# The Role of
# Family Relationships
## in Intergenerational Inequality in Education



Quoc Khanh Duong

**Propositions accompanying the dissertation**

# THE ROLE OF FAMILY RELATIONSHIPS IN INTERGENERATIONAL INEQUALITY IN EDUCATION

Quoc Khanh Duong

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1. Not all aspects of the intergenerational correlation of education are a problem; some may reflect permissible familial relationship goods. (This dissertation)
2. The corrected intergenerational transmission effect attributable to familial relationship goods is approximately 0.15 standard deviations. (This dissertation)
3. "Perfect mobility" - the statistical independence between parental and child outcomes - is a flawed ideal. (This dissertation)
4. Preserving familial relationship goods reduces educational mobility by approximately 0.24 to 0.27 standard deviations. (This dissertation)
5. Family practices that generate relational goods—shared activities, emotional support, and nurturing interactions—shape children's motivation and effort.
6. The goal of policy should not be to sever family bonds, but to flatten the slope of the Great Gatsby Curve.
7. Equality of opportunity cannot be achieved by eliminating family influence while preserving the institution of the family.
8. Nature and nurture are not independent but dynamically linked through a complex gene-environment system—a phenomenon known as the "nature of nurture."
9. Fairness in intergenerational mobility requires distinguishing between legitimate family influence, social privilege, and varying levels of individual effort.
10. Randomness is not inequality-driven—though it may appear as luck, which is morally neutral—and thus cognitive exposure to it in value formation does not constitute an injustice.

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**Doctoral dissertation**

# THE ROLE OF FAMILY RELATIONSHIPS IN INTERGENERATIONAL INEQUALITY IN EDUCATION

Quoc Khanh Duong

2026

Maastricht University

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# THE ROLE OF FAMILY RELATIONSHIPS IN INTERGENERATIONAL INEQUALITY IN EDUCATION

DISSERTATION

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# Summary

The apple does not fall far from the tree. Social scientists call this the intergenerational correlation of education, one of the most durable findings in modern mobility research. In many economies, parents' education remains a strong predictor of their children's outcomes. This suggests life chances are still tied to the circumstances of birth. This persistence is not merely a family-level phenomenon but is structurally amplified by economic inequality — a relationship captured by the Great Gatsby Curve. At the same time, liberal democracies are philosophically committed to the meritocratic principle that an individual's prospects should depend on their own effort and talent, not on their parents' social position. A high intergenerational correlation, therefore, challenges equality of opportunity, signalling a rigid opportunity structure and a possible limit on the education system as an engine of mobility.

This dissertation argues that navigating this tension requires moving beyond the raw correlation, which acts as a "black box" hiding the mechanisms inside. The central research question is: *How can a society committed to equality of opportunity accommodate the advantages that arise from family life?* To answer this question, the dissertation does not simply re-measure the correlation but disentangles and scrutinises its constituent channels, focusing on the family's role. It posits that the family is more than a channel for financial resources or genetic material; it is the primary site for generating *Familial Relationship Goods* — the intimate, constitutive, and partial practices like shared reading, shared meals, and authoritative guidance that are essential for human flourishing. The dissertation, therefore, seeks to distinguish which components of educational persistence reflect remediable social disadvantage and which arise from inevitable (even valuable) familial processes.

Pursuing this aim, the dissertation has three core objectives:

1. *Empirical refinement:* To estimate the transmission of Familial Relationship Goods to intergenerational educational persistence, correcting for methodological biases in traditional behavioural-genetic models.
2. *Normative benchmarking:* To develop and apply the "Fair Progress" benchmark — a realistic standard that treats a portion of intergenerational correlation as permissible.
3. *Empirical quantification:* To quantify the unavoidable inequality, or "cost," imposed on social mobility by preserving the transmission of Familial Relationship Goods.

