Gender Differences in the Genetics of Skill Formation *

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ABSTRACT: This paper examines why boys are lagging behind girls in early skills. Moving beyond mean comparisons, we integrate genetic endowments into a dynamic model of skill formation to characterize how biological and social mechanisms contribute to the distribution of gender gaps in early cognitive skills. We find substantial heterogeneity in the gender gap in early skills, which follows both socioeconomic and genetic gradients, with boys significantly lagging behind girls developmentally at the lower end of both distributions. Our model reveals that gender gaps are explained by a multitude of factors. The genetic gradient in the gender gap is explained by a higher sensitivity to genes for boys, while the socioeconomic gradient is explained by a higher sensitivity to investments and higher self-productivity of skills for boys. Parental investments further amplify early disparities, as disadvantaged boys receive the lowest levels of investment despite facing higher returns for these investments. Our findings highlight the complex interplay of genetic endowments and family environments in shaping gender gaps in early skills and underscore the importance of considering heterogeneity in both dimensions to understand the origins of this inequality.

KEYWORDS: Child Development; Skill Formation; Gender; Genetics; Family Investments.
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1 Introduction

In recent decades, a striking pattern has emerged in developed countries: women are increasingly outperforming men in educational achievement (Bertocchi and Bozzano, 2020; Reeves, 2022). These differences appear early in life, with girls showing advantages in verbal skills, reading and writing abilities, and socio-emotional development within the first few years (Palejwala and Fine, 2015; Beck et al., 2023). Two key patterns in these early gender gaps are particularly intriguing. First, boys show greater variability in their early skills compared to girls. Second, the gaps follow a socioeconomic gradient, with boys from disadvantaged backgrounds falling particularly far behind their female peers (Autor et al., 2023). These patterns suggest that boys' development may be more sensitive to their early childhood environment, especially parental investments, than girls' development (Bertrand and Pan, 2013; Fan, Fang, and Markussen, 2015). This paper examines how biological and social factors interact to produce these gender differences in early-life skill development.

Prior research has established that gender education gaps emerge during early childhood and that boys' development is particularly sensitive to their social environment. However, two crucial aspects remain largely unexplored: the role of genetics in explaining these gaps and the key mechanisms driving the social gradient. We address these questions by building on economic models of skill formation (Cunha and Heckman, 2008; Agostinelli and Wiswall, 2020; Attanasio et al., 2020). Our approach formally models how children acquire skills by estimating the technology of skill formation separately for boys and girls. We extend the traditional model by incorporating both biological factors (measured through genetic markers) and social factors (captured by socioeconomic status) that are determined before birth, along with observable differences in the early childhood environment such as parental investments, following the approach developed in our previous work (Houmark, Ronda, and Rosholm, 2024). Besides the sex chromosome, there are no gender differences in biological and social factors determined before birth.[1] Therefore, any gender differences in skills that emerge in early childhood must arise solely through differential responses to these initial

[1]While it is intuitive that there shouldn't be any gender differences in social factors determined before birth (assuming no parental sex selection), it is less clear whether the same applies to genetic factors. Our comparison of genetic effects across genders relies on two distinct facts. First, due to independent assortment, different chromosomes are inherited independently of each other, meaning that the inheritance of autosomes (chromosomes other than the sex chromosomes) is independent of the inherited sex chromosome. Second, previous research has established that the genetic architecture of educational attainment is very similar across sexes (Okbay et al., 2016; Lee et al., 2018), indicating that the genetic markers associated with educational attainment are highly correlated across genders. These two facts allow us to compare the genetic effects across genders in this paper, as any differences in the genetic effects on skill development between boys and girls can be attributed to differential responses to the same genetic influences rather than differences in the genetic influences themselves.

conditions. Our model captures the evolution of skills as a function of these initial conditions, allowing us to directly compare the relative importance of genetic versus social influences in shaping gender gaps in early-life cognitive ability. By providing a more comprehensive assessment of the determinants of early skill development, we aim to illuminate the key drivers of gender differences in human capital accumulation.

Our empirical analysis relies on data from the Avon Longitudinal Study of Parents and Children (ALSPAC), which allows us to measure children's skills at different stages of early development from ages 0 to 7. The study has collected detailed information on family investments and molecular genetic data from the child participants and both parents. From this genetic data, we construct polygenic indexes that summarize into a single score the effect of millions of genetic variants on observable traits like educational achievement and cognitive ability. These indexes have been widely used in social science research, predicting a range of economic and social outcomes.[2] Crucially, when we control for parental genes, variation in children's genetic indexes can be interpreted causally (Benjamin et al., 2024).

Our exploratory analysis reveals that gender gaps in early cognitive skills favor girls throughout the early childhood period. The gaps range from 0.30 standard deviations at ages 2-3 to 0.13 standard deviations at ages 6-7. Notably, the gender gaps in early cognitive skills are not constant across the social and genetic distributions. Instead, these gaps are mostly driven by boys at the lower end of both the socioeconomic and genetic distributions. That is, boys living in low socioeconomic status households and those with lower genetic potential for education increasingly lag in development compared to similar girls. While the heterogeneity in gender gaps across socioeconomic status has been previously documented (e.g., Autor et al. (2023)), the heterogeneity across the genetic spectrum is a novel finding.

To understand these patterns, we estimate a structural model of skill formation. This model allows us to decompose the gender gap in early skills into its different channels. We start by estimating the investment policy function, which characterizes how parents allocate investments in their child based on the child's skills and family environment. We find that parents invest more in girls than in boys on average across all ages, with the largest gaps emerging around ages 4-5. While parents reinforce initial differences in skills by investing more in boys and girls with a higher genetic potential for education and higher initial skills, we find that parents are more sensitive to the initial skills of boys. That is, parents tend to comparatively under-invest in boys from lower socioeconomic families and with lower initial

[2]PGIs for educational attainment have been shown to predict early childhood skills (Belsky et al., 2016; Houmark, Ronda, and Rosholm, 2024), school achievement (Ward et al., 2014; Houmark et al., 2022), educational attainment (Rietveld et al., 2013; Domingue et al., 2015; Okbay et al., 2016; Lee et al., 2018; Ronda et al., 2022), as well as earnings and wealth (Papageorge and Thom, 2019; Belsky et al., 2018; Barth, Papageorge, and Thom, 2020).

genetic potential in comparison to similar girls.

Our analysis reveals fundamental differences in the technology of skill formation that describe how boys and girls develop skills over time. We find that boys' skill development is generally more responsive to all inputs than girls'. First, when parents invest time and resources, these investments have a stronger effect on boys' development. Second, boys show stronger 'self-productivity' of skills—meaning that their current skills more strongly influence their future skill development. Third, their genetic predispositions have a larger impact on their development, particularly as they get older. This greater sensitivity to all inputs helps explain two key patterns: why we observe more variation in boys' skills overall, and why boys at both ends of the socioeconomic and genetic distributions show more extreme outcomes than girls.

To understand how these various factors combine to create gender gaps, we simulate children's skill development under different scenarios. Through our simulations, we uncover two key mechanisms that explain why girls typically receive more parental investment than boys. First, parents tend to invest more in children who already show higher skill levels—and since girls start with higher average skills, they receive more investment. Second, this pattern of reinforcing existing advantages is stronger for boys than girls. As a result, boys from disadvantaged backgrounds or with lower genetic predispositions receive particularly low levels of investment compared to similar girls. The combined effect is substantial: differences in parental investment patterns account for 18% of the observed gender gap in skills at ages 6-7.

The remaining variation in the gender gap is explained by gender differences in the technology of skill formation. Via the simulations, we learn that the socioeconomic gradient in the gender gap can be explained by boys being more sensitive to the inputs to the technology of skill formation. This is because the family socioeconomic environment influences both early skills and parental investments, and boys are more sensitive than girls to both of these inputs. In contrast, the genetic gradient in the gender gap is solely explained by gender differences in the direct effect of genes on skill formation. The simulations can also help us understand why boys are more likely to outperform girls at the tails of the skill distribution even though they lag girls developmentally on average. This is again because boys are more sensitive to early life conditions, and although that hinders the development of boys at the lower end of the socioeconomic and genetic distribution it also boosts the development of boys at the higher end of the distribution.

Lastly, while the model can help us better understand the variation in the gender gaps, it doesn't fully explain why girls develop at faster rates than boys on average. In the model, this is captured by differences in the total factor productivity of skills, with girls being more productive than boys at developing their skills conditional on their genetics and socioeconomic environment. Whether this is due to innate biological differences or due to unobserved social factors that are not accounted for by our model is left for future research.

Our analysis provides new insights into the origins of gender differences in early human capital accumulation by moving beyond mean differences and characterizing the distribution of gender skill gaps across both the biological and social spectrum. The finding that gender gaps are significantly larger among children with lower genetic endowments - and that this is driven primarily by boys' greater sensitivity to these genetic influences in the skill development process - highlights the importance of the nature-nurture interaction in shaping gender disparities. Our results also point to a more nuanced role of the family environment in driving these gaps, with parental investment behavior amplifying initial skill disparities more strongly among boys.

An important caveat to our findings is that differences in genetic sensitivity between boys and girls do not represent fixed or unchangeable developmental paths. While our analysis focuses primarily on parental investments, genetic effects can operate through many environmental channels. As emphasized in recent literature (Turkheimer et al., 2003; Harden, 2021), genes and environment constantly interact to shape development—neither operates in isolation. Consider this example: If schools tend to provide additional support only to boys with high genetic predispositions for academic achievement while supporting girls more uniformly, this would appear in our analysis as boys being more sensitive to their genetic endowments. In this case, changing school policies to provide more uniform support could reduce the apparent genetic sensitivity gap between boys and girls. The same principle applies to parental investments: if parents adjust their investments more strongly based on their sons' genetic predispositions than their daughters', this creates an apparent difference in genetic sensitivity that could be addressed through changes in parenting practices. Therefore, our findings highlight the complex interplay between genes and environment in shaping developmental outcomes and underscore the potential for environmental interventions to mitigate gender disparities.

Our findings have direct implications for education policy and research. For policymakers and educators, our results suggest specific intervention strategies: First, programs should prioritize boys from disadvantaged backgrounds, where gender gaps are largest and most consequential. Second, policies should recognize that the same interventions may have different effects on boys versus girls, requiring tailored approaches. For researchers, our work demonstrates the importance of moving beyond simple average differences between boys and girls. Understanding gender gaps requires examining the full distribution of outcomes and considering how biological and social factors interact. While our specific findings come from one cohort in one context, we provide a framework that can be applied more broadly as genetic and developmental data become available for other populations. This approach opens new avenues for understanding how genetic and environmental factors jointly shape gender differences in human capital development.

The remainder of the paper develops our analysis in several steps. We begin by describing our unique dataset and documenting the basic patterns of gender gaps in early childhood (Section 2). We then develop our conceptual and empirical framework for analyzing skill formation (Section 3). Section 4 presents our main estimation results on gender differences in the skill formation technology and investment functions. We then use these estimates to simulate counterfactual scenarios (Section 5) and decompose the sources of gender gaps (Section 6). We conclude by discussing the implications of our findings for policy and future research (Section 7).

2 Data and Preliminary Analysis

In this section, we introduce the ALSPAC dataset, describe the key variables used in our analysis, and provide a preliminary examination of the relationship between genes linked to educational attainment, socioeconomic status, and gender gaps in early skills. We demonstrate that substantial gender gaps in early skills exist and are more pronounced among children with lower genetic potential for education and those from low socioeconomic status households.

2.1 The Avon Longitudinal Study of Parents and Children (ALSPAC)

The ALSPAC is an ongoing British longitudinal birth cohort study that follows 14,541 women recruited during pregnancy between April 1991 and December 1992, along with their 14,062 children. Epidemiologic researchers from the University of Bristol collected the data to study the environmental and genetic factors affecting human health and development (Boyd et al., 2013; Fraser et al., 2013).[3] The study is particularly well-suited for our analysis as it collects detailed information on children's development, family socioeconomic background, and genetic information from both children and their parents, providing a comprehensive picture of the biological and socioeconomic factors influencing child development.

The developmental and socioeconomic data are based on questionnaires sent to the child's

[3]The study website (http://www.bristol.ac.uk/alspac/researchers/our-data/) provides a fully searchable data dictionary and variable search tool containing details of all available data. Ethical approval for this study was obtained from the ALSPAC Ethics and Law Committee and the Local Research Ethics Committees

primary caregiver (usually the mother) at regular intervals, starting before the child's birth.[4] The caregiver responds to questions about the child's development, behavior, parenting practices, activities, and home environment. The genetic data is derived from blood samples collected from a subset of children and their parents, with genotype data extracted and made available to researchers.[5]

Our analysis focuses on the first seven years of the child's life. We construct our analytic sample by including families with valid information on measures of childhood development and parental investments from ages 0 to 7. We exclude families with missing genetic information for the child or both parents or with missing information on many skill or investment measures.[6] Furthermore, we limit our sample to individuals of European ancestry, as genetic analyses using polygenic scores are only meaningful when comparing individuals of the same ancestry.[7] The resulting analytic sample contains information on 4,510 individuals, consisting of 2,298 males and 2,212 females.

2.2 Key Variables and Summary Statistics

2.2.1 Measures of Early Skills and Parental Investments

We utilize measures of early skills collected from the primary caregiver questionnaires for children aged 0 to 7. Specifically, we focus on measures related to child skill development from the "milestones" and "abilities and disabilities" sections of the questionnaires. In these sections, the primary caregiver is presented with a list of tasks that children gradually learn as they grow and is asked to indicate whether the child (i) "Can do it well" or "Does it often", (ii) "Can do it but not very well" or "Has done it once or twice", or (iii) "Has not yet done it". We select a subset of measures that capture children's ability to process new information, perform various tasks, and learn abstract concepts such as language. Table 1 displays the selected measures.

