscales ranging from 0 to 10, with higher scores indicating greater difficulties. Parental education is categorized using thresholds for upper secondary (Leaving Certificate or equivalent) and third-level qualifications.

The analytical sample includes 4,333 participants with complete data on Leaving Cert Maths outcomes, cognitive assessments, socioemotional indicators, and demographic controls. While 5,190 cohort members participated in Wave 4, item-level missingness (rather than attrition) is the main reason for reduced sample size.

To better understand group differences, Table 3 provides disaggregated summary statistics by father presence status.

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 (Raw)	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)					
Mother's Education: Upper Secondary	4,333	0.56	0.50	0.00	1.00
Mother's Education: Third Level	4,333	0.32	0.47	0.00	1.00
Father's Education: Upper Secondary	3,808	0.46	0.50	0.00	1.00
Father's 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)					
Mother's Education: Upper Secondary	4,253	0.56	0.50	0.00	1.00
Mother's Education: Third Level	4,253	0.36	0.48	0.00	1.00
Father's Education: Upper Secondary	3,435	0.49	0.50	0.00	1.00
Father's 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

Table 3: Summary Statistics by Father Presence Status (GUI Cohort '98)

Variable	Father Present	Father Absent	Difference
Panel A: Leaving Certificate Performance (Wave 4)			
Maths LC Points (Raw)	63.72	44.66	19.06***
Maths LC Points (Harmonized)	58.34	42.49	15.85***
Panel B: Cognitive Skills			
Wave 1 (Age 9)			
Reading Ability (logit)	0.27	-0.08	0.35***
Maths Ability (logit)	-0.54	-0.91	0.37***
Wave 2 (Age 13)			
Verbal Reasoning (logit)	0.06	-0.28	0.34***
Numerical Ability (logit)	0.06	-0.33	0.39***
BAS Matrix Reasoning (score)	117.8	112.4	5.38***
Panel C: Socioemotional Skills (SDQ)			
Wave 1 (Age 9)			
Emotional Symptoms	1.90	2.42	-0.52***
Conduct Problems	1.15	1.56	-0.42***
Hyperactivity	2.83	3.57	-0.74***
Peer Problems	1.03	1.52	-0.49***
Wave 2 (Age 13)			
Emotional Symptoms	1.65	2.21	-0.56***
Conduct Problems	0.99	1.39	-0.40***
Hyperactivity	2.40	3.22	-0.82***
Peer Problems	1.03	1.38	-0.36***
Panel D: Demographic and Family Characteristics			
Wave 1 (Age 9)			
Mother's Education (mean)	3.79	3.35	0.44***
Mother's Educ: Upper Secondary (Dummy)	0.57	0.53	0.03**
Mother's Educ: Third Level (Dummy)	0.29	0.19	0.10***
Income Quintile	3.54	2.52	1.02***
Mixed School	0.76	0.73	0.03
Wave 2 (Age 13)			
Mother's Education (mean)	3.96	3.62	0.34***
Mother's Educ: Upper Secondary (Dummy)	0.57	0.57	0.01
Mother's Educ: Third Level (Dummy)	0.33	0.25	0.08***
Income Quintile	3.40	2.72	0.68***
Fee-Paying School	0.11	0.05	0.06***
DEIS School	0.12	0.24	-0.12***
Religious School	0.67	0.43	0.24***
Mixed School	0.53	0.61	-0.08***
Gender (1 = male)	1.50	1.57	-0.07***

Note: Table reports means by father presence status. Differences reflect mean(present) - mean(absent). $^{***}p < 0.01$, $^{**}p < 0.05$.

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 shows that achievement at any stage builds on earlier experiences (Cunha & Heckman, 2007), and that the best times for intervention may differ depending on the skill or context (Knudsen et al., 2006). By following predictors from childhood into adolescence, this analysis shows how cognitive, socioemotional, and socioeconomic factors work together to shape educational outcomes. It also points to the need for policies that support different areas of development at different stages.

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, $\text{Cog}_{k,i,w}$ denotes cognitive skills, $\text{SocioEmotional}_{l,i,w}$ captures socioemotional traits, $\text{SES}_{n,i,w}$ includes socioeconomic status indicators, and $\text{School}_{x,i,w}$ 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 4 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 4: 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 5 (Wave 1 predictors) and Table 6

(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

The regression results in Tables 5 and 6 show clear patterns in what predicts Maths scores. The models using information from age 13 (Wave 2) explain much more of the differences in scores (adjusted R^2 around 0.39–0.40) compared to the models using information from age 9 (adjusted R^2 around 0.30). Factors measured closer to the exam have greater predictive power.

B.3.1 Cognitive Skills

Numerical skills are consistently stronger predictors of Maths scores than verbal skills, both at ages 9 and 13. This pattern matches the findings of Duncan et al. (2007), who showed that early maths skills are more important than early reading skills for later academic achievement. At age 9, a one standard deviation increase in numerical ability is linked to about 9.6 more points, and this grows to about 11.7 points at age 13 ($p < 0.001$). Reading ability and verbal reasoning also matter but have smaller effects, around 3.6–4.7 points ($p < 0.001$). The BAS Matrices test at age 13 has a small but very significant effect too ($\beta \approx 0.19$, $p < 0.001$).

B.3.2 Socioemotional Traits

Out of all the socioemotional traits, hyperactivity has the strongest and most consistent link to lower Maths scores. The negative effect gets a little stronger between ages 9 and 13 ($\beta \approx -1.5$ to -1.8, $p < 0.001$). Conduct problems are linked to lower scores at age 9 but do not have an effect by age 13. Emotional symptoms have a small effect at age 9 and a bigger effect by age 13. Problems with peer relationships do not seem to affect Maths scores at either age. This is in line with McClelland et al. (2007), who found that children with better attention and behaviour control in early childhood made faster progress in Maths and other academic skills.

B.3.3 Socioeconomic Factors

Parental education shows clear effects across all models. Higher levels of mother's education are linked to the biggest gains in Maths scores at age 9 ($\beta \approx 10$–12.8). Father's education also matters, with similar effects at age 9 ($\beta \approx 9.9$) and a smaller effect at age 13 ($\beta \approx 5.7$, both $p < 0.001$). Household income is positively linked to achievement at both ages, although the

Table 5: 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.*

effect is slightly weaker by age 13. Missing information on father's education is associated with lower Maths scores in both waves, which may reflect the impact of paternal disengagement.

B.3.4 School Factors

School factors start to matter more by age 13. Students in fee-paying schools score higher in Maths ($\beta \approx 4.2$–4.3, $p < 0.01$), while students in DEIS schools score lower ($\beta \approx -3.3$ to -4.8). Being in a mixed-gender school is linked to lower scores in one model, but the school's religious ethos does not seem to make a difference.