The argument unfolds across six chapters, each building on the last. Chapter 1 establishes the problem, situating the intergenerational correlation within the literature on the Great Gatsby Curve and introducing the concept of Familial Relationship Goods. Chapter 2 provides the indispensable theoretical foundation. It integrates behavioural-genetic variance-components models with political philosophy to decompose a child's outcome into genetic endowment, shared family environment, and a residual proposed to capture Familial Relationship Goods. This chapter establishes a taxonomy: financial resources are widely considered problematic; genetic transmission is contested (permissible under meritocracy, arbitrary under luck egalitarianism); and non-financial investment splits into problematic social privilege and permissible Familial Relationship Goods. The chapter operationalises the transmission effect of familial relationship goods as

> the environmental spillover of parents' cognitive exposure to randomness on the child's gene–environment system, transmitted through the direct, co-resident family relationship .

Guided by this framework, Chapter 3 fulfils the first objective. It implements a novel correction method, combining twin and adoption study estimators to account for gene-environment interplay, and applies this method to the Swedish context. The key empirical finding is this: a significant and identifiable portion of the intergenerational correlation — *approximately 0.15* — can be attributed to the transmission of Familial Relationship Goods. This finding quantifies the "relational work" of the family, isolating the permissible transmission channel from the mixture of natural and social advantages.

This empirical parameter becomes the foundation for the normative reconstruction in Chapter 4, achieving the second objective. The chapter shows that the conventional benchmark of "perfect mobility" (a statistical correlation of zero) is a flawed and misleading false benchmark. This benchmark is blind to the difficulty of educational transitions, indifferent to the harms of downward mobility, and — most critically — incompatible with the family, because achieving it would require abolishing Familial Relationship Goods. In its place, the dissertation offers the "Fair Progress" framework. This model accepts the approximately 0.15 parameter as a realistic baseline for a society, a baseline representing the permissible level of persistence stemming from family life. From this baseline, the framework derives an "Adjusted Mobility" metric, which reframes the central question from "Has all familial influence been eliminated?" to "Who benefits from societal growth and educational expansion?" This reframing shifts the goal from engineering statistical independence to assessing whether new opportunities are broadly shared or captured solely by the already-advantaged.

The synthesis of the empirical discoveries leads directly to the strategic and empirical analysis in Chapter 5, fulfilling the third objective. The chapter operationalises the "decoupling" strategy: a society seeking to balance mobility and family life must accept the private transmission of relational goods while using public institutions to *mitigate the conversion* of all forms of advantage (especially financial ones) into hardened inequalities. Applying Double/Debiased Machine Learning within this framework yields the thesis's central quantification: preserving the transmission of Familial Relationship Goods imposes a measurable, irreducible constraint on aggregate mobility. The "price" of protecting the family sphere is a reduction in educational mobility of 0.24 to 0.27 standard deviations. This estimate provides an empirical measure of the trade-off at the heart of the equality of opportunity trilemma.

The concluding synthesis, therefore, presents three findings. First, the *empirical refinement* isolates and quantifies the transmission of Familial Relationship Goods at approximately 0.15. Second, the *normative benchmarking* uses this finding to move beyond "perfect mobility" and establish the "Fair Progress" benchmark. Third, the *empirical quantification* identifies decoupling as the imperative and quantifies its necessary but limited ambition, given the 0.24 to 0.27 standard deviation cost. Together, these discoveries reframe the debate: the goal is not to eliminate the gravitational pull of the family tree but to flatten the slope of inequality — the Great Gatsby Curve — so that the apple's roll is determined more by a child's own agency and less by the elevation of the ground on which the tree stands.

The implications of this synthesis are significant for measurement, theory, and policy. For *measurement*, the dissertation argues for moving beyond the false benchmark of perfect mobility to the Adjusted Mobility metric, which asks a different question about the distribution of progress. For *social theory*, it provides a workable compromise between Liberal Equality of Opportunity (which tends to ignore the family's role) and Radical Egalitarianism (which would abolish it), a compromise grounded in the empirically defined baseline of permissible intergenerational correlation. For *policy*, it suggests shifting from pointless attempts to engineer mobility toward managing trade-offs via the decoupling strategy. This strategy involves, first, mitigating material stakes through progressive taxation, wage compression, and universal high-quality early childhood education (addressing the capacity gap); and second, broadening access to developmental goods through public mentoring and community programmes (addressing the incentive effect) — all while preserving family autonomy.