For family investments, we focus on measurements from the "you and your child" sections of the primary caregiver questionnaires. We select a subset of measures that capture aspects of the family environment related to behaviors and activities involving the child and parents. To achieve balance between parents, we include several measurements specific to both the

[4]Informed consent for the use of data collected via questionnaires and clinics was obtained from participants following the recommendations of the ALSPAC Ethics and Law Committee at the time.

[5]Consent for biological samples was collected in accordance with the Human Tissue Act (2004).

[6]When genetic information is available for the child and one parent, we can confidently impute the missing genetic information of the second parent using the method developed by Young et al. (2022).

[7]Genetic analysis using polygenic scores is only meaningful when comparing individuals of the same ancestry (see Martin et al. (2017) or Mostafavi et al. (2020) for a detailed discussion).

mother and the father, in addition to neutral measurements. For these measurements, the primary caregiver indicates whether the parent engages in certain activities with the child (e.g., "Frequency child goes to the library") and at what frequency: (i) "Nearly every day", (ii) "2-5 times per week", (iii) "Once per week", (iv) "Once per month", (v) "A few times per year", or (vi) "Never". Table 2 presents the selected measures.

Our main analysis, described in Section 3, employs a benchmark econometric model that includes a measurement system to identify the distributions of unobserved skills and investments using these observed measures. However, for the preliminary analysis presented in this section, we construct crude measures of skills and investments by averaging the available measures at each age and standardizing the aggregated measures to have a mean of zero and a variance of one for the full sample. Table 3 reports summary statistics for these crude measures, disaggregated by gender. Females comprise 49% of our sample. We observe substantial gender gaps in both skills and investments, with girls having significantly higher skills in all periods and girls also receiving significantly more parental investments in all but one period.

2.2.2 Measure of Socioeconomic Status

Socioeconomic status (SES) is a proxy for the economic and social resources present in the home the child is born into. Higher family SES thus indicates a higher quality environment during childhood, which is associated with investments in child development and the subsequent development of various skills and preferences (Falk et al., 2021). While there is no universally agreed upon measure of SES, it is common to use parental education and income which appears to capture substantial inequality in environmental quality of relevance for child development (Bradley and Corwyn, 2002; Bornstein et al., 2003). Following this tradition, we create an SES index based on family income and average parental educational attainment. We first standardize the income and education measures, then take the average and standardize it again to have a mean of zero and a standard deviation of one within our sample. We measure parental income and education in the first survey right after the child is born. This measure is used in the analysis as a proxy for home quality to investigate achievement gaps with respect to different childhood home environments.

2.2.3 Polygenic Index for Educational Attainment

The standard approach to quantifying the combined influence of millions of genetic variants is to summarize this variation into a so-called polygenic score or polygenic index (PGI). A PGI is a linear combination of the individual genetic variants weighted by how strongly the specific variants are thought to influence the outcome of interest. For our purpose, we therefore use PGIs for educational attainment and cognitive ability. The weights are externally derived in genome-wide association studies (GWAS).

Formally, a PGI for a particular outcome, p ($pgi_{i,p}$), is the best linear predictor based on the individual genetic variants g_{is} weighted by the strength of association between each SNP and the outcome of interest:

$$pgi_{i,p} = \sum_{s=1}^{S} \beta_s^p g_{is} \tag{1}$$

where g_{is} is individual i's variant at location s, and β_s^p is the GWAS weight for variant s and outcome p. Because g_{is} does not include the sex chromosomes, there are no general differences in this score between boys and girls.

For our empirical model, we utilize three different PGIs to correct for measurement error in the latent genetic factor (see Appendix A.1.2 for details). The PGIs are based on different GWAS samples and/or outcomes. Two of the PGIs capture genetic variants associated with educational attainment. The first is based on the GWAS conducted using 23andMe participants and the second is based on the GWAS sample in Lee et al. (2018) excluding 23andMe participants. The important point here is that the two indexes are then based on two different, non-overlapping samples. The third PGI comes from the GWAS for cognitive performance also based on the sample in Lee et al. (2018) excluding 23andMe participants[8]. When possible, we impute missing parental genotypes before constructing the PGIs. If the genotypes are observed for a parent-offspring pair, the genotype of the missing parent can be inferred using the method by Young et al. (2020).[9]

PGIs have several appealing features. A key advantage is that they allow for the measurement of genetic variation relevant to a particular outcome at the individual level. Because we have genetic information on children and their parents, we can fully exploit the natural experiment created by the inheritance process, whereby variation in the child's PGI is exogenous conditional on the parents' PGIs. Furthermore, our latent factor approach allows us to construct several independent measures of the genetic factor, enabling us to account

[8]We use the publicly available summary statistics at the SSGAC website, which includes the summary statistics of all meta-analysis of all discovery cohorts except 23andMe, as well as private summary statistics provided to us by 23andMe directly.

[9]The idea is that one allele on the missing parental genotype can be inferred exactly unless both the child and the observed parent are heterozygous (have exactly one minor allele). For example, in the case where the mother has two minor alleles (say, CC), and the child has only one minor allele (say, GC), the major allele (G) must have been inherited from the father. The other paternal allele is then known only in expectation based on information about the population frequencies for individuals from a similar ancestry group.

for measurement error in our estimates.

More importantly, the EA PGI can be used to study gender differences in the genetics of skill formation. First, the distribution of the EA PGI is equal across genders since the indexes are constructed using genetic variants from all autosomes (chromosomes other than the sex chromosomes), and the inheritance of autosomes is independent of the inherited sex chromosome due to independent assortment.[10] Second, previous research has shown that the genetic architecture of educational attainment is very similar across sexes, with a near-perfect correlation among the estimated effects of genetic markers on educational attainment across genders (Okbay et al., 2016; Lee et al., 2018). This implies that the same genetic markers that matter for the educational attainment of men also matter for the educational attainment of women. Therefore, differences in the average return to a combination of these markers (i.e., the EA PGS) are informative about true differences in returns to genes across genders.

However, some limitations to the use of PGIs should also be recognized. PGIs do not necessarily capture all relevant genetic effects. First, because the PGI only measures the linear effects of common variants, any gene-gene interactions or rare variants that influence skill formation will not be measured. The omission of rare variants leads to an underestimation of heritability for many traits (Wainschtein et al., 2022). Second, because there is no large GWAS for the cognitive ability of young children, our PGI might miss genetic variants that are important for our outcome but not for adult outcomes. However, this is not a major issue because we are interested in the cognitive development of children insofar as it translates into cognitive ability or educational attainment later in life. It also means that we only capture gender differences in the genetic influences on parental investments insofar as they are related to children's cognitive development or educational attainment. If other types of investments are productive only for other types of skills, we do not estimate how they depend on genetic endowments or how they differ across gender. Finally, a limitation is that the GWAS weights (β_j^ws in Equation 1) are always measured with some error, which generally leads to attenuation bias in the estimates of genetic effects. However, we have no reason to believe this attenuation bias should differ across genders, and the factor analytic approach detailed in Section 3.2 should correct for this error under reasonable assumptions.

2.3 Relating Genes and SES to the Gender Gap in Early Skills

To motivate the exercises carried out in the rest of the paper, we first present some preliminary evidence relating variation in the EA PGI and in SES to the gender gap in early life skill formation. We first explore whether the skill gradients across SES differ between

[10]Independent assortment ensures that the genetic inheritance is independent across all chromosomes.

boys and girls. This is similar to the exercises carried out by Autor et al. (2019). We then check whether the gradients are robust to controlling for genetic variation. Next, we perform the same exercise but start by estimating the gradients by child genetics and then explore whether they are robust to controlling for environmental variation.

Table 4 displays the estimates for the socioeconomic gradients. Panel A shows that, on average across the sample periods, the returns to SES are similar for boys and girls. For both genders, the importance of SES also appears to grow over time. However, we see a tendency for the importance of SES to grow faster for boys than for girls. By ages 6-7, the cognitive skill formation of boys is more sensitive to variation in SES. As girls on average have higher skills than boys (see Table 3, this is consistent with earlier findings about the gender gap being concentrated at the bottom of the socioeconomic distribution (Autor et al., 2019, 2023).

In Panel B, we see that the estimates are robust to controlling for genetic variation in the form of the PGIs for the child and both parents. This suggests that the socioeconomic gradients do not primarily reflect different sensitivities to genetics. However, a limitation of this reduced-form approach is that the PGIs are noisy proxies for the underlying genetic factor. This motivates the econometric model that we set up in Section 3 using a factor analytic approach to control for measurement error in the skill and investment measures as well as the genetic information.

Table 5 displays the corresponding estimates for the genetic gradients. Similar to what we showed for SES, the importance of genetics for early life skill formation appears to increase over the early childhood periods. We also observe a stronger genetic gradient for boys than for girls in all periods. This suggests that boys are not only more sensitive to socioeconomic disadvantage but also to genetic disadvantage. Importantly, even if genes are more important for the development of boys, it does not imply that this genetic effect operates independently of the environment. Indeed, one of the advantages of our structural model described in the next section is that it allows us to estimate to what extent these genetic effects operate through parental investments – one of many potential environmental channels missed by these reduced form estimates.

In Panel B, we again include the parental PGIs as controls. Unlike the estimates for SES, this has the additional advantage that we can interpret the estimates of the returns to the child's PGI as causal because the variation is random when conditional on parental genotypes. We find that the gender difference remains with respect to this causal genetic effect, as the skill formation of boys is more sensitive to differences in their PGI. For girls, the estimates are insignificant. However, as explained the PGI suffers from classical measurement error stemming from uncertainty in the PGI weights which will lead to attenuation bias (Benjamin et al., 2024) – an issue we return to in the next section.

3 Main Econometric Model

To better understand the dynamics highlighted in our preliminary analysis we estimate a structural model of skill formation for boys and girls separately. We closely follow the approach developed in Houmark, Ronda, and Rosholm (2024) to model the dynamics of biological and social influences on skill formation. We jointly estimate the evolution of skills and investments at different periods from birth until age 7. We control for parental genes to causally estimate the impact of genes on skill formation. We also treat child skills, parental investments, and the underlying genetic factors as latent variables to address measurement error. We estimate all parameters in the structural model separately for boys and girls

3.1 Model of Skill Formation

The model considers a family with a single child and two parents. We model the evolution of skills from birth ($t = 0$) until the end of the child's early development at age 7 in period $T = 5$. Skills are complex traits jointly determined by the child's genetic makeup, social environment, and interactions and experiences directly determined by parents, which we refer to as parental investments. All of these can be different for boys and girls. The model has three main components. First, we have the initial skill endowments function that describes how genetics and the social environment influence skills at very early ages (ages 0-2). Second, we have the investment policy function that describes how parental investments are decided in response to the child's current stock of skills, the child's genetic factor, and the family's social environment. Third, we have the technology of skill formation that describes how children's skills evolve as a function of the previous stock of skills, parental investments, the child's genetics, and the family's social environment. We describe these three functions in more detail below.

The Initial Skill Endowments Function:

The child is born in period 0 with a set of initial skill endowments. Let θ_{i0} be the skill endowment of child i at birth. The initial skill endowment is a function of the child's genetic factor (G_i), the family social environment captured in the model by parental genetic factors (G_i^m and G_i^f) as well as the measure of family socioeconomic status (SES_i). The latter factors capture unobserved early life and in utero investments and behaviors that influence initial endowments. The child's genetic factor, on the other hand, captures the idea that, for the same level of parental investments and behaviors, some children are more able to extract nutrients and other resources from their mother in utero and in early life. We allow both of these channels to be different for boys and girls, reflecting the possibility that social and genetic influences on early skills might be dependent on the child's sex.

Formally, we assume a log-linear specification for initial skills, so that:

$$\ln \theta_{i0} = \alpha_{1,g}\, G_i + \alpha_{2,g}\, G_i^m + \alpha_{3,g}\, G_i^f + \alpha_{4,g}\, SES_i + \varepsilon_{i0} \tag{2}$$

where ε_{i0} is an i.i.d., mean zero, and normally distributed shock to early skills, with a different variance for each gender (g). The $\alpha_{1,g}$ parameter captures the effect of the child's genetic factor on her initial stock of skills (i.e., effects during development in utero). The $\alpha_{2,g}$, $\alpha_{3,g}$, and $\alpha_{4,g}$ parameters capture how the association between her parents' genetic factors or the family's socioeconomic environment with the child's initial skills can differ for boys and girls.

The Investment Policy Function:

In order to model parents' investment decisions, we follow previous work by Attanasio, Meghir, and Nix (2020), Agostinelli and Wiswall (2020), and Attanasio et al. (2020) and rely on a reduced-form approximation of the parental behavior.[11] The reduced form specification is consistent with multiple structural models of parental investments (see Attanasio, Meghir, and Nix, 2020), and allows us to abstract from whether parents invest in their children either due to altruism, paternalistic interest in having well-educated children, or some other motivation.

The empirical specification for the investment policy function is:

$$\ln I_{it} = \gamma_{1,t,g} \ln \theta_{it} + \gamma_{2,t,g}\, G_i + \gamma_{3,t,g}\, G_i^m + \gamma_{4,t,g}\, G_i^f + \gamma_{5,t,g}\, SES_i + \eta_{it} \tag{3}$$

where η_{it} are i.i.d., mean zero, and normally distributed shocks with different variances for boys and girls.

This specification allows for parental investments to respond differently to boys' and girls' existing stock of skills ($\gamma_{1,t,g}$) and genetics ($\gamma_{2,t,g}$). These components capture both different parental strategic decisions across genders as well as the idea that different boys and girls might elicit different responses from their parents because of preferences and behavior

[11] Parental investment choices depend on parental preferences for child quality, parental budget constraints, and parents' beliefs about both the child's current skills and the technology parameters. All of these components could be influenced by parents' genetic factors. In principle, we could identify the separate genetic influences on investment choices using a structural model. However, a structural specification would either require detailed data on parental beliefs or assume that parents know the true production function, which goes against recent evidence (see, e.g., Cunha, Elo, and Culhane, 2013; Boneva and Rauh, 2018).