B.3.5 Gender Differences

At age 9, boys score about 3.4–3.9 points higher than girls in Maths ($p < 0.001$). By age 13, this difference becomes smaller and is no longer significant. This pattern fits with the idea that gender gaps can change during adolescence as other factors come into play (Fryer & Levitt, 2010).

B.3.6 Comparing Wave 1 and Wave 2 Predictors

Although the same main predictors matter at both ages, there are some shifts over time. Cognitive skills become stronger predictors by age 13, while the effect of mother's education becomes a little weaker. School environment factors become more important at age 13, and the negative effect linked to missing father's education becomes smaller. These results fit with developmental cascade models (Masten et al., 2005), which show that early advantages or disadvantages in skills and environments can build up over time and affect later academic outcomes.

Table 6: 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 ages 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 are strong predictors of Maths scores at age 15. In Wave 1 (Model 1), a one standard deviation increase in Numerical Ability is linked to a 0.563-point rise in Maths scores ($p < 0.001$), while a similar increase in Reading Ability is linked to a 0.366-point rise (Table 7). The same patterns appear at age 13 (Table 8), with both Numerical Ability and Reading Ability remaining strong predictors across Models 3 and 4 ($p < 0.001$ in all cases).

C.0.2 Socioemotional Factors

Socioemotional traits also matter for Maths achievement. Higher scores in Conduct Problems and Hyperactivity are linked to lower Maths scores at both ages. In Wave 1, higher Conduct Problems ($\beta = -0.092$, $p < 0.001$) and Hyperactivity ($\beta = -0.095$, $p < 0.001$) are both linked to worse outcomes. By Wave 2, the effect of Conduct Problems becomes smaller, but Hyperactivity continues to show a strong negative link to achievement. These results show that being able to manage behaviour remains important for doing well in school across the teenage years.

C.0.3 Socioeconomic Factors

Socioeconomic status is a consistent predictor of Maths scores. In Wave 1, higher household income (equivalised) is linked to better outcomes ($\beta = 0.156$ and $\beta = 0.121$, both $p < 0.001$ across Models 1 and 2). The effect becomes a little smaller after accounting for school factors in Wave 2 but remains statistically significant. This shows that early differences in family income continue to shape academic achievement, even after considering the type of school attended.

C.0.4 Parental Education

Both mother's and father's education are linked to higher Maths scores, with mother's education showing stronger effects. In Model 1, having a mother with a Bachelor's or Postgraduate degree is linked to a 0.882-point increase in Maths scores ($p < 0.001$). Adding father's education in

Table 7: 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.

Model 2 shows extra positive effects, but it also makes the effect of mother's education a little smaller. This suggests that the earlier models partly captured the influence of both parents.

Missing information on father's education is linked to much lower Maths scores. Students with no recorded information about their father's education score 0.87 points lower on average ($p < 0.001$). This shows that missing data is not random. Controlling for household income reduces the gap to 0.57 points, meaning that part of the difference is due to lower income among students with missing paternal information. Mother's education also explains part of the gap,

Table 8: 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.

but a significant penalty remains. This shows that it is important to account for selection bias when using parental education in models.

C.0.5 Gender Differences

Gender patterns change over time. In Wave 1, gender does not predict Maths scores. By Wave 2, being male is linked to significantly lower achievement (Model 3: $\beta = -0.149$, $p < 0.001$; Model 4: $\beta = -0.115$, $p < 0.01$). This new gender gap points to the possibility that factors during adolescence, such as socioemotional development and school environment, affect boys and girls differently.

This finding shows the need to look more closely at how gender interacts with behaviour and school experiences during the move into secondary education. It also points to the importance of interventions that help students with behaviour regulation and school engagement to reduce new gender gaps.

C.0.6 Summary

Overall, cognitive skills are the strongest predictors of Junior Certificate Maths scores, followed by socioemotional traits and socioeconomic background. Behavioural difficulties, especially hyperactivity, have a consistent negative effect. Parental education, especially mother's education, remains an important factor, and adding father's education helps to uncover patterns linked to family background. Socioeconomic status matters too, although its effect becomes smaller when school-level factors are included.

Finally, the gender gap, which is not present at age 9, becomes significant by age 13–15. This shows how academic inequalities can change over time. These results show why it is important to take a developmental view when designing policies to support academic success and fairness.

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 9, 10, and 11 show the changes in partnership status, marital status, and secondary caregiver questionnaire completion between Waves 1–2 and Waves 2–3. These changes provide important context for understanding the father absence variable used in the main decomposition analysis. The tables show several clear patterns: (1) a drop in secondary caregiver questionnaire completion over time, with a sharp fall between Waves 2 and 3 (from 5.4% to 11.8%); (2) relatively steady rates of partnership and marital breakdown between Waves 1–2 and 2–3; and (3) falling rates of new partnerships and marriages among primary caregivers who were single or never married at the start of the study.

These patterns support the use of secondary caregiver non-response as a proxy for paternal disengagement. This reflects not only physical absence but also falling involvement among fathers who are still living in the household. The rising rate of non-completion among present secondary caregivers (from 8.7% in Waves 1–2 to 15.8% in Waves 2–3) shows that questionnaire participation can capture different levels of family involvement, even when fathers are still part of 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 9: 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 10: 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 11: 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 12: 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 500 replications.

Table 13: 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 500 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 14: 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 500 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, which signals to 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 15: 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 16: 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 500 replications.

Table 17: 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 500 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 at both ages 9 and 13.

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 modestly 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 to skills or unobserved heterogeneity, largely drive the English achievement penalties linked to father absence.

The dominance of endowment effects, especially cognitive abilities and maternal education, points to early developmental mechanisms: children experiencing father absence may accumulate lower levels of key academic skills and resources during middle childhood, which persist into adolescence. In particular, weaker verbal reasoning abilities among students from father-absent households appear to be a key channel through which academic disadvantages materialize. These patterns reinforce the interpretation that father absence affects academic outcomes primarily by shaping the early skill formation process, rather than through altering the educational returns to existing skills.