The dissertation candidly acknowledges its limitations — its domain specificity to education, its contextual roots in the Nordic context, and the persistent measurement frontiers concerning gene-environment interplay. These limitations, however, chart a clear course for future research: an expansion agenda to apply the Fair Progress

benchmark to health, wealth, and well-being; a recoupling agenda to evaluate how state action can supplement relational goods without undermining the family; and an institutional agenda to compare how different welfare state models succeed at the decoupling strategy.

In its final reckoning, this dissertation argues that preserving the family as a sphere of particularistic love requires accepting a foundational limit to equality of opportunity. The goal is not a world without familial influence — an impossible and arguably undesirable goal — but a world where that influence is not destiny. The aim is not to cut down the tree, but to equalise the landscape. A society that balances these concerns is found in the perpetual, careful balancing of commitment to intimate bonds with dedication to ensuring that no child's future is foreclosed by the circumstances of their birth. The price of intimacy is real, quantified, and unavoidable; the promise of fair progress lies not in severing the roots that nourish us, but in tending to the ground on which all children grow.

# Samenvatting

De appel valt niet ver van de boom. In de sociale wetenschappen staat dit bekend als de intergenerationele correlatie van opleiding: een van de meest robuuste bevindingen binnen het hedendaagse mobiliteitsonderzoek. In veel economieën blijft het opleidingsniveau van de ouders een sterke voorspeller van de latere uitkomsten van hun kinderen. Dat wijst erop dat levenskansen nog altijd nauw verbonden zijn met de omstandigheden waarin iemand wordt geboren. Deze correlatie is niet louter een fenomeen op gezinsniveau, maar wordt ook structureel versterkt door economische ongelijkheid — een verband dat zichtbaar wordt in de Great Gatsby-curve.

Tegelijkertijd zijn liberale democratieën filosofisch verbonden aan het meritocratische ideaal dat iemands vooruitzichten zouden moeten afhangen van eigen inspanning en talent, en niet van de sociale positie van de ouders. Een hoge intergenerationele correlatie vormt daarom een uitdaging voor het ideaal van gelijke kansen. Zij wijst op een rigide kansenstructuur en op mogelijke grenzen aan het onderwijssysteem als motor van sociale mobiliteit.

Dit proefschrift betoogt dat het omgaan met deze spanning vereist dat we verder kijken dan de ruwe correlatie, die fungeert als een "black box" waarin de onderliggende mechanismen verborgen blijven. De centrale onderzoeksvraag luidt: **Hoe kan een samenleving die gelijke kansen nastreeft, omgaan met de voordelen die voortkomen uit het gezinsleven?**

Om deze vraag te beantwoorden, hermeet dit proefschrift de correlatie niet simpelweg, maar ontrafelt en onderzoekt het de afzonderlijke kanalen waaruit deze is opgebouwd, met bijzondere aandacht voor de rol van het gezin. Het proefschrift stelt dat het gezin meer is dan een kanaal voor financiële middelen of genetisch materiaal. Het is de primaire context waarin **Familiale Relatiegoederen** worden voortgebracht: intieme, constitutieve en partijdige praktijken, zoals samen lezen, gezamenlijke maaltijden en ouderlijke begeleiding, die essentieel zijn voor menselijke ontplooiing. Het proefschrift probeert daarom te onderscheiden welke componenten van onderwijspersistentie verwijzen naar vermijdbare sociale achterstand, en welke voortkomen uit onvermijdelijke — en zelfs waardevolle — familiale processen.

Met dit doel voor ogen kent het proefschrift drie kerndoelstellingen:

1. **Empirische verfijning:** het schatten van de bijdrage van Familiale Relatiegoederen aan intergenerationele onderwijspersistentie, met correctie

voor methodologische vertekeningen in traditionele gedragsgenetische modellen.

2. **Normatieve benchmarking:** het ontwikkelen en toepassen van de **Fair Progress**-benchmark: een realistische standaard die een deel van de intergenerationele correlatie als toelaatbaar beschouwt.
3. **Empirische kwantificering:** het kwantificeren van de onvermijdelijke ongelijkheid, of "kosten", die aan sociale mobiliteit worden opgelegd door het behoud van de overdracht van Familiale Relatiegoederen.