(e.g., enjoying being read stories). These two channels together capture the nurture-of-nature effect described in Houmark, Ronda, and Rosholm (2024), capturing how parental investments respond to the child's genetic makeup. Lastly, different families face different constraints and have different preferences for investments across gender, which are captured by $\gamma_{3,t,g}$, $\gamma_{4,t,g}$, and $\gamma_{5,t,g}$.

The Technology of Skill Formation:

As in Cunha, Heckman, and Schennach (2010), the child's skills in period $t+1$, θ_{it+1}, are determined by their current skills, θ_{it}, and parental investments I_{it}. In addition, we follow Houmark, Ronda, and Rosholm (2024) and allow the child's genetic factor, G_i, and the parents' genetic factors, G_i^m and G_i^f, to enter the production function of skills.

We assume a Cobb-Douglas technology specification in the form:

$$\begin{aligned} \ln\theta_{it+1} = &\ln A_{t,g} + \delta_{1,t,g}\ln\theta_{it} + \delta_{2,t,g}\,G_i + \delta_{3,t,g}\ln I_{it} \\ &+ \delta_{4,t,g}\,G_i^m + \delta_{5,t,g}\,G_i^f + \gamma_{6,t,g}\,SES_i + \epsilon_{it} \end{aligned} \tag{4}$$

where ϵ_{it} is a stochastic technology shock, which we assume is i.i.d. across individuals and time periods and is normally distributed with mean zero and variance $\sigma^2_{\epsilon,g}$.

The technology can differ across gender in a variety of ways. First, it is possible for $\ln A_{t,g}$, the total factor productivity (TFP) parameter at period t, to be different for boys and girls. This captures the possibility that girls might develop at a different rate than boys even when they have the same initial skills, genetics, and family environment. In the same vein $\delta_{1,t,g}$ and $\delta_{2,t,g}$ capture the possibility that the self-productivity of skills and genes can be different across genders. Similarly, parental investments and the social environment can influence boys and girls differently, which is captured by $\delta_{3,t,g}$, $\delta_{4,t,g}$, $\delta_{5,t,g}$, and $\delta_{6,t,g}$.

3.2 Identification and Estimation

Identification of the joint evolution of skills and investments is based on a factor analytic approach as in Cunha and Heckman (2008) and Cunha, Heckman, and Schennach (2010). The identification relies on the idea that, while children's skills and parental investments are unobserved latent constructs, we observe multiple measures of each latent factor and can infer both the distribution and scale of the latent factors from the covariance between the different observable measures. We rely on a similar idea to identify the distribution of genetic factors, where we treat different polygenic scores as observed measures of the unobserved genetic factor (see Houmark, Ronda, and Rosholm (2024) for a detailed discussion of this approach).

Formally, in each period t, we observe J measurements of the child's skills and K measurements of parental investments. For each child, mother, and father trio, we also observe P measurements of their genetics. Let m^{θ}_{ijt} denote the jth measurement of child i's skill at period t, let m^{I}_{ikt} denote the kth measurement of child i's parental investment at period t, and $pgi_{i,p}$ denote the pth measurement of the child's genetic factor. Following Attanasio, Meghir, and Nix (2020) and Agostinelli and Wiswall (2020), we assume a linear-log relationship between each measurement, the latent child skills θ_{it}, and latent parental investments I_{it}:

$$m^{\theta}_{ijt} = \mu^{\theta}_{j,t,g} + \lambda^{\theta}_{j,t,g} \cdot \ln \theta_{it} + \nu^{\theta}_{ijt} \tag{5}$$

$$m^{I}_{ikt} = \mu^{I}_{k,t,g} + \lambda^{I}_{k,t,g} \cdot \ln I_{it} + \nu^{I}_{ikt} \tag{6}$$

$$pgi_{i,p} = \mu^{G}_{p,g} + \lambda^{G}_{p,g} \cdot G_i + \nu^{G}_{ip} \tag{7}$$

where ν^{θ}_{ijt}, ν^{I}_{ikt} and ν^{G}_{ip} are i.i.d. measurement errors and $\lambda^{\theta}_{j,t,g}$, $\lambda^{I}_{j,t,g}$ and $\lambda^{G}_{p,g}$ are the factor loadings for skill measurement j, investment measurement k and polygenic index p. Note that we index each of these parameters by g, meaning that we allow these parameters to differ by gender. As in Agostinelli and Wiswall (2020), we make no further assumptions on the distribution of the measurement errors.

In Appendix A we discuss the assumptions needed for the identification of the latent factors θ_{it}, I_{it}, and G_i. We follow the same approach to identify maternal and parental genetic factors G^m_i and G^f_i. In short, the identification of the system is based on the assumption that the measurement errors are independent of each other and independent across time and on normalization on the location and scale of the latent factor. We refer the reader to Agostinelli and Wiswall (2020), Houmark, Ronda, and Rosholm (2024), and Appendix A for more details on the assumptions required for identification. In addition to these assumptions, identification of the evolution of the latent factor requires further restrictions on the location and scale of the latent factor. In particular, it requires us to observe the same measurement over time and impose the same value for the factor loading for that measurement over all the different periods. In practice, we are fixing the scale of the latent factor against this age-invariant measure.

It is also important to discuss the challenge of identifying group differences in latent factors. In practice, what we can directly observe from the data are gender differences in the average values and distributions of the observed measurements. In theory, there are two reasons that the distribution of measurements can differ across groups. While it is likely that it reflects actual differences in the unobserved latent factors, it is also possible that it captures group differences in the mapping from the latent factors and measurements. That is, even when the distribution of latent factors is the same across two groups, we might observe differences in the measurements if the mapping (factor loadings) are different for the two groups.

While we can never test it directly, we do not consider this a salient concern in our case since both the measurements of skills (see Table 1) and investments (see Table 2) are objective questions that should map in a similar way to unobserved skills and unobserved parental investments across gender. The argument for the genetic constructs could be potentially more debatable if not by previous analyses in Okbay et al. (2016) and Lee et al. (2018) that found that the male-female genetic correlation for years of education is close to one, meaning that the genetic variants related to educational attainment are extremely similar for both sexes.

Estimation of the model parameters is done in two steps. We first estimate all the parameters in the measurement systems for each skill, investment, and genetic factor. These are estimated separately for each gender using the variance-covariance matrix of the measurements for each latent factor. Once the measurement systems are estimated, we proceed with the estimation of the parameters in the technology of skill formation and investment policy function. The estimation strategy follows the approach developed in Agostinelli and Wiswall (2020), and is described in detail in Appendix A.

We rely on a bootstrap procedure for inference. We re-sample the individuals from our initial sample of boys and girls at random with replacement and re-do all estimation steps to obtain new model parameters under each new bootstrap sample. The entire procedure is replicated 1,000 times and is done separately for boys and girls. Using the bootstrap procedure, we compute the 95% confidence intervals that are reported in the paper. The procedure takes into account the joint error across all the estimation steps.

4 Main Results

Our structural model provides a framework to characterize the skill formation of boys and girls. In this section, we report the estimation of the key coefficients of the investment policy function and technology of skill formation separately by gender and discuss the differences in the parameter estimates across gender. We further explore the importance of these differences via simulations in Section 5.

4.1 The Investment Policy Function

We start by reporting on the investment policy function, which characterizes how parents allocate investments across children based on their characteristics. The parameter estimates can be found in Table 7 separately for boys (Panel A) and girls (Panel B). First, looking at the average levels of investments, $E[\ln I_{it}]$, we learn that parental investments are highest in early childhood for both genders. Across all periods, parents invest more in girls than boys, with particularly large differences at ages 4-5, where investments in girls are 0.036 points higher than in boys, which translates to about one-third of a standard deviation. This is consistent with average differences in parental time invested in teaching activities favoring girls documented by Baker and Milligan (2016). We explore the mechanisms behind these differences in Section 6.1.

Child genetic endowments have a positive effect on parental investments, with larger effects at younger ages. This means that parents reinforce initial skill differences by investing more in children with higher existing skills. This effect can be interpreted as causal since variation in children's genes is exogenous to environmental effects once we control for parental genes. This pattern has been previously documented by Breinholt and Conley (2023) and Houmark, Ronda, and Rosholm (2024). Similarly, we find that, in our sample, parents tend to reinforce initial differences in skills by investing more in children with a higher stock of skills. Because skills are influenced by genetic and socioeconomic conditions, this also implies that parents invest more in children who are initially advantaged genetically or socioeconomically. This is true for both boys and girls and there is no clear gender differences in this mechanism.

Both parental genes and family socioeconomic status are positively associated with investments for both genders. While estimates are noisy, we see some evidence that maternal genes are more positively associated with investments for girls, whereas paternal genes are more positively associated with investments for boys. This could reflect a gendered pattern in parental investments where parents spend relatively more time with their same-sex children. We also see some indication that mothers' genes generally matter more than fathers'. There are no clear patterns in the influence of SES on parental investments across gender.

4.2 The Technology of Skill Formation

Next, we examine the technology of skill formation, which describes how skills evolve over time based on current skills, parental investments, and child and family characteristics. Parameter estimates are presented in Table 8 separately for boys (Panel A) and girls (Panel B).

First, looking at the average levels of skills, $E[\ln \theta_{it}]$, we see that girls have higher average skill levels than boys at every period, with the gap increasing over time. At ages 6-7, girls' skills are about 0.25 standard deviations higher than boys'. The variance in skills, $Var(\ln \theta_{it})$, is initially smaller for boys but becomes significantly larger later in childhood compared to girls. This is a theme we will come back to when discussing mechanisms in Section 6.

The child's genetic endowment has a direct positive effect on skill formation even after accounting for family environment, investments, and prior skills. This effect, which can be interpreted as causal (see Houmark, Ronda, and Rosholm (2024)), increases over time and is larger for boys, although gender differences are not statistically significant. An initial genetic advantage thus continues to pay dividends for the future realization of skills given the same current observable conditions.

Parental genes do not significantly influence skill formation once we control for family SES and investments. Family SES does have an additional positive influence on skill formation after accounting for investments. However, there are no clear differences in this effect across gender.

There are also no statistically significant gender differences in the self-productivity of skills, the returns to investments, or the total factor productivity. However, the point estimates suggest that boys have higher self-productivity of skills and returns to investments in most periods, while girls tend to have higher total factor productivity, which explains their higher average skill levels. We return to these patterns in Section 6.

5 The Distribution of the Gender Gaps

How do the gender differences in the technology of skill formation and investment policy function translate into differences in early childhood skills? In this section, we use model simulations to map the distribution of gender skill gaps under different initial conditions. By equalizing specific factors across genders, we isolate the influence of each factor on the overall distribution of the gender gap.

5.1 Simulating the Skills of Boys and Girls

Our model has 4 main initial factors that make up a child's "accident of birth": the child's genetic factor (G), the mother's genetic factor (G^m), the father's genetic factor (G^f), and the family socioeconomic status (SES). These four factors capture the initial allocation of advantages and disadvantages that are both randomly determined and inherited from the previous generation, leading to subsequent inequality in skill formation. Given these factors, the child's gender, and exogenous shocks (η_t and ϵ_t), we can use the estimated model parameters to simulate a child's expected skill development trajectory depending on their gender.

We randomly draw 10,000 values from the joint distribution of the 4 initial factors (Equation 8):

$$\begin{pmatrix} G_k \\ G_k^m \\ G_k^f \\ SES_k \end{pmatrix} \sim N(\mu, \mathbf{\Sigma}) \tag{8}$$

where $\mu = 0$ for all 4 factors and Σ is the joint covariance matrix of the 4 parameters shown in Table 6. This approach relies on the fact that the 4 initial factors are normally distributed by construction.

For each draw, we simulate 100 trajectories by further drawing shocks to skill formation ($\epsilon_{k,s,t}$) and the investment function ($\eta_{k,s,t}$) over time, using the gender-specific shock variances estimated in the model. This process gives us a simulated dataset mapping initial conditions and shocks to latent skills (θ) and parental investments (I) for boys and girls, which can be represented by:

$$\ln \theta^m_{k,s,t} = \Phi^m_t(G_k, G^m_k, G^f_k, SES_k, \{\epsilon_{k,s}\}, \{\eta_{k,s}\} | g = m) \tag{9}$$
$$\ln \theta^f_{k,s,t} = \Phi^f_t(G_k, G^m_k, G^f_k, SES_k, \{\epsilon_{k,s}\}, \{\eta_{k,s}\} | g = f) \tag{10}$$
$$\ln I^m_{k,s,t} = \Theta^m_t(G_k, G^m_k, G^f_k, SES_k, \{\epsilon_{k,s}\}, \{\eta_{k,s}\} | g = m) \tag{11}$$
$$\ln I^f_{k,s,t} = \Theta^f_t(G_k, G^m_k, G^f_k, SES_k, \{\epsilon_{k,s}\}, \{\eta_{k,s}\} | g = f) \tag{12}$$

where Φ^m_t and Φ^f_t are the mappings translating the initial factors and shocks to skills for boys and girls, and Φ^m_t and Φ^f_t are the mappings translating the initial factors and shocks to parental investments for boys and girls.

We use these simulations to explore how gender skill gaps vary across the distributions of initial genetic endowments and family environments.

5.2 Gender Differences in the Distribution of Skills

Using the approach discussed in Section 5.1 we can explore how the gender gap in skills at ages 6-7, the last period in our data, varies across both the child's genetic factor and her family environment. For all the analyses in this section, we describe the gap from the perspective of girls, so that a negative value in the gender gap implies that boys are lagging in their skill development compared to similar girls. Also, for all analyses, the skills are standardized with respect to the distribution of girls' skills.

The distribution of the gender gaps in skills at ages 6-7 can be seen in Figure 2. Figure 2(a) plots the kernel density distribution of the gender gaps. We also report on the mean and standard deviation of the gap in the first row of Table 9.On average, girls' skills are about 0.25 standard deviations higher than that of boys. However, there is significant variation in the distribution, with about 17% of boys having higher latent skills than girls with similar genetics, family environment, and developmental shocks. This figure shows how averages can be deceiving and that there is important variation in the average gender skill gaps.