Several factors from developmental psychology, sociology, and neuroscience help explain these findings. First, early skill formation theories suggest that father absence during childhood can limit the development of cognitive skills such as verbal reasoning, with early deficits compounding over time (Cunha & Heckman, 2007; Heckman, 2006). Second, attachment theory emphasizes that stable family structures contribute to stronger emotional security and better language development, whereas father absence may reduce linguistic stimulation and increase stress, both of which can impair verbal skill acquisition (Amato, 2005; Bowlby, 2008). Third, sociological theories such as resource dilution and role strain suggest that single-parent households often have fewer financial, emotional, and time resources to support children's academic development (Carlson & Corcoran, 2001; McLanahan & Sandefur, 2009). Finally, neuroscience research shows that early-life stress associated with family disruption can affect brain areas involved in language and executive functioning, further contributing to skill gaps

(Lupien et al., 2009; Shonkoff et al., 2012). Together, these mechanisms are consistent with the pattern that father absence affects academic achievement primarily through early differences in skill endowments.

Table 18: 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 500 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 19: 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 500 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 20: 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 21: 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 22: 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 500 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 23: 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 24: 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 25: 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 results for English show quite a different pattern compared to Maths. As we can see in Tables 26 and 27, girls outperform boys by around 0.31 points at age 15, and interestingly, this gap is almost entirely explained by differences in how skills translate into achievement, rather than by the skills themselves. In Wave 1, the actual skill difference is essentially zero, while girls gain about 0.27–0.32 points due to better returns on their skills (coefficients). Additionally, there is a small positive interaction effect (0.044, significant at the 5% level) suggesting that even though boys have slightly better cognitive and behavioural scores, girls' advantage comes from how effectively they use these skills. By Wave 2, boys actually have better cognitive skills, like Verbal Reasoning and Numerical Ability, yet girls continue to achieve higher English scores through better productivity (turning their endowments into outcomes more efficiently).

Girls also benefit slightly from having fewer issues with Hyperactivity and Conduct Problems, but the biggest boost comes from school environments, especially co-educational schools. These environments significantly help girls by improving confidence and reducing stereotype threats, consistent with previous research suggesting girls thrive in mixed-gender contexts due to social learning and positive peer influences (Eccles et al., 1990; Raver, 2002).

When we look at family background (Tables 28 and 29), having a father present gives a 0.68-point advantage in English at both ages, smaller than the gap observed for Maths. In Wave

1, more than half (53%) of this gap comes from differences in skills, especially Reading Ability and mother's education. By Wave 2, skills explain even more (63%), driven mainly by Verbal Reasoning, while differences in returns become smaller and interactions remain negligible. This suggests that a father's involvement plays a key role in developing children's early literacy skills and enriching language exposure at home, as found in previous studies (Yeung et al., 2002).

Looking at gender-specific impacts of father absence (Tables 30–31), girls experience slightly larger penalties (0.75 points) compared to boys (0.63 points). For girls, both skills and how effectively they use these skills matter more, particularly Conduct Problems and maternal education. This indicates that having a father present may strengthen maternal support and behavioural development in ways that particularly benefit girls' literacy outcomes.

Overall, these English results point to some important subject-specific patterns:

- Gender gaps in English are mainly driven by differences in returns to skills, with girls showing greater engagement, motivation, and possibly benefiting from higher teacher expectations in language subjects (Durlak et al., 2011).
- Father absence affects English achievement mostly through early cognitive skill gaps, showing the importance of father-child language interactions during childhood (Downey, 1995; Evans & Schamberg, 2009).
- School context, especially mixed-gender classrooms, improves girls' English performance, likely through positive peer effects and supportive classroom environments that are especially helpful for literacy skills.

Targeted family literacy programmes, such as encouraging fathers to read and tell stories with their children, could help close these early skill gaps. In schools, promoting mixed-gender peer support and creating activities that engage boys in literacy (such as boys' reading groups or male mentors) could help reduce both gender and father-absence gaps in English.

Table 26: 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 500 replications was used to estimate standard errors.

Table 27: 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 500 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 28: 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 500 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 29: 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: 500 replications.

Table 30: 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 500 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 31: 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 500 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 are not captured by measured variables. †Other school variables (DEIS School, Mixed School, Religious School) were included in the model but none showed significant effects.

K Appendix K. Distributional Decomposition of Gender Gaps in Maths Achievement

While in the main analysis I employ Oaxaca-Blinder decompositions to examine mean differences in Maths achievement between boys and girls, this approach cannot capture how these gaps vary across the entire distribution of scores. To address this limitation, I complement the main analysis with DiNardo-Fortin-Lemieux (DiNardo et al., 1996) decompositions, which provide three key advantages:

1. Unlike Oaxaca-Blinder, which focuses solely on mean differences, DFL decomposition allows for examination of gender gaps across the entire achievement distribution, revealing whether gaps are larger or smaller at different performance levels.

2. The DFL approach does not impose the linearity assumptions required by Oaxaca-Blinder, allowing for a more flexible modeling of the relationship between characteristics and outcomes.

3. By analyzing decomposition results at specific quantiles (0.1, 0.25, 0.5, 0.75, 0.9), I can identify whether the composition and structure effects differ for low-, medium-, and high-achieving students.

K.1 Decomposition of Gender Differences

Following the approach in the main analysis, I implement separate decompositions for age 9 and age 13 predictors, with and without controls for father's education. The methodology follows the reweighting procedure described by DiNardo et al. (1996), where a counterfactual distribution is created by reweighting girls' Maths scores using propensity weights derived from a logistic regression of gender on observed characteristics.

The distance between girls' actual scores (red) and the counterfactual (green) represents the composition effect (differences in characteristics), while the distance between the counterfactual and boys' scores (blue) shows the structure effect (differences in returns to characteristics). In most cases, both effects contribute to the overall gender gap, with the composition effect being particularly strong at middle quantiles.

At lower quantiles (0.1-0.3), giving girls boys' characteristics would have minimal impact or even decrease their scores in some cases. At middle and upper quantiles, however, the composition effect becomes much more important, showcasing the fact that observable characteristics explain more of the gender gap for middle and high-achieving students.