De argumentatie ontvouwt zich over zes hoofdstukken, die elk voortbouwen op het voorgaande. Hoofdstuk 1 schetst het probleem, plaatst de intergenerationele correlatie binnen de literatuur over de Great Gatsby-curve en introduceert het concept van Familiale Relatiegoederen.

Hoofdstuk 2 biedt de noodzakelijke theoretische fundering. Het integreert gedragsgenetische variantiecomponentenmodellen met politieke filosofie om de uitkomsten van kinderen te ontleden in genetische aanleg, gedeelde gezinsomgeving en een restwaarde dat wordt geïnterpreteerd als de bijdrage van Familiale Relatiegoederen. Het hoofdstuk ontwikkelt daarbij een taxonomie. Financiële middelen worden doorgaans als problematisch beschouwd; genetische overdracht is normatief omstreden — toelaatbaar binnen meritocratische opvattingen, maar willekeurig vanuit geluksegalitaristisch perspectief — en niet-financiële investeringen vallen uiteen in problematisch sociaal privilege enerzijds en toelaatbare Familiale Relatiegoederen anderzijds. Het hoofdstuk operationaliseert het overdrachtseffect van Familiale Relatiegoederen als:

> de omgevingsspillover van de cognitieve blootstelling van ouders aan willekeur op het gen-omgevingssysteem van het kind, werkend via de directe, samenwonende familierelatie.

Geleid door dit kader vervult Hoofdstuk 3 de eerste doelstelling. Het hoofdstuk implementeert een nieuwe correctiemethode, waarin schatters uit tweeling- en adoptiestudies worden gecombineerd om rekening te houden met gen-omgevingsinteractie. Deze methode wordt toegepast op de Zweedse context. De belangrijkste empirische bevinding is dat een significant en identificeerbaar deel van de intergenerationele correlatie — ongeveer 0,15 — kan worden toegeschreven aan de overdracht van Familiale Relatiegoederen. Daarmee kwantificeert het hoofdstuk het "relationele werk" van het gezin en isoleert het een toelaatbaar overdrachtskanaal binnen de bredere mix van natuurlijke en sociale voordelen.

Deze empirische parameter vormt de basis voor de normatieve reconstructie in Hoofdstuk 4, waarmee de tweede doelstelling wordt gerealiseerd. Het hoofdstuk laat zien dat de conventionele benchmark van "perfecte mobiliteit" — een statistische correlatie van nul — gebrekkig en misleidend is. Deze benchmark is blind voor de moeilijkheid van onderwijsovergangen, onverschillig voor de schade van neerwaartse mobiliteit en, bovenal, onverenigbaar met het gezin, omdat het bereiken ervan zou vereisen dat Familiale Relatiegoederen worden afgeschaft.

Als alternatief ontwikkelt het proefschrift het **Fair Progress**-kader. Dit model aanvaardt de parameter van ongeveer 0,15 als een realistische basislijn: het toelaatbare niveau van persistentie dat voortvloeit uit het gezinsleven. Vanuit deze basislijn leidt het kader een **Aangepaste Mobiliteitsmaatstaf** af. Daarmee verschuift de centrale vraag van "Is alle familiale invloed geëlimineerd?" naar "Wie profiteert van maatschappelijke groei en onderwijsuitbreiding?" Deze herformulering verlegt de focus van het construeren van statistische onafhankelijkheid naar het beoordelen of nieuwe kansen breed worden gedeeld, dan wel vooral worden opgeëist door groepen die al bevoorrecht zijn.

De synthese van de empirische bevindingen leidt vervolgens tot de strategische en empirische analyse in Hoofdstuk 5, waarmee de derde doelstelling wordt vervuld. Dit hoofdstuk operationaliseert de **ontkoppelingsstrategie**. Een samenleving die mobiliteit en gezinsleven met elkaar in evenwicht wil brengen, moet de private overdracht van relatiegoederen aanvaarden, maar tegelijkertijd publieke instituties inzetten om de omzetting van voordelen — in het bijzonder financiële voordelen — in verharde ongelijkheden te beperken.