To better understand this variation, in Figures 2(b) and 2(c) we plot the gender gap in skills at ages 6-7 over the distribution of the child's initial skills and family environment. We do so in two ways. First, in blue, we plot the raw relationship in the data when we simulate the skills and investments using the observed covariance between the 4 initial factors. Second, in red, we plot the relationship due to each specific factor (G_i and SES_i). We do so by re-simulating the skills and investments but assuming the 4 initial factors are independent. This breaks the correlation between the factors and is akin to varying one of the factors while holding all other factors constant, allowing us to estimate the influence of each initial factor separately.

Figure 2(b) plots the gender gaps in skills at ages 6-7 as a function of SES. It confirms previously documented findings that boys appear more sensitive to the environment than girls (Bertrand and Pan, 2013; Autor et al., 2019). That is, the gender gap is higher among children growing up in disadvantage than among children growing up in more advantageous environments. Figure 2(b) also shows that this heterogeneity is partially explained by differences in genetics among high and low SES families as the heterogeneity across SES decreases once we account for the correlation between SES and genetic factors. Hence, what appears to be a greater sensitivity to environmental conditions among boys turns out to partly reflect a greater sensitivity to genetic endowments. This leads to the results in Figure 2(c).

Figure 2(c) shows one of the key new findings from our paper. The gender gaps in skills are highly dependent on the child's genetic factor (G_i). For children with a high genetic potential for education, we see that boys develop at a similar or higher rate than girls. However, at the other end of the distribution, for children with a low genetic potential for education, boys significantly lag behind girls. This is true even after we account for the correlation between the child's genetic factor and environmental effects.

These results can reconcile two seemingly contradictory patterns - that boys both fall behind girls on average in school but are also over-represented among the highest achieving students (see e.g., Penner and Paret (2008), Baye and Monseur (2016), and Machin and Pekkarinen (2008)). Because boys are more sensitive to genetics and the family environment than girls, their skill distribution is more variable than girls, meaning that they are both over-represented at the bottom and at the top of the skill distribution, whereas girls are more likely than boys to be at the middle of the distribution. Also, given that girls are significantly ahead developmentally than boys on average, this means that the left tail of the skill distribution consists almost exclusively of boys.

6 Mechanisms Behind the Distribution of Gender Gaps

In addition to mapping the heterogeneity in the gender gaps, the model can also help us understand what are the mechanisms that explain the heterogeneity documented in Figure 2(a). For example, is the heterogeneity across SES explained by differences in parental investments? Or can the differences in the self-productivity of skills help explain why some boys are developmentally ahead of girls? To answer these questions we re-simulate the investments and skills of boys while changing the parameters in their investment policy function and technology of skill formation to resemble the parameter estimates for girls. As we equate each of the different parameters, we restrict each of the channels via which the development of boys and girls differ, allowing us to understand the relevance of the different channels.

6.1 Gender Differences in Parental Investments

We first focus on possible gender differences in parental investments. The blue line in Figure 3(a) plots the distribution of the gender differences in parental investments at ages 4-5. We focus on ages 4-5 since this is the period where the gender differences in investments are the largest and the period where investments matter the most for subsequent skill development. In Section 6.1.1, we instead illustrate the accumulated effect of investments in all periods for the gender gap in skills in the last period. As can be seen from the blue line in Figure 3(a), the gap in investments is consistently negative, meaning that girls tend to receive a higher amount of investments than boys. On average, girls receive about a 0.36 standard deviation higher investment level than boys. This is consistent with previous findings from the literature looking at gender gaps in parental investment in developed countries (see e.g., Baker and Milligan (2016) and Bibler (2020)).[12]There is also significant variation in the

[12]Although it is important to note that the reverse pattern is observed in developing countries (see e.g., Barcellos, Carvalho, and Lleras-Muney (2014)).

gender gap in investments, with the gap being close to zero for some children and up to one standard deviation for others.

Figures 3(b) and 3(c) plot the distribution of the gap across socioeconomic status (SES_i) and child genes (G_i) respectively. The blue lines plot the relationship assuming the 4 inputs are independent. Figure 3(b) shows that there is very little variation in the gender gap in investments, if anything, the gap seems to be larger in higher socioeconomic status families. In contrast, 3(c) shows a substantial heterogeneity across the child's genetic factor, with boys with lower genetic potential for education receiving a significantly lower level of parental investments than comparable girls.

To better understand why such heterogeneity exists we sequentially change each parameter in the investment policy function for boys to resemble that of girls. That is, we re-simulate investments and skills for boys imposing the same parameters in the investment policy function that were estimated for girls. We first change the returns to environmental effects for boys ($\gamma_{3,t}$, $\gamma_{4,t}$ and $\gamma_{5,t}$ in Equation 3) to be equal to that of girls. Represented by the red line in the graphs, this produces very little change in the investment gaps besides slightly decreasing their overall variance. For the genetic heterogeneity, this is expected because the variation in the child's genes is exogenous conditional on parental genes. For the socioeconomic heterogeneity, this implies that it does not result directly from different investment profiles across SES for boys and girls.

We then further equate the returns to skills and genes ($\gamma_{1,t}$ and $\gamma_{2,t}$ in Equation 3). Represented by the orange curves, this change substantially decreases the variance in the investment gap as seen in Figure 3(a). Moreover, it almost eliminates the heterogeneity in the investment gaps across socioeconomic status and child genes as seen in Figures 3(b) and 3(c). This shows that a significant part of the gender differences in investment can be attributed to differences in how parents respond to the skills and behaviors of boys and girls.

The average gap in investments, however, remains substantial and mostly closes only once we equate the intercept ($\gamma_{0,t}$), illustrated by the purple curves. The reason that the gap does not close completely is because of the average difference in skills between boys and girls. Parents reinforce initial differences in skills by investing more in children with higher skill levels, all else equal. Since girls have higher skill levels than boys on average, we observe higher investments for girls even after we account for differences in the investment policy function.

These results together demonstrate why girls receive higher levels of investment from their parents. First, parents tend to reinforce skill differences, and since girls have higher skill levels on average than boys parents tend to invest more in them. Second, this reinforcing behavior is significantly stronger for boys than girls, meaning that boys with lower levels of skills and a lower propensity for education receive significantly lower levels of investments than comparable girls. Unfortunately, our data does not allow us to explain why parents are more responsive to the skills of boys than girls when allocating investments. There are many possible explanations, including whether this is induced by the child (e.g. girls are more likely to ask to be taken to a museum all else equal) or by the parent (e.g. optimal allocation of investments is different across gender). Future research should look into these different possibilities.

6.1.1 Parental Investments and Gender Gaps in Skills

The gender differences in parental investments documented above can partially explain the observed differences in skills. This is shown in Figure 4, where we re-do the exercise in Figure 3 but consider the effect on latent skills at ages 6-7. Again, the blue curves plot the baseline gender gaps in skills with the 4 initial factors as independent, and the purple curve represents the gender gaps in skills when all the parameters in the policy function for boys are set as the parameters estimated for girls.

Figure 4(a) shows how the distribution of the skill gaps changes once we account for differences in the investment policy for boys and girls. We also document how the average skill gap and the variance of the gap changes as we equalize the investment policy function across gender in panel B of Table 9. The overall distribution of gender gaps moves to the right (smaller gaps), and on average the skill gap decreases from 0.26 standard deviations to 0.21 standard deviations, a reduction of about 18%. Figures 4(b) and 4(c) also show that this reduction in the gender skill gap happens across the whole for families across the socioeconomic spectrum and for children with different genetic endowments. The remainder of the gap is explained by differences in the technology of skill formation, which we discuss in the next section.

6.2 Gender Differences in the Technology of Skill Formation

While differences in parental investments across genders explain some of the gender differences in skill formation, most of the variation is due to gender differences in the technology of skill formation. We follow a similar approach to the one discussed in the previous section to better understand which parameters in the technology are important for explaining both the variance and the mean of the gender gaps in skills. That is, we re-simulate the investment and skills of boys imposing the same parameters in the technology of skill formation that were estimated for girls. The results from this exercise are shown graphically in Figure 5 and numerically in panel C of Table 9.

We start the analysis where we left off, imposing the policy investment parameters estimated for girls onto the simulation for boys, represented by the navy blue curves in Figure 5. We then change the returns to environmental effects in the technology of skill formation of boys ($\delta_{4,t}$, $\delta_{5,t}$ and $\delta_{6,t}$ in Equation 4) to be equal to that of girls. This is represented by the red line, which overlaps the blue line in the three graphs, meaning that equalizing returns to environments produces very little change in the gender skill gap distribution. Again, this is expected for the genetic heterogeneity but is particularly interesting when looking at the heterogeneity of the gender gap across family SES in Figure 5(b), since it implies that the heterogeneity across socioeconomic environments is not driven by different returns to SES.

We then equalize the direct effect of the child's genetic factor in the technology of skill formation ($\delta_{3,t}$ in Equation 4). This significantly decreases the variance in the gender gaps as shown by the orange curve in Figure 5(a). It also completely explains the heterogeneity in the gender gaps across the child's genetic factor. This implies that, in contrast to what we just showed for SES, most of the heterogeneity in gender skill gaps across genetics can be attributed to gender differences in the direct effect of genes on skill formation. In other words, boys are significantly more sensitive in early life to genetics related to educational attainment than girls are.

The remaining gender differences can be attributed to (i) gender differences due to different returns to parental investments, (ii) different returns to own skills (self-productivity), and (iii) other unexplained differences in development captured by the total factor productivity parameter ($\delta_{2,t}$, $\delta_{1,t}$, and $\ln At$ in Equation 4). We equate each of these mechanisms one by one and illustrate the remaining gender skill gap by the purple curve, the green curve, and the light blue curve, respectively, in Figure 5. Equating the returns to parental investments and the self-productivity of skills reverses the heterogeneity in the gender skill gap across SES (Figure 5(b). Equating the self-productivity parameter seems to be especially important for closing most of the variance in gender gaps (Figure 5(a). The higher self-productivity of skills for boys can partially explain why boys are more likely to outperform girls at the right tail of the skill distribution even though they lag behind girls on average. Due to the higher returns, boys at the top of the skill distribution tend to accumulate skills faster than comparable girls, increasing their advantage at the top of the distribution.

While these two mechanisms help explain the variance in the gender gaps, the majority of the average gender gap in skills is still unexplained by our model and is captured by gender differences in the total factor productivity ($\ln At$). Whether this is due to biological differences between girls and boys that cannot be explained by social surveys, or this is due to unobserved factors that are not accounted for by our model and data (e.g., gender differences in socio-emotional skills) is left as an important question for future research.

7 Discussion and Conclusion

To better understand the biological and social determinants of early gender gaps in skills and their implications for policy, we incorporated genetic factors into a dynamic model of skill formation. We modeled and estimated the joint evolution of cognitive skills and parental investments from birth to age 7 separately for boys and girls. Our analysis documents several important differences in the skill formation process between boys and girls. First, we find that boys are more sensitive to their own genetic endowments: Conditional on current skills and parental investments, the future skill development of boys is more sensitive to their genetic potential for education such that some boys accumulate cognitive skills more rapidly while others accumulate more slowly relative to girls with similar genetic potential. This greater genetic sensitivity largely explains why the gender gap in skills is so much larger among children with lower polygenic indexes. It also explains why, even while girls outperform boys on average, boys with particularly high genetic potential tend to outperform girls with similar potential. We also find a stronger association between the child's genetic potential and parental investments among boys (Figure 3(c)), indicating that parents are more likely to reinforce initial genetic differences when allocating resources to sons relative to daughters.

It is important to stress that the different sensitivity to own genetic endowments should not be interpreted as an effect operating independently of the environment. Within our framework, this direct genetic effect captures genetic differences that causally affect skill formation independently only of the specific environment that we call parental investments. Thus, the effect may operate through other environmental channels that are unobservable to us. For example, it has been found that girls from a young age allocate more of their own time to educational activities (Nguyen et al., 2022). If this difference in self-investments is more concentrated at the lower end of the genetic distribution, it could help to explain how the direct genetic effect shapes the gender skill gap.

Our estimated model also reveals a higher degree of skill self-productivity among boys. That is, the rate at which current skills beget future skills is greater for boys compared to girls, especially at the higher end of the initial skill distribution. This helps explain why the most skilled boys eventually outperform even the most skilled girls as initial skill gaps are amplified over time. Finally, we find that eliminating gender differences in parental investments can close about one-fifth of the early gender gap in skills, as girls start out with higher average skill levels and benefit from the greater tendency of parents to reinforce these initial skill differences among sons.

Yet, the majority of the early gender skill gap cannot be explained by investment differences or even by gender differences in the productivity of investments or skills in our model. Instead, it is captured by a sizable gap in the total factor productivity of skills in favor of girls. Whether this residual gap reflects intrinsic biological differences between boys and girls in early childhood or the influence of unmodeled factors like non-cognitive skills is an important question for future research.

Together, these findings highlight the importance of looking beyond mean differences when studying gender gaps in early skills and point to new directions for policies aimed at closing these gaps. Our findings suggest that policies aiming to close early gender gaps in skills would be most effective if targeted to boys at the lower end of the genetic and socioeconomic spectrum. More broadly, our analysis underscores the need to consider both social and biological factors to fully understand the roots of gender differences in human capital development.

A limitation of our analysis is that we measure genetic influences using polygenic indexes constructed from GWAS on educational attainment and cognitive performance. These indexes proxy for genetic influences on early childhood cognitive development, but they may miss genetic pathways operating through other non-cognitive or health-related domains that nevertheless shape skill formation. Another constraint is that we focus exclusively on cognitive skills due to data limitations. It is likely that gender differences in early non-cognitive skills play an important role in explaining later educational disparities, and this is a fruitful avenue for future work as new data becomes available.