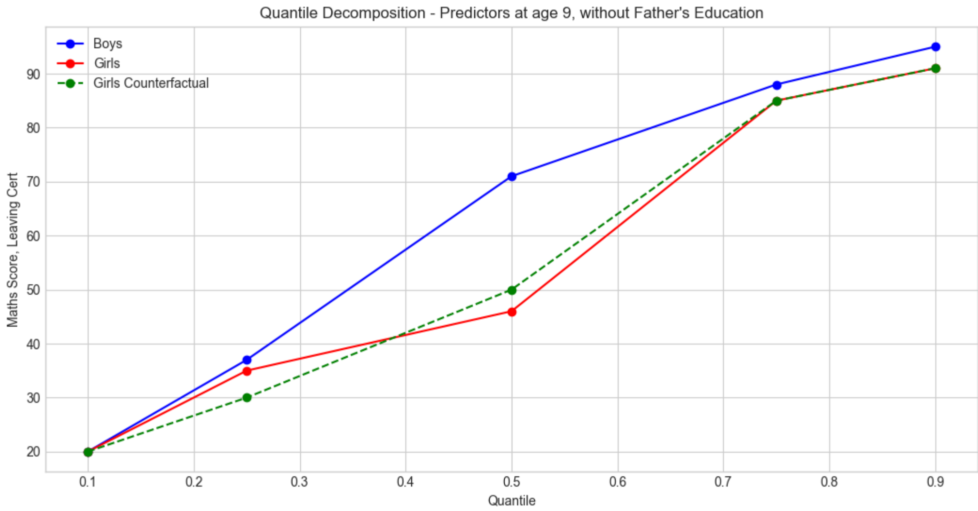

Figure 3: DiNardo-Fortin-Lemieux Decomposition of Maths Achievement by Quantile, Using Age 9 Predictors. This figure shows the Maths score distributions for boys (blue), girls (red), and a counterfactual distribution (green dashed line) representing what girls' scores would look like if they had the same characteristics as boys. The gender gap varies substantially across the distribution, increasing from approximately 2 points at the 10th percentile to 5 points at the median and 7 points at the 90th percentile. The distance between the red and green lines represents the composition effect (differences in characteristics), while the distance between green and blue lines shows the structure effect (differences in returns to characteristics). Notably, at lower quantiles (0.1-0.3), giving girls boys' characteristics would actually decrease their scores, while at middle and higher quantiles, it would substantially improve them.

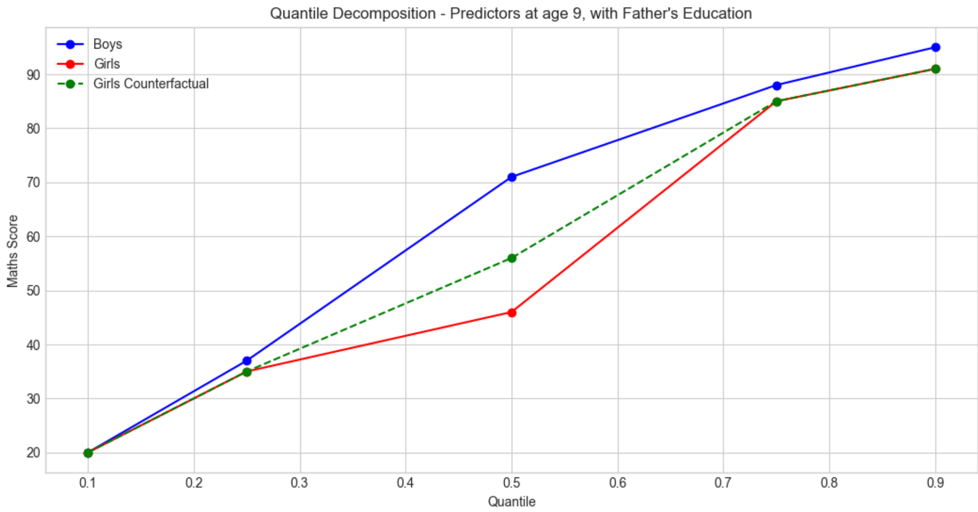

Figure 4: DiNardo-Fortin-Lemieux Decomposition of Maths Achievement by Quantile, Using Age 9 Predictors Including Father's Education. This figure shows Maths score distributions for boys (blue), girls (red), and the counterfactual distribution (green dashed line) representing what girls' scores would look like if they had the same characteristics as boys, including father's education. Compared to the model without father's education (Figure 3), several important differences emerge: 1) At lower quantiles (0.1-0.25), the counterfactual now closely tracks girls' actual scores rather than falling below them; 2) At middle quantiles (0.5), the composition effect becomes substantially larger, with the counterfactual line moving closer to boys' scores; 3) The gender gap at the median increases to approximately 25 points, with the composition effect accounting for about 45% of this gap. These differences show the importance of paternal education in explaining gender disparities, particularly for students in the middle of the distribution.

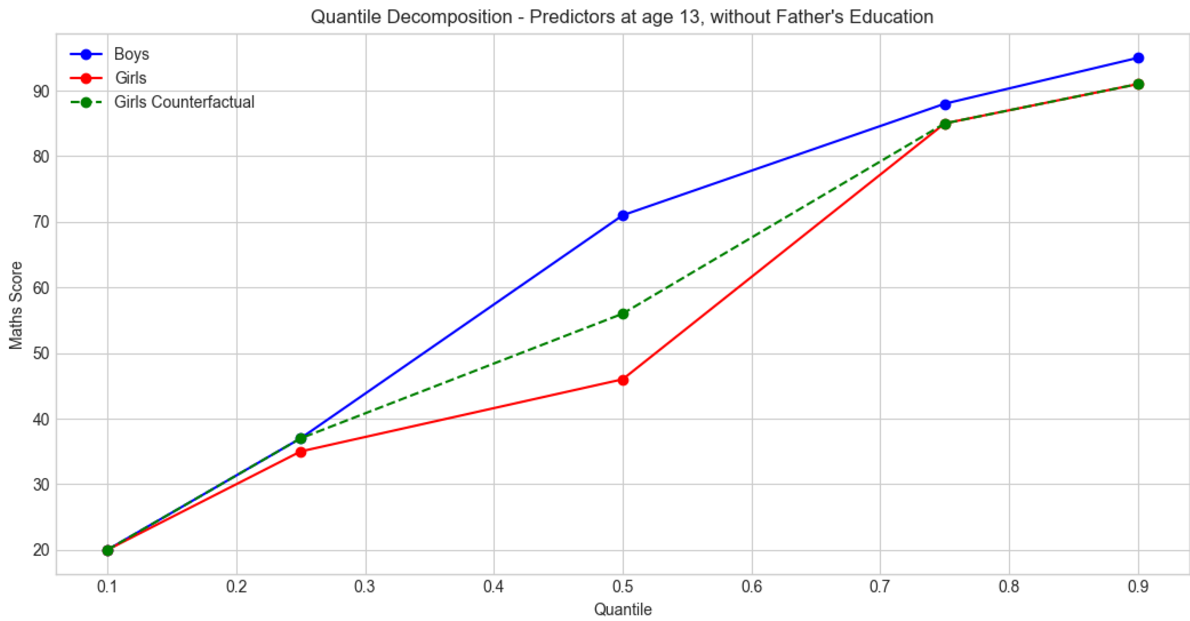

Figure 5: DiNardo-Fortin-Lemieux Decomposition of Maths Achievement by Quantile, Using Age 13 Predictors Without Father's Education. This figure displays Maths score distributions for boys (blue), girls (red), and the counterfactual distribution (green dashed line) representing what girls' scores would look like if they had the same characteristics as boys. The gender gap is minimal at the lowest quantile (0.1) but increases substantially through the middle and upper quantiles, reaching approximately 5 points at the 0.9 quantile. The composition effect (distance between red and green lines) is positive across most of the distribution and particularly large at the median (0.5), where giving girls the same characteristics as boys would improve their scores by about 11 points, accounting for approximately 45% of the total gender gap at that point. This suggests that by age 13, a substantial portion of the Maths gender gap can be attributed to differences in observed characteristics such as cognitive abilities and educational environment, especially for middle-performing students.