Binnen dit kader wordt gebruikgemaakt van dubbel/vertekeningsgecorrigeerd machinaal leren. Dat levert de centrale kwantificering van deze dissertatie op: het behoud van de overdracht van Familiale Relatiegoederen legt een meetbare en onherleidbare beperking op aan totale mobiliteit. De "prijs" van het beschermen van de familiesfeer is een vermindering van onderwijsmobiliteit met 0,24 tot 0,27 standaarddeviaties. Deze schatting biedt een empirische maat voor de afweging die centraal staat in het trilemma van gelijke kansen.

De slotconclusie presenteert drie hoofdbevindingen. Ten eerste isoleert en kwantificeert de empirische verfijning de overdracht van Familiale Relatiegoederen op ongeveer 0,15. Ten tweede maakt de normatieve benchmarking het mogelijk om voorbij de benchmark van "perfecte mobiliteit" te gaan en de Fair Progress-benchmark vast te stellen. Ten derde identificeert de empirische kwantificering ontkoppeling als een noodzakelijke strategie, terwijl zij tegelijk de beperkte ambitie daarvan zichtbaar maakt, gegeven de kosten van 0,24 tot 0,27 standaarddeviaties.

Samen herformuleren deze bevindingen het debat. Het doel is niet om de zwaartekracht van de familiestamboom volledig uit te schakelen, maar om de helling van ongelijkheid — de Great Gatsby-curve — af te vlakken. Zo wordt de positie van de appel minder bepaald door de hoogte van de grond waarop de boom staat, en meer door het eigen handelen van het kind.

De implicaties van deze synthese zijn aanzienlijk voor meting, theorie en beleid. Voor meting betoogt het proefschrift dat we afstand moeten nemen van de valse benchmark van perfecte mobiliteit en moeten overstappen op de Aangepaste Mobiliteitsmaatstaf, die een andere vraag stelt over de verdeling van vooruitgang. Voor sociale theorie biedt zij een werkbaar compromis tussen Liberale Gelijkheid van Kansen, die de rol van het gezin onvoldoende erkent, en Radicaal Egalitarisme, dat het gezin dreigt te ondermijnen. Dit compromis is gegrond in een empirisch gedefinieerde basislijn van toelaatbare intergenerationele correlatie.

Voor beleid suggereert het proefschrift een verschuiving van vruchteloze pogingen om volledige mobiliteit te construeren naar het beheren van afwegingen via de ontkoppelingsstrategie. Deze strategie omvat ten eerste het verminderen van materiële inzet via progressieve belastingheffing, looncompressie en universele, hoogwaardige vroegkinderlijke educatie — gericht op het verkleinen van de capaciteitskloof. Ten tweede beoogt zij de toegang tot ontwikkelingsgoederen te verbreden via openbare mentoring en gemeenschapsprogramma's met behoud van gezinsautonomie.

Het proefschrift erkent ook enkele beperkingen: haar domeinspecificiteit tot onderwijs, haar contextuele verankering in de Noordse context en de blijvende meetproblemen rond gen-omgevingsinteractie. Deze beperkingen vormen echter ook een duidelijke agenda voor toekomstig onderzoek. Die agenda omvat ten eerste een uitbreiding van de Fair Progress-benchmark naar domeinen als gezondheid, vermogen en welzijn; ten tweede een onderzoeksagenda naar de vraag hoe publieke voorzieningen relatiegoederen kunnen aanvullen zonder het gezin te ondermijnen; en ten derde een institutionele agenda waarin wordt vergeleken hoe verschillende welvaartsstaatmodellen slagen in de ontkoppelingsstrategie.

In haar uiteindelijke afweging betoogt dit proefschrift dat het behoud van het gezin als sfeer van particularistische liefde vereist dat we een fundamentele grens aan gelijke kansen erkennen. Het doel is niet een wereld zonder familiale invloed — een onmogelijk en waarschijnlijk onwenselijk ideaal — maar een wereld waarin die invloed geen lotsbestemming wordt. Het doel is niet om de boom om te hakken, maar om het landschap te egaliseren.