It is also critical to recognize that our empirical findings pertain to a single cohort in a particular context, and thus may not generalize to other settings or to more recent cohorts. The gender differences we estimate may vary across countries and time periods with different institutions, norms, and policies. Moreover, our analytic sample is restricted to European-ancestry individuals due to well-known challenges with the portability of polygenic indexes to non-European populations (Martin et al., 2017; Mostafavi et al., 2020). This points to the urgent need to diversify genetics research and expand GWAS studies to other ancestries to ensure that advances in this field do not exacerbate existing health and social inequities (Martin et al., 2019). While we believe the key insights from incorporating genetics into social science models of child development are broadly relevant, we cannot test for any differences in these processes across ancestry groups until more representative genetic data becomes available.

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Tables and Figures

Table 1: Measures of Child Skills

	Period	0	1	2	3	4	5
Measure	Age	0-2	2-3	3-4	4-5	5-6	6-7
1	Can build tower of 8 bricks	X	X	X			
2	Plays cards (or board games)		X	X	X	X	X
3	Plays peek-a-boo	X					
4	Can focus eyes on small object	X					
5	Can build tower of 4 bricks	X					
6	Freq. names things	X					
7	Combines two different words		X				
8	Can copy vertical line with pencil		X				
9	Can copy and draw a circle		X	X			
10	Uses plurals		X	X			
11	Uses possessives		X	X			
12	Adds -ing to words		X	X			
13	Adds -ed to words		X	X			
14	Can copy and draw a plus sign / cross			X			
15	Can copy and draw a square			X	X		
16	Can write their name				X		
17	Can write any numbers				X		
18	Knows at least 10 letters				X		
19	Can read simple words				X		
20	Can read a story with <10 words per page				X		
21	Can count up to 20				X		
22	Can read a story with >10 words per page				X	X	X
23	Can count up to 100				X	X	X
24	Can play any board games				X	X	X

Notes: This table reports the individual measures of child skills. An X indicates that the measure is available in that period and is used in the estimation.

Table 2: Measures of Investments

	Period	0	1	2	3	4
Measure	Age	0-2	2-3	3-4	4-5	5-6
1	Freq. goes to places of interest	X	X	X	X	X
2	Freq. goes to library	X	X	X	X	X
3	Freq. mum reads to child	X	X	X	X	X
4	Freq. partner sings to child	X	X	X	X	X
5	Freq. child taken to park	X	X	X		
6	Freq. mum shows child picture books	X		X		
7	Freq. partner shows child picture books	X		X		
8	Freq. partner plays with toys with child	X		X		
9	Freq. partner reads to child	X		X	X	X
10	Freq. goes to swimming pool or sports area				X	X
11	Freq. goes to special classes or clubs				X	X

Notes: This table reports the individual measures of child investments. An X indicates that the measure is available in that period and is used in the estimation.

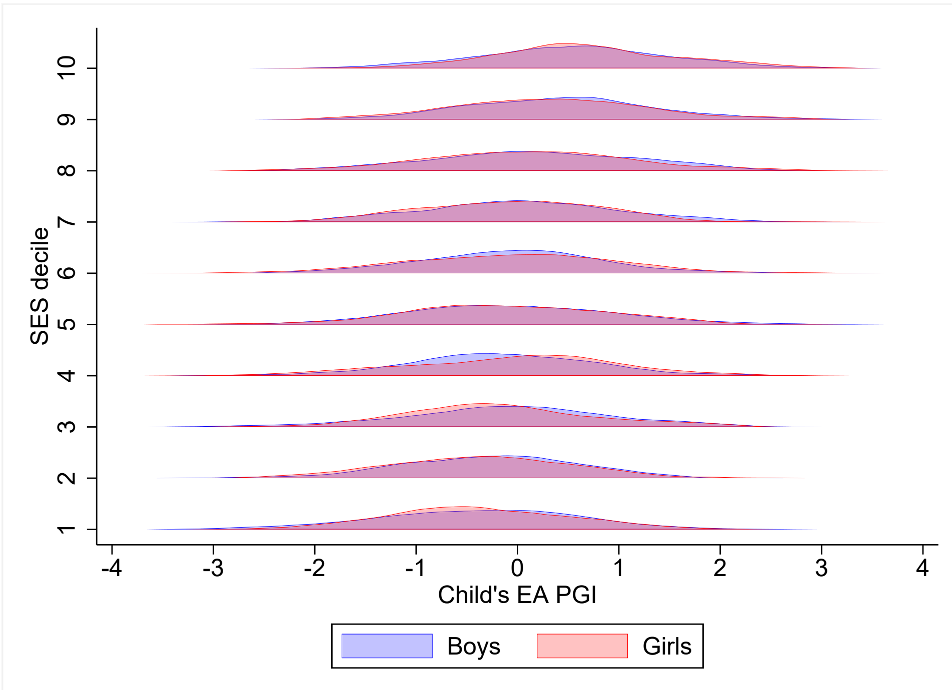


Figure 1: Distribution of Children's EA PGI by Family SES: This figure plots the density of the standardized educational attainment polygenic index (EA PGI) of children, separately for each gender and decile of family socioeconomic status (SES). The figure highlights three important facts: (i) the distribution of the EA PGI is the same for boys and girls due to independent assortment, which means that the inheritance of chromosomes is independent of the sex chromosomes; (ii) the child's EA PGI is correlated with the family environment, likely because the child's EA PGI is correlated with their parents' EA PGI, which in turn influences the family social environment; and (iii) despite the correlation between the child's EA PGI and family environment, there is significant overlap in the distribution of genetic potential for education across all family SES deciles, indicating that family environment does not fully determine a child's genetic potential for educational attainment.

Table 3: Standardized Measures of Skills and Investments by Gender

	Boys	Girls	Diff
Skills Period 1	-0.0386	0.0401	***
	(0.548)	(0.543)	
Skills Period 2	-0.146	0.152	***
	(0.586)	(0.574)	
Skills Period 3	-0.112	0.117	***
	(0.629)	(0.522)	
Skills Period 4	-0.0882	0.0917	***
	(0.633)	(0.527)	
Skills Period 5	-0.0881	0.0915	***
	(0.748)	(0.628)	
Skills Period 6	-0.0641	0.0665	***
	(0.756)	(0.603)	
Inv. Period 1	-0.0222	0.0231	**
	(0.553)	(0.538)	
Inv. Period 2	-0.0307	0.0319	***
	(0.606)	(0.585)	
Inv. Period 3	-0.0127	0.0132	
	(0.536)	(0.537)	
Inv. Period 4	-0.0537	0.0558	***
	(0.488)	(0.523)	
Inv. Period 5	-0.0438	0.0455	***
	(0.489)	(0.492)	
N	2298	2212	4510

Notes: This table reports means and standard deviations for the standardized skill and investment measures separately for boys and girls. The last column reports the significance of a t-test for different means.

Table 4: SES and Skills by Age

Ages:	[0-2[	[2-3[	[3-4[	[4-5[	[5-6[	[6-7[
Panel A (boys):						
SES	0.072***	0.116***	0.193***	0.266***	0.221***	0.200***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.023)
R_2	0.005	0.013	0.031	0.059	0.040	0.031
N	2298	2298	2298	2298	2298	2298
Panel B (boys):						
Child's PGI	0.044	-0.017	-0.026	0.080**	0.108***	0.089**
	(0.038)	(0.037)	(0.040)	(0.040)	(0.040)	(0.041)
Mother's PGI	0.008	0.017	0.009	-0.022	0.006	-0.005
	(0.029)	(0.028)	(0.030)	(0.030)	(0.030)	(0.031)
Father's PGI	-0.037	0.025	0.041	-0.003	0.003	0.004
	(0.032)	(0.031)	(0.034)	(0.034)	(0.034)	(0.035)
SES	0.060***	0.107***	0.184***	0.248***	0.190***	0.173***
	(0.023)	(0.022)	(0.024)	(0.024)	(0.024)	(0.024)
R_2	0.008	0.012	0.031	0.060	0.051	0.038
N	2298	2298	2298	2298	2298	2298
Panel A (girls):						
SES	0.097***	0.157***	0.200***	0.257***	0.228***	0.151***
	(0.021)	(0.021)	(0.019)	(0.019)	(0.019)	(0.019)
R_2	0.009	0.025	0.049	0.079	0.061	0.028
N	2212	2212	2212	2212	2212	2212
Panel B (girls):						
Child's PGI	-0.014	0.034	0.001	0.059*	0.040	0.007
	(0.040)	(0.039)	(0.035)	(0.035)	(0.036)	(0.035)
Mother's PGI	0.016	-0.004	0.040	0.015	0.012	0.014
	(0.030)	(0.029)	(0.026)	(0.026)	(0.026)	(0.026)
Father's PGI	0.000	-0.040	0.010	-0.029	-0.005	-0.006
	(0.034)	(0.032)	(0.029)	(0.029)	(0.030)	(0.030)
SES	0.093***	0.152***	0.182***	0.242***	0.220***	0.143***
	(0.023)	(0.022)	(0.020)	(0.020)	(0.020)	(0.020)
R_2	0.005	0.025	0.053	0.081	0.063	0.026
N	2212	2212	2212	2212	2212	2212

Notes: This table reports parameter estimates from regressions used to link the SES index to children's skills across childhood. To estimate the sensitivity to SES, we regress at each age the skill measure on the SES index separately for boys and girls. In Panel B, we add the child and parental polygenic indexes to the regressions. Skills have been standardized as described in the data section, with missing values set equal to the median for that measure, allowing for a maximum of ten such imputations per summary index. The polygenic indexes were constructed using the summary statistics in Lee et al. (2018) without the 23andMe information with the imputed parental genotypes. Standard errors are reported in parenthesis.

Table 5: EA PGI and Skills by Age

Ages:	[0-2[	[2-3[	[3-4[	[4-5[	[5-6[	[6-7[
Panel A (boys):						
Child's PGI	0.038*	0.036*	0.054**	0.130***	0.162***	0.133***
	(0.021)	(0.021)	(0.023)	(0.023)	(0.022)	(0.023)
R_2	0.001	0.001	0.002	0.015	0.022	0.014
N	2298	2298	2298	2298	2298	2298
Panel B (boys):						
Child's PGI	0.044	-0.017	-0.026	0.080**	0.108***	0.089**
	(0.038)	(0.037)	(0.040)	(0.040)	(0.040)	(0.041)
Mother's PGI	0.008	0.017	0.009	-0.022	0.006	-0.005
	(0.029)	(0.028)	(0.030)	(0.030)	(0.030)	(0.031)
Father's PGI	-0.037	0.025	0.041	-0.003	0.003	0.004
	(0.032)	(0.031)	(0.034)	(0.034)	(0.034)	(0.035)
SES	0.060***	0.107***	0.184***	0.248***	0.190***	0.173***
	(0.023)	(0.022)	(0.024)	(0.024)	(0.024)	(0.024)
R_2	0.008	0.012	0.031	0.060	0.051	0.038
N	2298	2298	2298	2298	2298	2298
Panel A (girls):						
Child's PGI	0.019	0.043**	0.077***	0.110***	0.100***	0.048**
	(0.021)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
R_2	0.000	0.002	0.009	0.015	0.011	0.003
N	2212	2212	2212	2212	2212	2212
Panel B (girls):						
Child's PGI	-0.014	0.034	0.001	0.059*	0.040	0.007
	(0.040)	(0.039)	(0.035)	(0.035)	(0.036)	(0.035)
Mother's PGI	0.016	-0.004	0.040	0.015	0.012	0.014
	(0.030)	(0.029)	(0.026)	(0.026)	(0.026)	(0.026)
Father's PGI	0.000	-0.040	0.010	-0.029	-0.005	-0.006
	(0.034)	(0.032)	(0.029)	(0.029)	(0.030)	(0.030)
SES	0.093***	0.152***	0.182***	0.242***	0.220***	0.143***
	(0.023)	(0.022)	(0.020)	(0.020)	(0.020)	(0.020)
R_2	0.005	0.025	0.053	0.081	0.063	0.026
N	2212	2212	2212	2212	2212	2212

Notes: This table reports parameter estimates from regressions used to link the polygenic index for educational attainment to children's skills across childhood. To test the sensitivity to the EA PGI, we regress at each age the skill measure on the polygenic index separately for boys and girls, controlling for and the first 15 principal components of the genetic matrix. In Panel B, we add the parental polygenic indexes and SES to the regressions. Skills have been standardized as described in the data section, with missing values set equal to the median for that measure, allowing for a maximum of ten such imputations per summary index. The polygenic indexes were constructed using the summary statistics in Lee et al. (2018) without the 23andMe information with the imputed parental genotypes. Standard errors are reported in parenthesis.

Table 6: Initial Factors Covariance Matrix

Factor:	G_i	G_i^m	G_i^f	SES_i
G_i	1.00	0.56	0.68	0.26
G_i^m		1.00	0.09	0.26
G_i^f			1.00	0.21
SES_i				1.00

Notes: This table reports the covariance matrix for the 4 initial factors at birth.