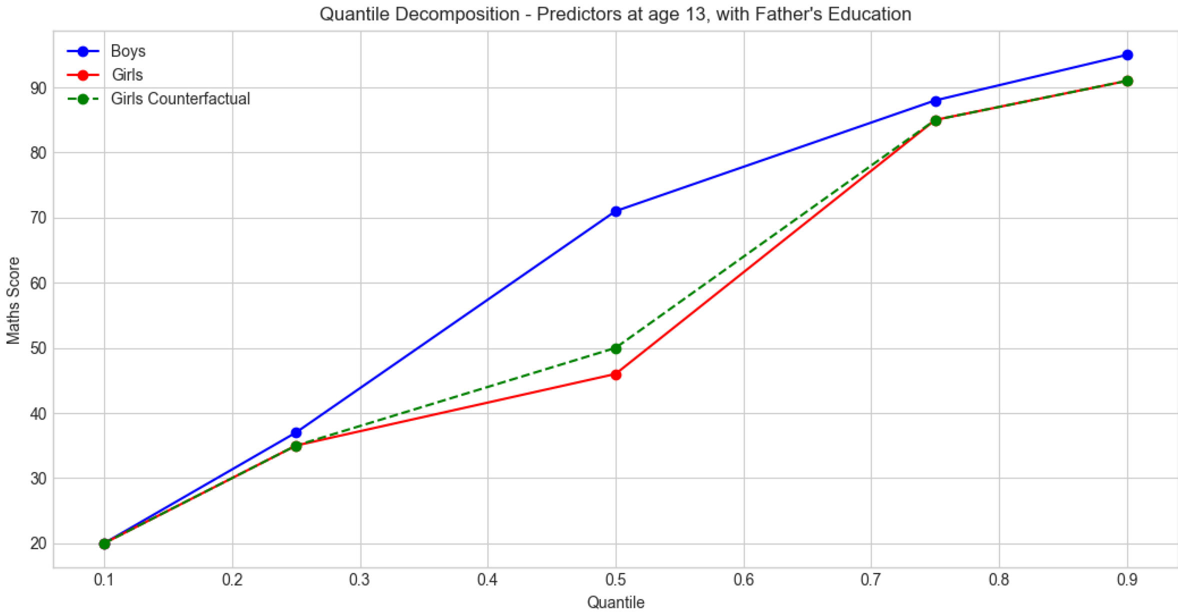

Figure 6: DiNardo-Fortin-Lemieux Decomposition of Maths Achievement by Quantile, Using Age 13 Predictors With Father's Education. This figure displays Maths score distributions for boys (blue), girls (red), and the counterfactual distribution (green dashed line) representing what girls' scores would look like if they had the same characteristics as boys, including father's education. Similar to the model without father's education, the gender gap increases across the distribution, but including father's education reveals important differences: 1) The counterfactual remains closer to the girls' actual distribution at lower quantiles (0.1-0.25); 2) The composition effect at the median (0.5) remains substantial, with an approximately 5-point improvement in girls' scores; 3) At higher quantiles (0.7-0.9), the counterfactual almost perfectly overlaps with girls' actual scores, suggesting that observable characteristics (including father's education) explain very little of the gender gap among high-achieving students. This indicates that at age 13, the role of father's education in Maths achievement varies considerably across the performance distribution, with the largest influence observed among middle-performing students.

Table 32: DiNardo-Fortin-Lemieux Decomposition of Maths Achievement by Quantile

Quantile	Boys	Girls	Gap	Age 9, No Father's Educ.		Age 9, With Father's Educ.		Age 13, No Father's Educ.		Age 13, With Father's Educ.	
				Counterfactual	Comp%	Counterfactual	Comp%	Counterfactual	Comp%	Counterfactual	Comp%
0.10	20	20	0	20	N/A	20	N/A	20	N/A	20	N/A
0.25	37	35	2	35	0%	35	0%	37	100%	35	0%
0.50	71	46	25	50	16%	56	40%	56	40%	50	16%
0.75	88	85	3	85	0%	85	0%	85	0%	85	0%
0.90	95	91	4	91	0%	91	0%	91	0%	91	0%
Mean	60.83	55.80	5.04	56.80	19.9%	58.26	48.8%	58.66	56.9%	58.24	48.5%

Note: ”Comp%” represents the percentage of the gender gap explained by differences in observed characteristics (composition effect). ”N/A” indicates that the gap at that quantile is approximately zero. Values in the ”Counterfactual” columns show what girls' scores would be if they had the same characteristics as boys while maintaining their own returns to those characteristics.

The DiNardo-Fortin-Lemieux decomposition results presented in Figures 3-6 and Table 32 complement and extend the Oaxaca-Blinder findings by revealing how gender gaps vary across the Maths achievement distribution. While the Oaxaca-Blinder decomposition showed average gender gaps of 4-5 points favouring boys, the DFL analysis demonstrates that these gaps are dramatically non-uniform across the distribution.

As illustrated in Table 32, the gender gap is mostly concentrated at the median (0.5 quantile), where boys outperform girls by 25 points. In contrast, there is no gap at the lowest quantile (0.1), only a small 2-point gap at the 0.25 quantile, and modest gaps of 3-4 points at the upper quantiles (0.75 and 0.9). This pattern of a substantial middle-distribution gap is consistently visible across all four figures, where the distance between the blue (boys) and red (girls) lines peaks around the middle of the distribution.

The role of observable characteristics (composition effect) varies markedly across the achievement distribution. At the median, Table 32 shows that the composition effect accounts for 16% of the gap when using age 9 predictors without father's education (Figure 3), rising to 40% when father's education is included (Figure 4). Similarly, with age 13 predictors, the composition effect explains 40% of the median gap without father's education (Figure 5) but falls to 16% when father's education is included (Figure 6). These varying percentages are visible in the figures as differences in the distance between the red (girls) and green (counterfactual) lines.