Een samenleving die deze belangen in evenwicht brengt, is een samenleving die voortdurend en zorgvuldig balanceert tussen toewijding aan intieme banden en toewi-

jding aan het waarborgen dat de toekomst van geen enkel kind wordt afgesloten door de omstandigheden van zijn of haar geboorte. De prijs van intimiteit is reëel, kwantificeerbaar en onvermijdelijk. De belofte van eerlijke vooruitgang ligt daarom niet in het doorknippen van de wortels die ons voeden, maar in het bewerken van de grond waarop alle kinderen opgroeien.

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This writing marks the end of my PhD journey in Maastricht and the beginning of a new chapter in research. To my future self: stay strong, trust your abilities, and take care of yourself during the hard times. Hold onto the dream of becoming a book author and work steadily to make it happen. These research findings aren't just academic outputs — they reflect life lessons that will shape my future work. They'll form the foundation for future books about opportunity — books for people facing hardship, and for people like me who want freedom from the constraints of money, time, and place.

Quoc Khanh Duong
Turku, Finland
August 3, 2026

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# 1

# General Introduction

## 1.1 The Apple and the Slope

"The apple does not fall far from the tree" serves as a foundational metaphor in social science. This proverb captures the well-established tendency for children to resemble their parents in educational attainment, representing one of the most consistent findings in the study of social stratification (Black et al., 2005; Corak, 2013; van der Weide et al., 2024). Researchers formalise this pattern as the Intergenerational Correlation of Education (ICE). The ICE is a statistical measure of how strongly a parent's education level is associated with their child's later attainment. Social scientists use this measure as a primary indicator of social mobility because it summarises the extent to which a person's life chances are independent of their social origins (Jerrim & Macmillan, 2015). In a fully open and meritocratic society, educational outcomes would show only a weak link to parental background. A high ICE, by contrast, signals that a child's prospects remain closely tied to their birth family, reflecting a rigid opportunity structure and limited intergenerational mobility (Narayan et al., 2018).

In practice, this link is substantial across advanced economies. Raw intergenerational correlations in education in Western Europe and the United States typically range between 0.40 and 0.46 (Fleury & Gilles, 2018). This finding implies that family background remains one of the strongest predictors of academic success. Multiple transmission mechanisms produce this persistence, including financial resources, non-financial parental investments, genetic factors, and the intergenerational transmission of values and aspirations (Jerrim & Macmillan, 2015). When the ICE remains high,

concerns arise that the education system functions less as a vehicle for equalising opportunities and more as a mechanism of social reproduction, thereby reinforcing existing inequalities across generations (Boliver & Capsada-Munsech, 2024). This intergenerational persistence extends beyond the parent-child dyad either horizontally — through the inclusion of aunts, uncles, and cousins from the parental generation (Adermon et al., 2021) — or vertically — through the addition of grandparents and great-grandparents (Solon, 2018).

This persistence does not, however, exist in isolation. The Great Gatsby Curve (GGC) situates intergenerational correlation within its broader macroeconomic context. This curve illustrates that the intergenerational correlation of economic outcomes is structurally amplified by inequality, rather than being purely an individual- or family-level phenomenon (Corak, 2013; Durlauf et al., 2022; Jerrim & Macmillan, 2015). Societies with higher income inequality — such as the United States and the United Kingdom — systematically exhibit higher intergenerational correlation. This pattern reflects both stronger constraints on downward mobility and greater advantages for children born into wealthier families (Corak, 2013). Conversely, more equal societies, particularly those in the Nordic region (Denmark, Finland, Norway, and Sweden), show lower intergenerational correlation. In these countries, institutional arrangements, more equitable access to resources, and less dispersed wage structures weaken the link between parental status and child outcomes (Corak, 2013). Thus, the GGC demonstrates that intergenerational persistence is not merely a result of family choices or inherited traits but is shaped by structural factors that determine how far the apple can roll from the parental tree.