Table 7: Investment Policy function

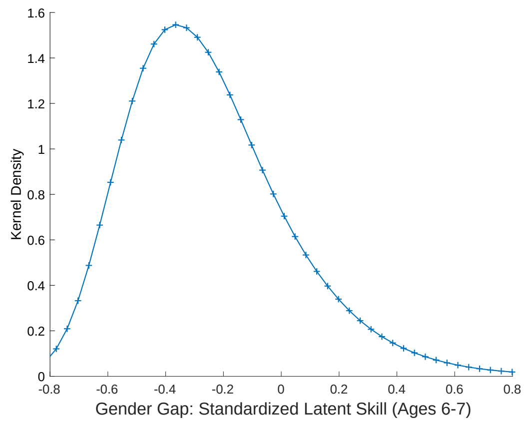
Panel A:			Boys		
	Ages 0-2	Ages 2-3	Ages 3-4	Ages 4-5	Ages 5-6
	(1)	(2)	(3)	(4)	(5)
G_i	0.022	0.027	0.018	0.005	-0.003
	[-0.004, 0.044]	[-0.011, 0.057]	[0.001, 0.035]	[-0.003, 0.014]	[-0.012, 0.008]
G_i^m	0.017	0.033	0.001	0.003	0.001
	[-0.003, 0.036]	[0.005, 0.069]	[-0.014, 0.016]	[-0.004, 0.010]	[-0.005, 0.007]
G_i^f	0.008	0.017	0.003	0.003	0.013
	[-0.013, 0.029]	[-0.009, 0.055]	[-0.012, 0.019]	[-0.004, 0.012]	[0.004, 0.021]
SES_i	0.108	0.151	0.084	0.042	0.038
	[0.091, 0.127]	[0.130, 0.177]	[0.068, 0.101]	[0.035, 0.051]	[0.027, 0.047]
$\ln \theta_{it}$	0.297	0.664	0.134	0.060	0.074
	[0.220, 0.354]	[0.514, 0.809]	[0.099, 0.170]	[0.042, 0.080]	[0.049, 0.094]
Constant	4.210	2.798	3.148	2.595	2.530
	[4.122, 4.324]	[2.406, 3.193]	[3.036, 3.264]	[2.518, 2.664]	[2.450, 2.624]
$E[\ln I_{it}]$	4.627	4.496	3.550	2.791	2.783
$Var(\ln I_{it})$	0.102	0.151	0.050	0.009	0.007
Panel B:			Girls		
	Ages 0-2	Ages 2-3	Ages 3-4	Ages 4-5	Ages 5-6
	(1)	(2)	(3)	(4)	(5)
G_i	0.030	0.014	0.005	-0.009	0.002
	[-0.005, 0.064]	[-0.020, 0.056]	[-0.015, 0.024]	[-0.018, 0.000]	[-0.007, 0.009]
G_i^m	0.004	0.050	0.022	0.015	0.006
	[-0.016, 0.028]	[0.014, 0.076]	[0.008, 0.038]	[0.007, 0.022]	[0.001, 0.012]
G_i^f	-0.009	-0.005	0.006	0.011	0.003
	[-0.037, 0.018]	[-0.034, 0.017]	[-0.012, 0.025]	[0.003, 0.020]	[-0.003, 0.009]
SES_i	0.113	0.159	0.070	0.043	0.040
	[0.098, 0.136]	[0.137, 0.191]	[0.055, 0.086]	[0.033, 0.052]	[0.027, 0.047]
$\ln \theta_{it}$	0.320	0.570	0.155	0.082	0.092
	[0.245, 0.400]	[0.439, 0.727]	[0.112, 0.205]	[0.056, 0.108]	[0.059, 0.114]
Constant	4.191	3.053	3.084	2.554	2.489
	[4.062, 4.301]	[2.636, 3.406]	[2.923, 3.225]	[2.440, 2.647]	[2.403, 2.608]
$E[\ln I_{it}]$	4.657	4.557	3.564	2.827	2.810
$Var(\ln I_{it})$	0.100	0.172	0.049	0.010	0.007

Notes: This table reports the parameter estimates for the investment policy function (Equation 3) separately for boys (Panel A) and girls (Panel B). Each column corresponds to a different developmental period. We report the associated 95% bootstrap confidence intervals in brackets.

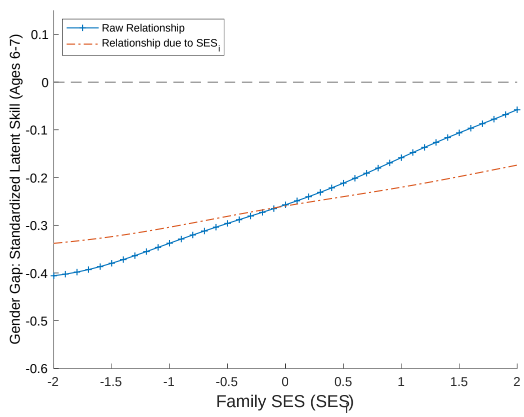
Table 8: Technology of Skill Formation

Panel A:	Boys					
	Ages 0-2	Ages 2-3	Ages 3-4	Ages 4-5	Ages 5-6	Ages 6-7
	(1)	(2)	(3)	(4)	(5)	(6)
G_i	0.012	-0.001	-0.005	0.036	0.031	0.012
	[-0.015, 0.037]	[-0.013, 0.009]	[-0.033, 0.020]	[0.014, 0.058]	[0.010, 0.053]	[-0.005, 0.026]
G_i^m	0.001	0.000	-0.009	-0.005	0.006	-0.002
	[-0.016, 0.015]	[-0.008, 0.009]	[-0.024, 0.007]	[-0.021, 0.012]	[-0.010, 0.027]	[-0.010, 0.009]
G_i^f	-0.008	0.004	0.009	-0.007	-0.001	0.004
	[-0.032, 0.014]	[-0.005, 0.013]	[-0.009, 0.030]	[-0.025, 0.012]	[-0.022, 0.014]	[-0.010, 0.018]
SES_i	0.023	0.013	0.039	0.060	0.033	0.019
	[0.006, 0.035]	[0.006, 0.019]	[0.026, 0.057]	[0.045, 0.078]	[0.021, 0.049]	[0.010, 0.032]
$\ln \theta_{it}$		0.186	0.886	0.368	0.488	0.450
		[0.145, 0.221]	[0.682, 1.277]	[0.314, 0.413]	[0.422, 0.531]	[0.371, 0.520]
$\ln I_{it}$		0.085	0.131	0.136	0.274	0.167
		[0.069, 0.101]	[0.094, 0.170]	[0.100, 0.193]	[0.162, 0.369]	[0.083, 0.260]
$\ln A$	1.409	1.904	0.133	1.664	1.057	1.517
	[1.392, 1.430]	[1.805, 2.019]	[-0.998, 0.766]	[1.364, 1.901]	[0.761, 1.407]	[1.142, 1.941]
$E[\ln \theta_{it}]$	1.409	2.560	2.993	3.249	3.408	3.512
$Var(\ln \theta_{it})$	0.030	0.012	0.058	0.089	0.074	0.034
Panel B:	**Girls**					
	Ages 0-2	Ages 2-3	Ages 3-4	Ages 4-5	Ages 5-6	Ages 6-7
	(1)	(2)	(3)	(4)	(5)	(6)
G_i	-0.009	0.003	0.008	0.023	0.013	0.003
	[-0.035, 0.013]	[-0.007, 0.013]	[-0.012, 0.023]	[0.008, 0.044]	[-0.007, 0.034]	[-0.008, 0.013]
G_i^m	0.010	-0.002	0.003	-0.000	-0.001	-0.001
	[-0.007, 0.029]	[-0.010, 0.006]	[-0.010, 0.020]	[-0.014, 0.015]	[-0.013, 0.013]	[-0.009, 0.007]
G_i^f	0.006	-0.002	0.006	-0.009	0.000	-0.002
	[-0.015, 0.024]	[-0.010, 0.005]	[-0.007, 0.023]	[-0.023, 0.005]	[-0.015, 0.017]	[-0.012, 0.008]
SES_i	0.032	0.020	0.036	0.063	0.043	0.012
	[0.017, 0.049]	[0.013, 0.027]	[0.024, 0.049]	[0.052, 0.080]	[0.032, 0.059]	[0.005, 0.021]
$\ln \theta_{it}$		0.209	0.793	0.318	0.459	0.425
		[0.169, 0.256]	[0.605, 1.146]	[0.252, 0.359]	[0.404, 0.501]	[0.355, 0.505]
$\ln I_{it}$		0.082	0.094	0.100	0.189	0.159
		[0.064, 0.096]	[0.056, 0.136]	[0.069, 0.148]	[0.127, 0.274]	[0.086, 0.241]
$\ln A$	1.458	1.951	0.584	2.007	1.431	1.621
	[1.436, 1.485]	[1.836, 2.066]	[-0.506, 1.219]	[1.756, 2.248]	[1.119, 1.717]	[1.293, 1.980]
$E[\ln \theta_{it}]$	1.458	2.639	3.104	3.351	3.501	3.556
$Var(\ln \theta_{it})$	0.035	0.014	0.037	0.060	0.049	0.020

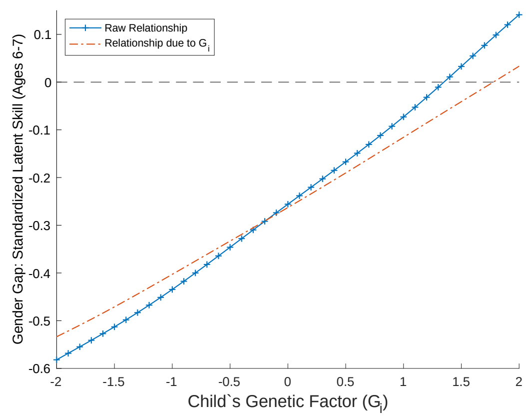
Notes: This table reports the parameter estimates for the technology of skill formation separately for boys (Panel A) and girls (Panel B). We report the parameter for the initial skill function (Equation 2) in the first column, and the parameter estimates for the technology of skill formation (Equation 4) at different child ages in columns 2-6. We report the associated 95% bootstrap confidence intervals in brackets.



(a) Density Distribution of Gender Gaps

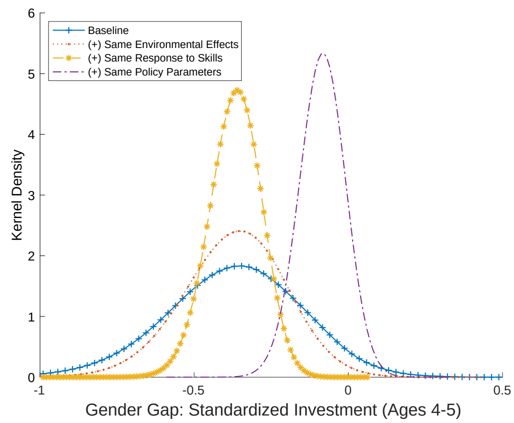


(b) Gender Gaps Across SES_i

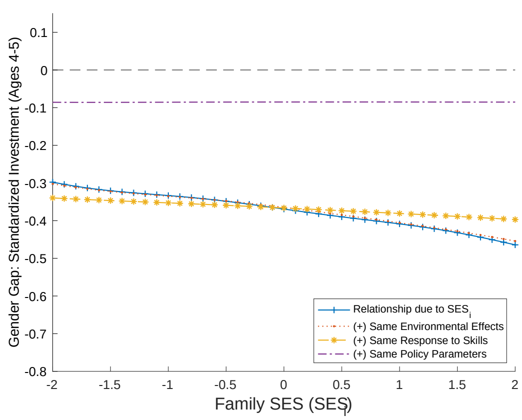


(c) Gender Gaps Across G_i

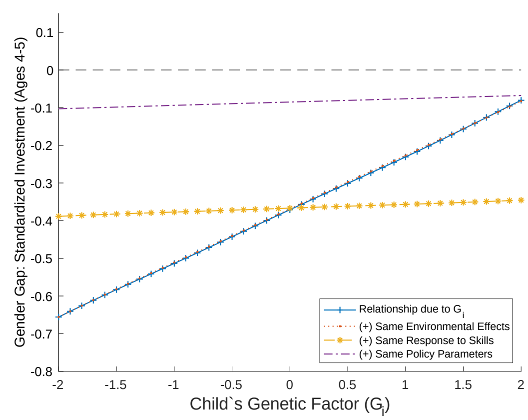
Figure 2: Distribution of Gender Gaps in Skills at Ages 6-7: This figure illustrates the heterogeneity in the distribution of gender gaps across child genes (G_i) and family socioeconomic status (SES_i). The gaps are constructed as the difference in the average standardized skill for boys in comparison to girls at ages 6-7. A negative value means that on average boys are lagging girls in skills. The figures show that the distribution of gender gaps is not constant and that boys with lower propensity for education (low G_i) and living in low SES families are those predominantly lagging girls in their development. The graphs also compare the raw heterogeneity with the heterogeneity estimated after we account for the correlation between model inputs. It shows that a significant proportion of the heterogeneity in gender gaps across SES can be attributed to genetic mechanisms.



(a) Density Distribution of Gender gaps in Investment



(b) Gender gaps in Investment across SES_i



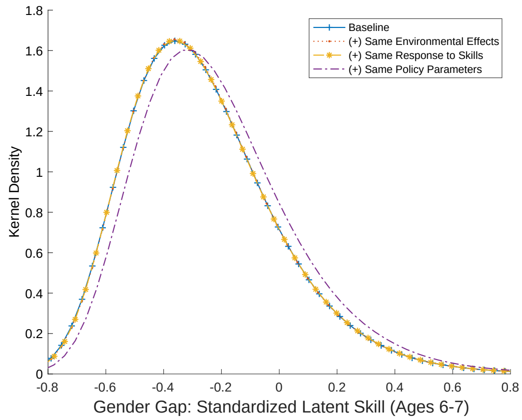
(c) Gender gaps in Investment across G_i

Figure 3: Distribution of Gender Gaps in Investments at Ages 4-5: This figure illustrates the heterogeneity in the distribution of parental investments and the underlying mechanisms. The gaps are constructed as the difference in the average standardized parental investment for boys in comparison to girls at ages 4-5. A negative value means that on average boys receive lower levels of investments than girls. These figures show that (i) the boys receive lower investments than girls, (ii) that boys with lower propensity for education (low G_i) in particular receive lower levels of investment than similar girls, (iii) that the heterogeneity in the investment gaps across genetics can be explained by differences in the parental response to skills for boys and girls, and (iv) that even after we equalize the policy function the gap in investments remain due to the gaps in skills and the fact that parents tend to invest more in children with higher stock of skills.