Table 32 shows that at the 0.25 quantile, age 13 predictors without father's education (Figure 5) explain 100% of the gap, while other models explain 0%. This is visible in Figure 5 where the green counterfactual line perfectly overlaps with the blue boys' line at this quantile. At higher quantiles (0.75 and 0.9), all models show 0% composition effects, indicating that unobserved factors or differential returns to characteristics (structure effect) drive the entire gender gap among high achievers.

The inclusion of father's education substantially alters the decomposition results in ways that vary by age. As shown in Table 32, at the mean, including father's education increases the composition effect from 19.9% to 48.8% with age 9 predictors (comparing Figures 3 and 4). At the median, it increases the composition effect from 16% to 40% with age 9 predictors, but decreases it from 40% to 16% with age 13 predictors (comparing Figures 5 and 6). This suggests that the role of paternal education in explaining gender disparities changes between ages 9 and 13.

The overall pattern revealed in Table 32 and Figures 3-6 is that the gender gap in Maths achievement has a complex distributional structure that evolves with age. Both the magnitude of the gender gap and the relative importance of composition versus structure effects vary substantially across the achievement distribution. These findings suggest that interventions aimed at closing the gender gap may need different approaches for low- versus high-achieving students, with particular attention to middle-performing students where the gap is largest and observable characteristics explain a meaningful portion of the disparity.

K.2 Decomposition of Father Absence Effects

After looking at mean differences in the main analysis, I now use DiNardo-Fortin-Lemieux decompositions to see how father absence affects Maths scores across the full range of student performance. This helps us understand whether father absence matters more or less for low, middle, or high achievers.

Like with the gender analysis, I run separate decompositions using predictors from age 9 (Wave 1) and age 13 (Wave 2), and I analyze boys and girls separately. The counterfactual shows what students with absent fathers would score if they had the same characteristics as students with present fathers, but keeping their own returns to those characteristics. Table 33 summarizes the decomposition results across different quantiles for all four analyses, showing the magnitude of gaps and the percentage explained by composition effects.

Figure 7 shows the decomposition for boys using age 9 predictors. There is a big gap between boys with present fathers (red line) and absent fathers (blue line) across all performance levels, but it is biggest at the median (0.5 quantile), reaching about 28.5 points (see Table 33). The counterfactual distribution (green dashed line) shows that differences in characteristics (composition effect) explain about 63% of the average gap, as shown in Table 33. This composition effect is much stronger at the median (88%) than at the bottom (25% at the 0.1 quantile). This suggests that for boys, things like family background and cognitive skills explain most of the father absence penalty for middle performers, but not as much for lower performers.

Figure 8 shows the same decomposition for girls using age 9 predictors. Girls also show a substantial father absence gap (15.2 points on average), but it is distributed differently. The gap is biggest at the 0.75 quantile (29 points) and smaller at the median (9 points), as detailed in Table 33. Differences in characteristics explain about 54% of the average gap, but this varies a lot: from 25% at the bottom, to only 11% at the median, then up to 35% at the 0.75 quantile. This means that for girls, unobservable factors or differences in how characteristics translate to outcomes (structure effect) matter more than for boys, especially at the median.

Figures 9 and 10 show the same analysis but using age 13 predictors. For boys (Figure 9), the pattern stays similar to what we saw with age 9 predictors, but observable characteristics explain even more of the gap at the median (89%, as shown in Table 33) while explaining less at the upper middle range (38% at the 0.75 quantile). This suggests that as boys move through early adolescence, measured characteristics like test scores and behaviour become more important in explaining middle-range performance gaps, while other unmeasured factors matter more for higher performers.

For girls (Figure 10), age 13 predictors explain more of the average gap (63% compared to 54% with age 9 predictors, see Table 33). The composition effect's contribution jumps substantially at the median (67%, up from just 11% at age 9) and at the highest levels (50% at the 0.9 quantile). This means that things we can measure at age 13 - like cognitive abilities, behaviour, and school environment - do a better job explaining why girls with absent fathers underperform, especially in the middle and upper parts of the distribution.

One interesting pattern across all four graphs is that the father absence penalty gets smaller at the very top (0.9 quantile), dropping to just 4-6 points for both boys and girls (Table 33). This might mean that high-achieving students are more resilient to father absence, or that other protective factors become more important for these students.

The quantile decomposition shows something important that we miss when looking just at averages: the father absence penalty varies a lot across different performance levels and is made up differently at different points in the distribution. For both boys and girls, observable characteristics matter more in the middle of the distribution and when measured at age 13. On the flip side, unmeasured factors or differences in how characteristics translate into outcomes matter more for the lowest performers, with structure effects accounting for 75% of the gap at the 0.1 quantile across all analyses (Table 33).

When we compare these father absence results to the gender gap results from earlier in this Appendix, we see some interesting differences. While the gender gap is mostly concentrated at the median (see Table 32), the father absence penalty is substantial across almost the entire distribution. This suggests that family structure has more widespread effects on achievement than gender. Also, observable characteristics explain more of the father absence penalties than they do for gender gaps, suggesting that the things we can measure - like cognitive skills, behaviour problems, and family resources - are more directly linked to father absence effects.

These findings matter for policy. The big role of composition effects, especially for boys and in the middle of the distribution, suggests that targeted programs focused on specific measurable characteristics (like cognitive skills, behaviour, or school environment) might help reduce father absence penalties. But the persistent role of structure effects, especially for lower performers, suggests we also need broader changes to address the full range of disadvantages linked to father absence.