Education operates as the principal mechanism through which inequality translates into intergenerational persistence (Jerrim & Macmillan, 2015). The first channel — the capacity gap — reflects that families differ substantially in the financial and non-financial resources available for educational investment (Becker & Tomes, 1986; Breen & Jonsson, 2005; Duncan & Murnane, 2011; Solon, 2009). In unequal societies, wealthy parents can afford superior prenatal care, high-quality early childhood programmes, private schooling, tutoring, and enrichment activities, while less advantaged families face significant resource constraints (Becker, 2011; Cunha et al., 2006). Compounding this disparity, public investment in education tends to be lower in high-inequality countries, limiting the ability of the school system to offset family-level gaps (Jerrim & Macmillan, 2015). The second channel — the incentive effect — arises because greater inequality increases the wage premium associated with educational attainment (Autor, 2014). When the return to a degree is high relative to lower levels of education, the economic stakes of academic success rise (Hout, 2012). This situation strengthens the motivation of advantaged parents to invest aggressively in their children's education and to defend their educational status, ensuring that their

family's advantages are preserved (Jerrim & Macmillan, 2015). Together, these two channels produce a feedback loop: high inequality enhances both the means and the incentive for families at the top to reproduce advantage, while simultaneously limiting opportunities for those at the bottom.

## 1.2 Decomposing the Apple

The persistent resemblance between parents and children in educational attainment — the Intergenerational Correlation of Education (ICE) — remains a foundation finding in social science. Yet its raw value functions as a "black box" that obscures the mechanisms underlying social mobility (Torche, 2015b). While policymakers often interpret a high ICE as indicating limited social mobility, multiple distinct sources can produce this correlation. In fact, the observed persistence represents a combination of separate transmission channels. To design effective interventions, researchers distinguish three primary, interlinked pathways that jointly generate intergenerational resemblance: the causal (nurture) channel, the genetic (nature) channel, and the selection and correlation effects that complicate simple causal accounts.

The causal, or nurture, channel captures the direct environmental inputs that parental education provides to children. This channel operates through both financial and non-financial dimensions. Financial resources include direct expenditures on schooling, tuition, private tutoring, and enrichment activities such as summer camps and extracurricular programmes (Jerrim & Macmillan, 2015). In highly unequal societies like the United States, high-income families spend nearly seven times more on such educational investments than low-income families, creating pronounced differences in children's early advantages (Corak, 2013; Durlauf et al., 2022). Non-financial resources include cultural capital and family influences, reflecting practices such as parental guidance and shared reading, through which parents actively foster skills, habits, and expectations that help children navigate complex institutional settings (Brighouse & Swift, 2014; Bukodi & Goldthorpe, 2013). These non-material investments — shaping language, social skills, and motivation — can be as consequential as financial inputs, yet they often remain invisible in raw measures of expenditure (Kalil & Ryan, 2024). Together, these environmental inputs explain part of the causal effect of parental education on children's attainment, though societal inequality and institutional arrangements strongly mediate their magnitude.

The genetic, or nature, channel reflects the heritable transmission of abilities and traits, including cognitive skills, personality characteristics, and other endowments

that educational systems value (Branigan et al., 2013; Engzell & Tropf, 2019). Evidence from polygenic indices and behavioural genetics shows that inherited abilities contribute substantially to the observed ICE. This contribution helps explain why children from highly educated families tend to replicate their parents' success even without differential investment (Grätz & Petrini, 2025; Plomin, 2018). Meritocratic theories often treat this transmission as the "natural lottery" — a neutral outcome of inheritance (Grätz, 2024). Nevertheless, heritability remains a key component of intergenerational resemblance, demonstrating that the apple does not fall far from the tree partly because of the intrinsic endowments parents pass on to their children.

Complicating the story further are selection and correlation effects, which link the causal and genetic channels. Assortative mating[1] concentrates educational and genetic advantages within households, thereby amplifying both the environmental and hereditary resources available to children (Bingley et al., 2022; Sunde et al., 2025). Gene-environment correlations (rGE) mean that parents with strong genetic endowments are more likely to create enriched environments that reinforce the same traits — a phenomenon sometimes described as the "nature of nurture" (Kong et al., 2018). For example, a parent with high cognitive ability may both transmit favourable genes and provide a literacy-rich home environment (Friend et al., 2009), producing outcomes that reflect the interaction of nature and nurture rather than either channel in isolation. Epigenetic mechanisms further blur this boundary, as environmental exposures can modify gene expression in heritable ways, reinforcing the interdependence of these channels and highlighting the difficulty of isolating purely causal effects from observational data (Webster & Phillips, 2025).