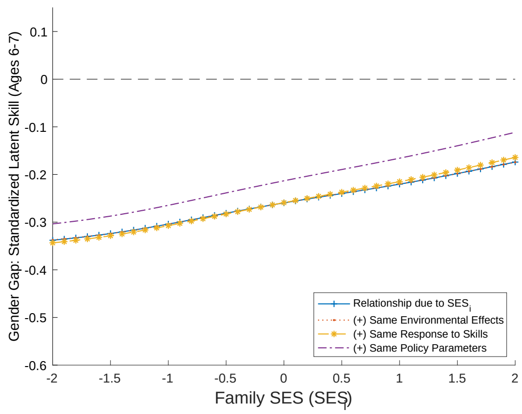
Table 9: MECHANISMS AND THE GENDER GAPS IN SKILLS AT AGES 6-7

	Avg. Gap	Std. Gap	Avg. Gap low G_i	Avg. Gap high G_i	Avg. Gap low SES_i	Avg. Gap high SES_i
Panel A: Correlation Among Initial Factors						
Baseline Correlated Inputs	-0.250	0.281	-0.490	0.014	-0.361	-0.129
	[-0.338, -0.178]	[0.171, 0.466]	[-0.653, -0.299]	[-0.170, 0.178]	[-0.590, -0.178]	[-0.279, 0.066]
Baseline Uncorrelated Inputs	-0.260	0.261	-0.449	-0.056	-0.312	-0.195
	[-0.351, -0.180]	[0.170, 0.541]	[-0.796, -0.091]	[-0.394, 0.293]	[-0.562, -0.109]	[-0.342, 0.033]
Panel B: Equalizing Parameters in the Investment Policy Function						
(+) Same Environmental Effects	-0.260	0.260	-0.449	-0.055	-0.312	-0.194
	[-0.350, -0.180]	[0.159, 0.537]	[-0.797, -0.090]	[-0.392, 0.295]	[-0.545, -0.128]	[-0.342, 0.010]
(+) Same Response to Skills	-0.259	0.262	-0.436	-0.067	-0.316	-0.188
	[-0.349, -0.181]	[0.176, 0.529]	[-0.779, -0.109]	[-0.396, 0.264]	[-0.547, -0.134]	[-0.335, 0.021]
(+) Same Policy Parameters	-0.213	0.269	-0.392	-0.019	-0.275	-0.137
	[-0.305, -0.133]	[0.179, 0.536]	[-0.727, -0.064]	[-0.367, 0.328]	[-0.500, -0.085]	[-0.296, 0.068]
Panel C: Equalizing Parameters in the Technology of Skill Formation						
(+) Same Environmental Effects	-0.213	0.265	-0.392	-0.017	-0.268	-0.144
	[-0.300, -0.126]	[0.094, 0.506]	[-0.732, -0.055]	[-0.360, 0.329]	[-0.393, -0.149]	[-0.286, -0.036]
(+) Same Genetic Effects	-0.214	0.227	-0.215	-0.206	-0.274	-0.148
	[-0.301, -0.126]	[0.082, 0.412]	[-0.300, -0.134]	[-0.290, -0.123]	[-0.400, -0.165]	[-0.290, -0.044]
(+) Same Returns to Investments	-0.217	0.215	-0.220	-0.208	-0.242	-0.189
	[-0.301, -0.127]	[0.074, 0.409]	[-0.302, -0.139]	[-0.288, -0.122]	[-0.339, -0.126]	[-0.281, -0.081]
(+) Same Self-Productivity	-0.225	0.168	-0.219	-0.227	-0.206	-0.247
	[-0.315, -0.141]	[0.078, 0.371]	[-0.309, -0.139]	[-0.316, -0.141]	[-0.285, -0.126]	[-0.348, -0.156]
(+) Same Total Factor Productivity on θ_i	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]

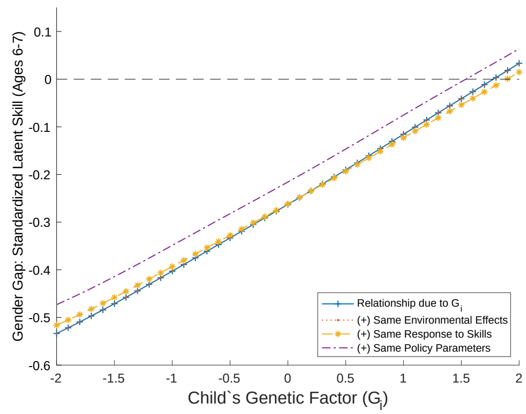
Notes: This table numerically describes the values behind the exercises shown in Figures 2, 4, and 5. It describes how the mean and variance of the gender gap in skills at ages 6-7 change once we equalize the investment policy function and technology of skill formation across gender. The skill gaps are constructed as the difference in the average standardized skills for boys in comparison to girls at ages 6-7. A negative value means that on average boys lag in development to similar girls. In the first column, we report the average standardized skill gap under the different simulations. The second column reports the standard deviation of the gap across all simulations and initial factor draws. The third and forth columns report the average standardized skill gap for children below the 20th percentile and those above the 80th percentile of the genetic factor. Similarly, the fifth and sixth columns report the average standardized skill gap for children below the 20th percentile and those above the 80th percentile of the socioeconomic factor. Panel A correspond to the exercise done in Figure 2, panel B correspond to the exercise done in Figure 4, and panel C to the exercise done in Figure 5. We report the 95th confidence intervals for each estimate in brackets.



(a) Density Distribution of Gender gaps in Skills

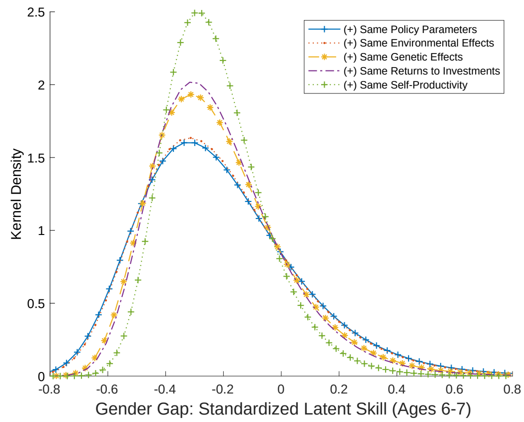


(b) Gender gaps in Skills across SES_i

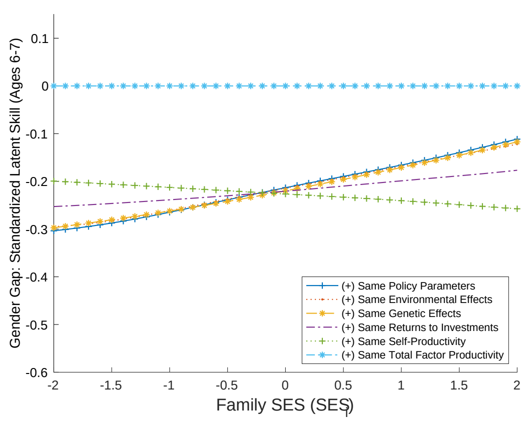


(c) Gender gaps in Skills across G_i

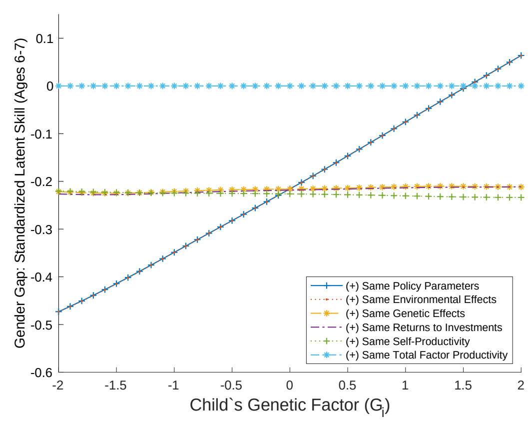
Figure 4: Parental Investments and Gender Gaps in Skills at Ages 6-7: This figure illustrates how the heterogeneity in gender gaps in skills is dependent on gender differences in parental investments. The skill gaps are constructed as the difference in the average standardized skills for boys in comparison to girls at ages 6-7. A negative value means that on average boys lag in development to similar girls.



(a) Density Distribution of Gender gaps in Skills



(b) Gender gaps in Skills across SES_i



(c) Gender gaps in Skills across G_i

Figure 5: Technology of Skill Formation and Gender Gaps in Skills at Ages 6-7: This figure illustrates how the heterogeneity in gender gaps in skills is dependent on gender differences in the technology of skill formation. The skill gaps are constructed as the difference in the average standardized skills for boys in comparison to girls at ages 6-7. A negative value means that on average boys lag in development to similar girls.

Appendix

"Gender Differences in the Genetics of Skill Formation"

Mikkel Aagaard Houmark and Victor Ronda

Appendix A Additional Information on Identification and Estimation

Appendix A.1 Identifying Assumptions

Identification of the joint evolution of skills and investments is based on a factor analytic approach as in Cunha and Heckman (2008) and Cunha, Heckman, and Schennach (2010). We observe multiple measures of children's skills and parental investments in each period. While each measure is an imperfect proxy of the underlying skill or investment, the availability of multiple measures of the same construct can be used to identify the underlying latent skill or investment. Similarly, the evolution of skills can be tracked by the availability of the same measure across different periods. We rely on a similar idea to identify the distribution of genetic factors. We follow the approach outlined in Houmark, Ronda, and Rosholm (2024) that relies on three distinct measures of the genetic factor (different polygenic scores) to identify the distribution of the child's and parents' genetic factors.

Appendix A.1.1 Identification of Latent Skills and Investments

Formally, in each period t, we observe J measurements of the child's skills and K measurements of parental investments. Let m^{θ}_{ijt} denote the jth measurement of child i's skill at period t, and let m^{I}_{ikt} denote the kth measurement of child i's parental investment at period t. Following Attanasio, Meghir, and Nix (2020) and Agostinelli and Wiswall (2020), we assume a linear-log relationship between each measurement, the latent child skills θ_{it}, and latent parental investments I_{it}:

$$m^{\theta}_{ijt} = \mu^{\theta}_{j,t,g} + \lambda^{\theta}_{j,t,g} \cdot \ln \theta_{it} + \nu^{\theta}_{ijt} \tag{13}$$

$$m^{I}_{ikt} = \mu^{I}_{k,t,g} + \lambda^{I}_{k,t,g} \cdot \ln I_{it} + \nu^{I}_{ikt} \tag{14}$$

where ν^{θ}_{ijt} and ν^{I}_{ikt} are i.i.d. measurement errors and $\lambda^{\theta}_{j,t,g}$ and $\lambda^{I}_{j,t,g}$ are the factor loading for skill measurement j and investment measurement k for gender g, meaning that we allow these parameters to differ across gender.[13] As in Agostinelli and Wiswall (2020), we make no further assumptions on the distribution of the measurement errors.

[13] We don't find that differences in these parameters across gender are statistically significant. Also, in estimates upon request, we forced the system to be gender the same for boys and girls and found no significant difference in the estimates of the technology of skill formation and investment policy function.

Identification of the system is based on the assumption that the measurement errors are independent of each other and independent across time and on normalization on the location and scale of the latent factor. We refer the reader to Agostinelli and Wiswall (2020), Houmark, Ronda, and Rosholm (2024) for more details on the assumptions required for identification. In addition to these assumptions, identification of the evolution of the latent factor require further restrictions on the location and scale of the latent factor. In particular, it requires us to observe the same measurement over time and impose the same value for the factor loading for that measurement over all the different periods. In practice, we are fixing the scale of the latent factor against this age-invariant measure.

To identify the latent investment, we chose the "Frequency the child goes to places of interest" as our age-invariant measure since it is available across all periods and is strongly related to parental investments (see Table 2).[14] Unfortunately, we do not have a measure that is asked at all periods for the latent skill. Our measures of skills capture different child development achievements, such as being able to use plurals or read simple words. These achievements are age specific since most children are able to complete some of the tasks after a certain age, and few young children can complete other tasks. For this reason, no question is put to the child in all six periods. Identification is then obtained from two separate measures that are asked at many but not all periods (see Table 1). The survey asks whether the child "Can build a tower of 8 bricks" in periods 0, 1, and 2. Similarly, the survey asks the mother if the child "Can play card games (or board games)" in periods 1, 2, 3, 4, and 5. Since the two measures overlap at some periods and cover all periods together, we use them to identify the location and scale of the latent skills across periods. Other combinations are possible and do not alter our main findings.

Formally, let the measure "Frequency the child goes to places of interest" be described by $k = 1$, "Can build a tower of 8 bricks" be described by $j = 1$ and "Can play card games (or board games)" by $j = 2$, we make the following normalizing assumption on the three measures:

$$m^I_{i1t} = 0 + 1 \cdot \ln I_{it} + \nu^I_{i1t} \quad \text{for} \quad t \in \{0, 1, 2, 3, 4\} \quad \text{and} \quad g \in \{m, f\} \tag{15}$$

[14]Other measures that are available across all periods are "Frequency the child goes to a library", "Frequency the mother reads to the child", and the "Frequency the mum's partner sings to the child". Results are similar when we use one of the other three measures to fix the scale of parental investments.

and

$$m^{\theta}_{i1t} = 0 + 1 \cdot \ln \theta_{it} + \nu^{\theta}_{i1t} \quad \text{for} \quad t \in \{0, 1, 2\} \quad \text{and} \quad g \in \{m, f\} \tag{16}$$

$$m^{\theta}_{i2t} = \mu_{2,1,g} + \lambda_{2,1,g} \cdot \ln \theta_{it} + \nu^{\theta}_{i2t} \quad \text{for} \quad t \in \{1, 2, 3, 4, 5\} \quad \text{and} \quad g \in \{m, f\} \tag{17}$$

where $\mu_{2,1,g}$ and $\lambda_{2,1,g}$ are identified in period 1 using the normalization on the first measure.