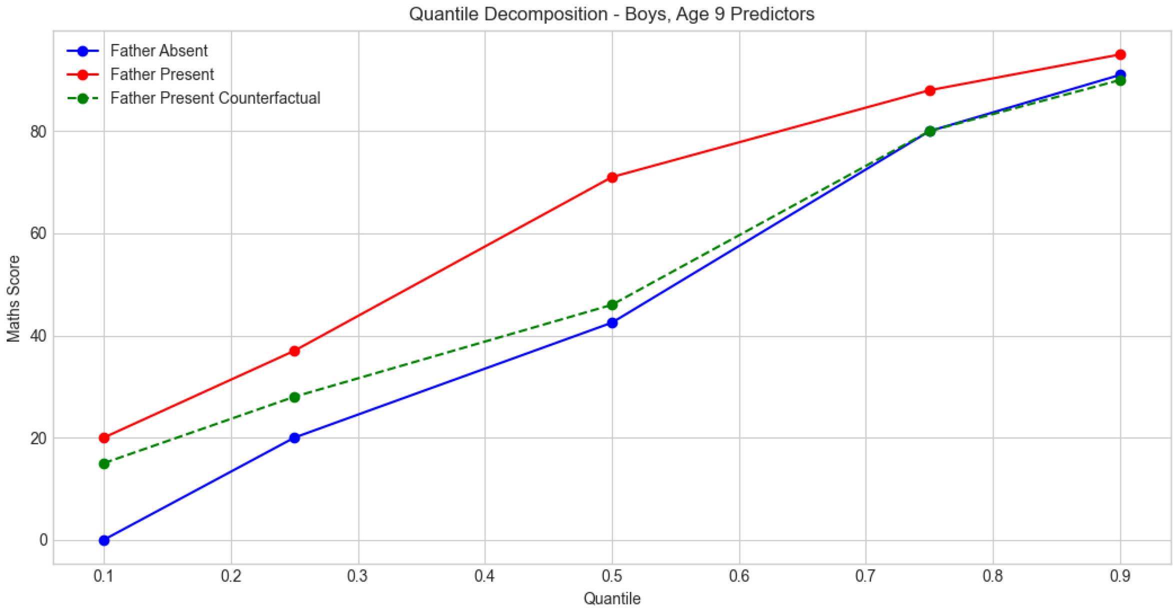

Figure 7: DiNardo-Fortin-Lemieux Decomposition of Father Absence Effects on Maths Achievement by Quantile, Using Age 9 Predictors for Boys. This figure shows the Maths score distributions for boys with present fathers (red), boys with absent fathers (blue), and a counterfactual distribution (green dashed line) representing what boys with absent fathers' scores would look like if they had the same characteristics as boys with present fathers. The father absence gap is substantial across the entire distribution but largest at the median (0.5 quantile) at approximately 28.5 points. The composition effect (distance between blue and green lines) explains about 63% of the average gap but varies considerably across the distribution (from 25% at the lowest quantile to 88% at the median), then diminishing at higher quantiles. This indicates that observable characteristics like cognitive skills and family background explain most of the father absence penalty for middle-achieving boys but less for lower-achieving boys.

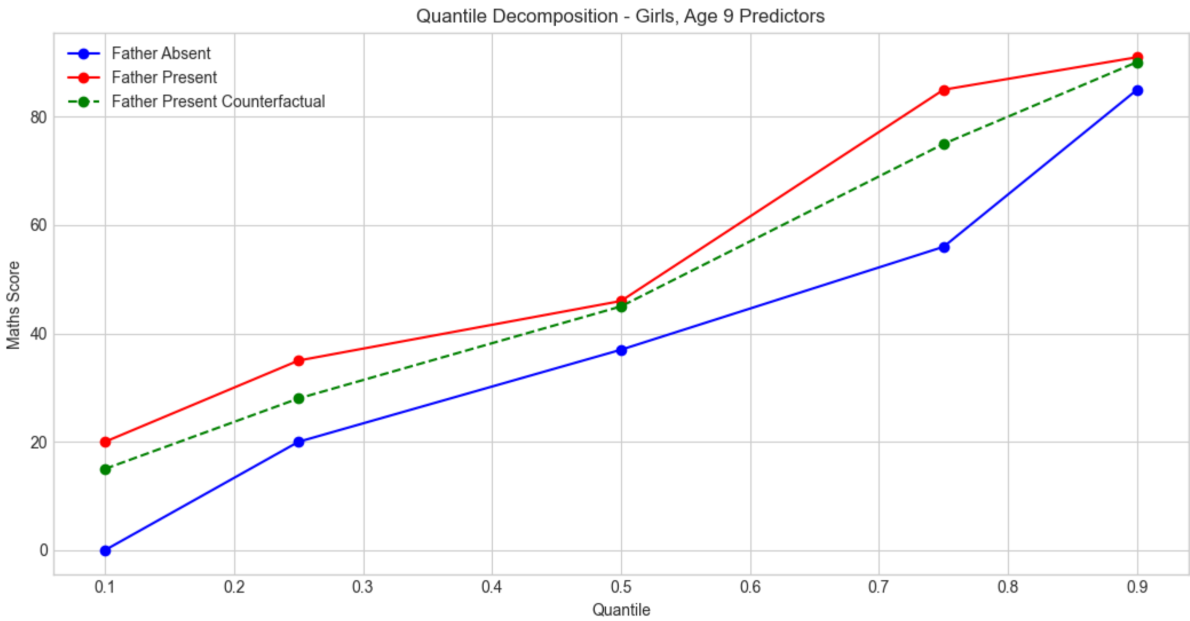

Figure 8: DiNardo-Fortin-Lemieux Decomposition of Father Absence Effects on Maths Achievement by Quantile, Using Age 9 Predictors for Girls. This figure displays Maths score distributions for girls with present fathers (red), girls with absent fathers (blue), and the counterfactual distribution (green dashed line). Unlike for boys, the father absence gap for girls is largest at the 0.75 quantile (29 points) rather than at the median. The composition effect explains about 54% of the average gap but is particularly low at the median (11%) and higher at the 0.75 quantile (34%). This pattern suggests that for girls, unobservable factors or differences in returns to characteristics (structure effect) play a more substantial role than observable characteristics, especially in the middle of the distribution. The gap narrows considerably at the highest quantile (0.9), where father absence seems to have a smaller impact on high-achieving girls.