Since we impose the same location restriction for both boys and girls, this restriction also helps us identify differences in skills and parental investments across gender. In fact, such a restriction is necessary for us to identify gender differences, otherwise we cannot separately identify gender differences in the underlying latent skills to gender differences in the factor loadings relating these latent skills to the observed measures.

Appendix A.1.2 Identifying the Genetic Factor

In Houmark, Ronda, and Rosholm (2024), we show that a similar logic can be applied to identify the genetic factor of children and their parents. The approach relies on assuming the latent genetic factor is a linear combination of different genetic makers in the same way that polygenic scores are constructed,[15] and on the availability of three distinct polygenic scores.

Formally, let $pgi_{i,p}$ be a polygenic index for a trait related to G_i, we assume that:

$$pgi_{i,p} = \lambda^{G}_{p,g} G_i + \zeta^{p}_{i} \text{for} \quad g \in \{m, f\} \tag{18}$$

Identification of the genetic factor relies on the assumption that the measurement error is independent across PGIs. That is, it relies on the assumption that:

$$\zeta^{p}_{i} \perp\!\!\!\perp \zeta^{p'}_{i} \;\; \forall p \neq p' \tag{19}$$

This assumption is plausible for PGIs constructed from independent GWA studies with no sample overlap if we assume that η^{p}_{j} mainly captures estimation error in the GWAS. However, this assumption would not hold if the β_js are systematically misestimated, for example, due to not correctly controlling for population stratification in the GWAS. In this case, the bias for each SNP would be similar across GWA studies, and Assumption 19 would fail. As a general rule, any bias in the original GWAS will carry over to downstream analyses and

[15] As explained in Houmark, Ronda, and Rosholm (2024), at first this seems like a very strong assumption. However, there is much empirical and theoretical evidence that most genetic variance for polygenic phenotypes can be explained by the additive (linear) component (see, for example, the discussion in Hill, Goddard, and Visscher, 2008).

cannot be addressed ex-post using standard measurement error methods. This highlights the importance of a proper GWAS design for any downstream analyses. Since there are only two large independent GWA studies of educational attainment, we rely on a PGI constructed from the cognition GWAS as our third measure of the genetic factor. Suppose we again assume that η_j^p captures only the estimation error in the GWAS. In that case, it is also plausible that Assumption 19 will hold for PGIs constructed using two distinct, but related, outcomes since there will be overlap in the genetic signal from the two outcomes, but the estimation error will be independent across the two estimates.

More importantly for the current analyses, we need to assume that the relationship between G_i, the true unobserved genetic factor for skill formation, and the observed polygenic index $pgi_{i,p}$ is the same for boys and girls. This assumption is required for us to understand gender differences in the genetics of skill formation. The reason is that we cannot separately identify whether the observed gender differences in the relationship between the polygenic indexes and skills are due to gender differences in the relationship between the unobserved genetic factor and skills or due to gender differences in the relationship between the polygenic indexes and the unobserved genetic factor. This is important to keep in mind when interpreting the results in our paper.

Appendix A.2 Estimation

Estimation of the model parameters is done in two steps. We first estimate all the parameters in the measurement systems for each skill, investment, and genetic factor. These are estimated separately for each gender using the variance-covariance matrix of the measurements for each latent factor. Once the measurement systems are estimated, we proceed with the estimation of the parameters in the technology of skill formation and investment policy function. The estimation strategy follows the approach described in Agostinelli and Wiswall (2020) and Houmark, Ronda, and Rosholm (2024).

Appendix A.2.1 Estimation of the Measurement System

Given the normalization restrictions, we can estimate all parameters of the measurement system for latent skills and investments and the means and distribution of the latent variables. The parameters of the measurement system include the factor loadings (λ_{jt}^{θ} and λ_{kt}^{I}), the measurement means (μ_{jt}^{θ} and μ_{kt}^{I}) and the variance of the measurement errors ($\sigma_{jt,\theta}^2$ and $\sigma_{kt,I}^2$). These parameters can be estimated directly from ratios of the covariance between different measurements, from the measurement means, and from the measurement variance.

Consider three measurements of latent investments in period 1 (m^I_{11}, m^I_{21}, and m^I_{31}). Recall that we assume $\lambda^I_{11} = 1$ and that the measurement errors are independent, so we can write the covariance between each pair of measurements as:

$$
\begin{aligned}
Cov(m^I_{11}, m^I_{21}) &= 1 \cdot \lambda^I_{21} \cdot Var(\ln I_1) \\
Cov(m^I_{11}, m^I_{31}) &= 1 \cdot \lambda^I_{31} \cdot Var(\ln I_1) \\
Cov(m^I_{21}, m^I_{31}) &= \lambda^I_{21} \cdot \lambda^I_{31} \cdot Var(\ln I_1)
\end{aligned}
$$

As first shown in Carneiro, Hansen, and Heckman (2003), we can use these three identities to identify the three unknowns (λ^I_{21}, λ^I_{31} and $Var(\ln I_1)$). To see this, note that:

$$
\begin{aligned}
Var(\ln I_1) &= \frac{Cov(m^I_{11}, m^I_{21}) \cdot Cov(m^I_{11}, m^I_{31})}{Cov(m^I_{21}, m^I_{31})} \\
\lambda^I_{21} &= \frac{Cov(m^I_{21}, m^I_{31})}{Cov(m^I_{11}, m^I_{31})} \\
\lambda^I_{31} &= \frac{Cov(m^I_{21}, m^I_{31})}{Cov(m^I_{11}, m^I_{21})}
\end{aligned}
$$

We can extend this procedure to include additional measurements beyond the first three. When the model is over-identified we take the means of different combinations of measurements as our estimates. The procedure can be applied to all periods to identify all factor loadings (λ^I_{kt}). The factor loadings for the latent skills can be identified in a similar manner, with the additional step that we must first estimate λ_{21} before estimating the factor loadings in the later periods.

Once the variance of the latent variable ($Var(\ln I_t)$ and $Var(\ln \theta_t)$) and the factor loadings are identified, we can also identify the mean of the latent variables ($E[\ln I_t]$ and $E[\ln \theta_t]$), and then the measurement means (μ^I_{kt} and μ^θ_{jt}). To see this, note that since we assume $\mu^I_{1t} = 0$, we have that:

$$
E[\ln I_t] = E[m^I_{1t}]
$$

Similarly, we have that:

$$
\mu^I_{kt} = E[m^I_{kt}] - \lambda^I_{kt} \cdot E[\ln I_t]
$$

The estimation procedure for the latent skill is similar but with the additional step that we need to set $\mu^\theta_{2t} = \mu^\theta_{21}$, which can be identified in period 1 from the assumption that $\mu^\theta_{11} = 0$.

Lastly, once all other parameters are identified, we can identify the variance of the measurement errors ($\sigma^2_{jt,\theta}$ and $\sigma^2_{kt,I}$) from each measurement variance. These follow from the following identity:

$$\begin{aligned}\sigma^2_{kt,I} =& Var(m^I_{kt}) - (\lambda^I_{kt})^2 \cdot Var(\ln I_t)\\ \sigma^2_{jt,\theta} =& Var(m^\theta_{jt}) - (\lambda^\theta_{jt})^2 \cdot Var(\ln \theta_t)\end{aligned}$$

Appendix A.2.2 Estimation of Genetic Factor Measurement System

The availability of three polygenic indexes that satisfy Assumption (19) is sufficient to identify G_i. To see that, without loss of generality, assume that $Var(G_i) = 1$ and $E[G_i] = 0$. Then the λ^G_p can be identified by the covariances between the three indexes:

$$Cov(pgi_{i,1}, pgi_{i,2}) = \lambda^G_1 \lambda^G_2 Var(G_1) + Cov(\zeta^1_i, \zeta^2_i) \tag{20}$$

$$= \lambda^G_1 \lambda^G_2 \tag{21}$$

So that:

$$\lambda^G_1 = \frac{Cov(pgi_{i,1}, pgi_{i,2}) * Cov(pgi_{i,1}, pgi_{i,3})}{Cov(pgi_{i,2}, pgi_{i,3})} \tag{22}$$

Appendix A.3 Estimating the Technology of Skill Formation and the Investment Policy Function

Once the parameters of the measurement system are identified, we can estimate the remaining parameters in the technology of skill formation (Equation 4), the investment function (Equation 3), and in the early skills function (Equation 2). To do so, we again follow Agostinelli and Wiswall (2020) and construct "residual" measures of skills and investments. The residual measures can be used in a regression framework to identify the remaining parameters in the model. Formally, for each measure of latent skills, investments, and genetic factor, we construct "residual measures" by subtracting the estimated measurement mean and dividing by the estimated factor loading, such that:

$$\widetilde{m}^{\theta}_{ijt} = \frac{m^{\theta}_{ijt} - \mu^{\theta}_{jt}}{\lambda^{\theta}_{jt}} = \ln \theta_{it} + \frac{\nu^{\theta}_{ijt}}{\lambda^{\theta}_{jt}} \tag{23}$$

$$\widetilde{m}^{I}_{ikt} = \frac{m^{I}_{ikt} - \mu^{I}_{kt}}{\lambda^{I}_{kt}} = \ln I_{it} + \frac{\nu^{I}_{ikt}}{\lambda^{I}_{kt}} \tag{24}$$

$$\widetilde{pgi}_{i,p} = \frac{pgi_{i,p}}{\lambda^{G}_{p}} = G_i + \frac{\zeta^{p}_{i}}{\lambda^{G}_{p}} \tag{25}$$

We use these residual measures to estimate the remaining parameters. For example, to estimate the investment policy function (Equation 3), we can use the kth residual measurement for the latent investment, the jth residual measurement for the latent skill, and the kth residual genetic factor for the latent genetic factor instead of the true unobserved latent variables.[16]

$$\widetilde{m}^{I}_{ikt} = \gamma_{1,t}\widetilde{m}^{\theta}_{ijt} + \gamma_{2,t}\,\widetilde{pgi}_{i,p} + \gamma_{3,t}\,\widetilde{pgi}^{m}_{i,p} + \gamma_{4,t}\,\widetilde{pgi}^{f}_{i,p} + \gamma_{x,t}\,X^{I}_{it} + \widetilde{\eta_{it}} \tag{26}$$

where $\widetilde{\eta_{it}} = \eta_{it} + \frac{\nu^{I}_{ikt}}{\lambda^{I}_{kt}} - \gamma_{1,t}\frac{\nu^{\theta}_{ijt}}{\lambda^{\theta}_{jt}} - \gamma_{2,t}\frac{\zeta^{p}_{i}}{\lambda^{G}_{p}} - \gamma_{3,t}\frac{\zeta^{p,m}_{i}}{\lambda^{G,m}_{p}} - \gamma_{4,t}\frac{\zeta^{p,f}_{i}}{\lambda^{G,f}_{p}}$.

Estimation of equation 26 by OLS would yield inconsistent estimates of the γ coefficients because the residual measures are correlated with their measurement errors which are included in the residual term $\widetilde{\eta_{it}}$. A common solution in the literature, which we follow here, is to use an instrumental variables estimator with the vector of excluded measurements $[m^{\theta}_{ij't}]$ as instruments for $\widetilde{m}^{\theta}_{ijt}$, and $[pgi_{i,p'}]$ as instruments for $\widetilde{pgi}_{i,p}$. This instrumental variables strategy yields consistent estimators of the γ coefficients. A similar approach is used to estimate the parameters of the technology of skill formation (eq. 4) and early skills function (eq. 2). Since this is an innovation, we also prove the consistency of our IV estimator when using imputed parental polygenic indexes. We show the proof in Appendix C.

The key identifying assumption is that all shocks and measurement errors are independent of each other and across time. Formally, we array the skill formation shocks ϵ_t in a vector ϵ,

[16] In practice, we can use all possible combinations of investments and skill measurements to estimate the model parameters. There are many possible ways to use this large amount of measures. In our preferred specification, our parameters are averages of all possible combinations of measures for each period.

the investment shocks η_t in a vector η, and assume that

$$
\begin{aligned}
\epsilon_t &\perp\!\!\!\perp \epsilon_{t'} \;\; \forall t \neq t', & (27)\\
\eta_t &\perp\!\!\!\perp \eta_{t'} \;\; \forall t \neq t', & (28)\\
\epsilon &\perp\!\!\!\perp \eta, & (29)\\
(\epsilon, \eta) &\perp\!\!\!\perp (\nu^{\theta}\nu^{\mathbf{I}}, \zeta). & (30)
\end{aligned}
$$

Assumptions (27) and (28) maintain the independence of the shocks over time, and (29) maintains the independence between shocks to investments and skills. This means that we treat shocks and innovations to the investment policy function as exogenous. This is a potentially strong assumption that is commonly made in the literature (see, e.g., Agostinelli and Wiswall, 2020). Relaxing this assumption is possible if instruments are available, as in Attanasio et al. (2020). Common instruments are price variations across regions and across time. Unfortunately, our sample was born in the same year and region, making it difficult for the same strategy to be implemented. In addition, we need to assume that the measurement errors are independent of the shocks to investments and skills (Assumption 30). This assumption means that conditional on the latent investments (I_{it}), skills (θ_{it}), and genetic factors (G_i, G_i^m, G_i^f) the remaining information on the measurements is unrelated to the process of skill formation.

There are other important assumptions in how we specify our model. In particular, it is worth highlighting that we assume that the relationship between log-latent investments and skills and the measures of those latent variables is linear and homogeneous across families (Equation 6). This assumption could be violated in a variety of ways. One such violation could happen if a given parent-child interaction does not reflect the underlying latent investment in the same way across different families. Say, for example, that for high PGI parents, taking their child to a 'place of interest' is a strong signal of investment in child skill formation, whereas for low PGI parents, going to a 'place of interest' is a less strong signal of investment, perhaps because the different families go to different places. In this scenario, λ_k^I would be different for different families, which is a violation of our model. Unfortunately, we cannot test for this type of violation, and allowing for heterogeneity in λ_k^I would significantly complicate our estimation and identification strategies.