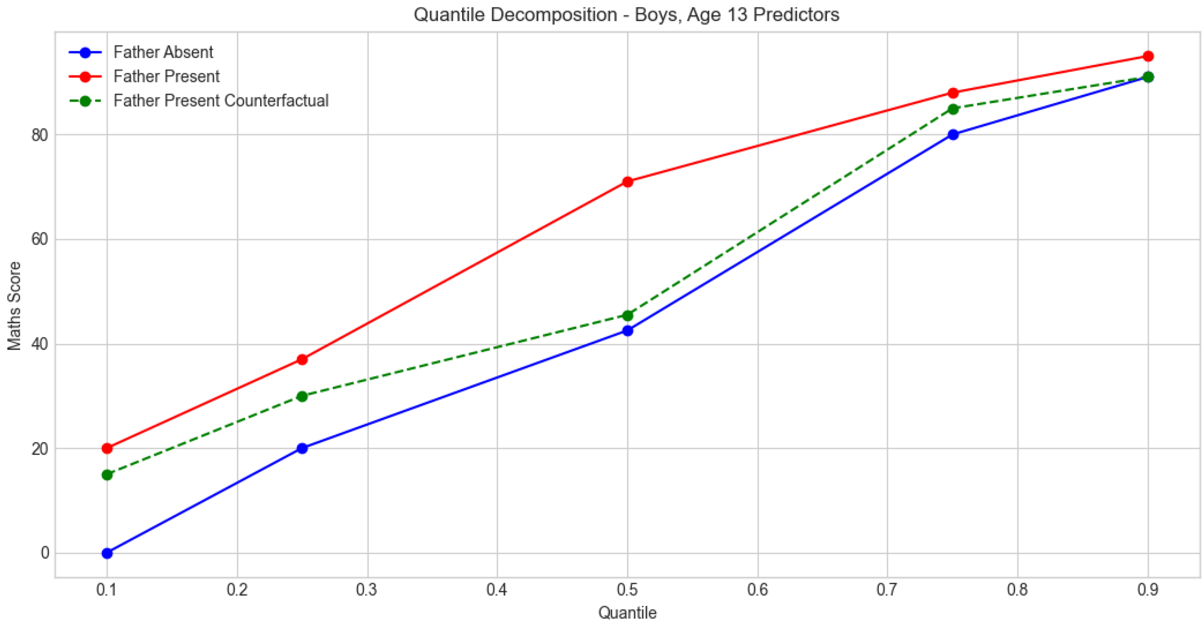

Figure 9: DiNardo-Fortin-Lemieux Decomposition of Father Absence Effects on Maths Achievement by Quantile, Using Age 13 Predictors for Boys. This figure shows how the father absence penalty for boys changes when using predictors measured at age 13 instead of age 9. The pattern remains similar to Figure K5, with a substantial gap across the distribution that peaks at the median. However, the composition effect's contribution increases at the median (89%) while decreasing at the 0.75 quantile (38%) compared to age 9 predictors. This suggests that as boys progress through early adolescence, observable characteristics like cognitive abilities, behaviour, and school environment become even more important in explaining middle-range performance gaps, while structure effects gain importance at higher performance levels. The convergence of all three lines at the highest quantile indicates that father absence has less impact on the highest-achieving boys.

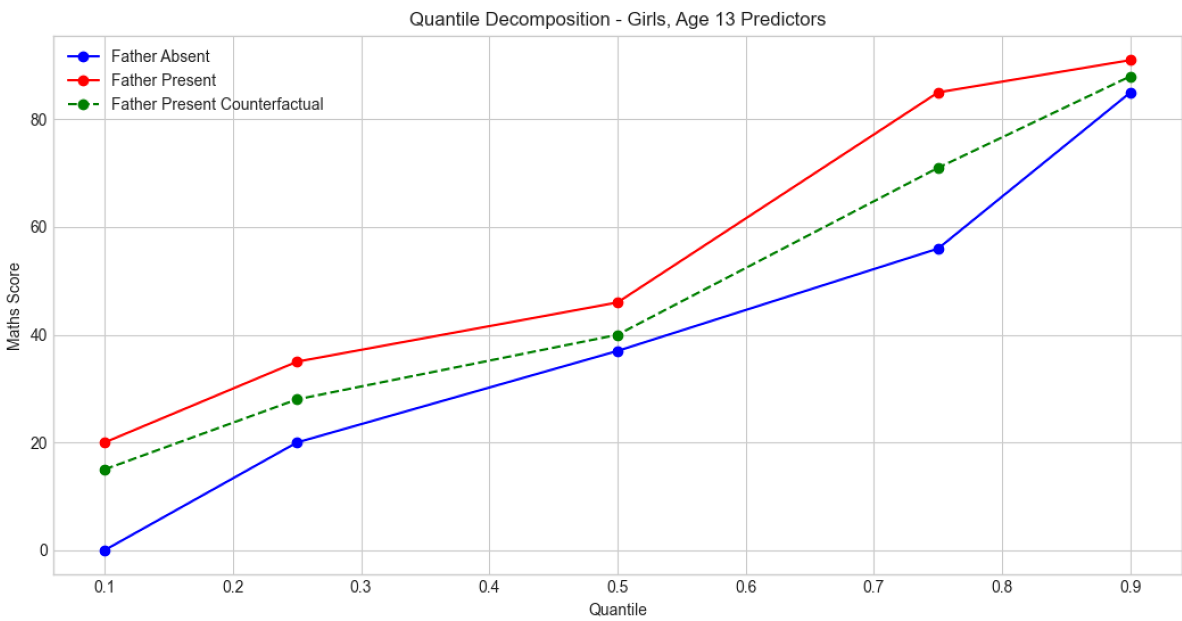

Figure 10: DiNardo-Fortin-Lemieux Decomposition of Father Absence Effects on Maths Achievement by Quantile, Using Age 13 Predictors for Girls. This figure displays how the father absence penalty for girls changes when using predictors measured at age 13. Compared to age 9 predictors (Figure 8), the composition effect plays a substantially larger role, explaining 63% of the average gap (up from 54%). Most notably, the composition effect's contribution increases dramatically at the median (67%, up from just 11% at age 9) and at the highest quantile (50% at the 0.9 quantile). This indicates that observable characteristics measured at age 13 have greater explanatory power for the father absence penalty among girls, especially in the middle and upper portions of the distribution. This finding suggests that cognitive abilities, behaviour, and school environment measured in early adolescence are particularly important in understanding why girls with absent fathers tend to underperform in Maths.

Table 33: DiNardo-Fortin-Lemieux Decomposition of Father Absence Effects on Maths Achievement by Quantile

Quantile	Father Present	Father Absent	Gap	Boys, Age 9 Predictors		Girls, Age 9 Predictors		Boys, Age 13 Predictors		Girls, Age 13 Predictors	
				Counterfactual	Comp%	Counterfactual	Comp%	Counterfactual	Comp%	Counterfactual	Comp%
0.10	20	0	20	15	25%	15	25%	15	25%	15	25%
0.25	37	20	17	28	53%	28	47%	30	41%	28	47%
0.50	71	42.5	28.5	46	88%	46	11%	45	89%	40	67%
0.75	87	58	29	80	0%	75	34%	85	38%	70	48%
0.90	95	90	5	91	-25%	92	15%	91	0%	88	50%
Mean	60.83	47.27	13.56	52.33	63%	47.60	54%	53.03	58%	46.17	63%

Note: ”Comp%” represents the percentage of the father absence gap explained by differences in observed characteristics (composition effect). Values in the ”Counterfactual” columns show what father-absent students’ scores would be if they had the same characteristics as father-present students while maintaining their own returns to those characteristics. Gap values represent the difference between father-present and father-absent scores. Negative percentages indicate where the counterfactual would widen rather than narrow the gap.