A reality check on the causal weight of parental education comes from empirical research employing twin studies, adoption designs, and instrumental-variables (IV) approaches (Fleury & Gilles, 2018; Holmlund et al., 2011). Twin studies, which compare children of identical parents with differing education levels, show that once researchers control for shared genetic endowments, the direct impact of parental schooling often diminishes substantially (Lundborg et al., 2018). Adoption studies, which remove the genetic link while maintaining the environmental input, typically find considerably smaller effects of parental education on adopted children than on biological children (Sacerdote, 2007). Instrumental-variable strategies, such as compulsory schooling reforms in Norway, generate exogenous variation in parental education that isolates causal effects from selection (Black et al., 2005). Across these designs, the direct causal effect of additional parental schooling is modest, generally estimated between 0.10 and 0.15 (Fleury & Gilles, 2018; Holmlund et al., 2011). For instance,

[1] Assortative mating refers to the tendency of individuals to choose partners with similar characteristics, such as educational attainment, income, or innate abilities.

Swedish registry data reveal that a raw intergenerational correlation of 0.17 declines to 0.03 in adoption-based estimates and to 0.07 in twin-based models (Holmlund et al., 2011), indicating that much of the ICE is driven by heritable and bundled familial traits rather than by environmental investment alone.

The key insight is this: the observed ICE largely reflects the bundled transmission of parental traits — genetic, cultural, and relational — rather than a simple story of resource inequality. The "black box" of intergenerational persistence therefore contains a mixture of heritable ability, socioeconomic factors, and family contributions. Consequently, a high intergenerational correlation does not automatically signal a failure of social policy; rather, it reveals the complex interplay of inherited endowments, parental guidance, and structural inequalities that together shape children's educational trajectories. This insight helps explain why the apple does not fall far from the tree even in contexts with active social policies.

## 1.3 Familial Relationship Goods

How and why do parents' educational advantages transmit to their children? In other words, what explains the persistent parent-child correlation in educational attainment, and what role does the family play in producing it? Empirical research consistently demonstrates that children's educational outcomes are strongly related to those of their parents, as measured by the ICE (Corak, 2013; Durlauf et al., 2022; Jerrim & Macmillan, 2015). Yet while the correlation is robust, understanding the mechanisms that generate it requires moving beyond simple measures of financial resources or heritable ability. The family is more than a channel for money or genes; it is a site of intimate, enduring, and partial relationships in which children acquire capacities, dispositions, and habits that shape both their immediate educational outcomes and their lifelong trajectories (Brighouse & Swift, 2014; Gheaus, 2018). To study the intergenerational transmission of advantage, one must first clarify what makes a family a family. The defining characteristic of the family lies in these relationships: parents exercise care, guidance, and authority that are partial toward their own children, providing continuity, intimacy, and structure that non-familial relationships cannot replicate. These interactions create a secure base from which children develop emotionally, cognitively, and morally, cultivating motivation, self-discipline, language skills, and social competencies that directly influence their success in school and beyond (Gundersen, 2024). In this sense, the parent-child correlation in education is not merely a reflection of money or genes, but also of the relational and developmental work embedded in everyday family life.

This relational dimension is captured by the concept of *Familial Relationship Goods* (FRGs) proposed by Brighouse and Swift (2014), which identifies the specific benefits that arise only within the parent-child relationship. These benefits include practices such as reading bedtime stories, sharing meals, and providing authoritative guidance that reflects parental values, interests, and personal style. Such practices are constitutive of the family: they are valuable in themselves, not merely as instruments for improving educational outcomes (Segall, 2011). For children, FRGs provide the emotional security, cognitive stimulation, and moral formation necessary for healthy development, laying the foundation for capacities that educational settings later recognise and reward (Elliot Major, 2024; Gundersen, 2024). For adults, participating in FRGs generates distinctive forms of joy, self-realisation, and personal growth that purely adult relationships cannot replicate (Brighouse & Swift, 2014). Importantly, the benefits of FRGs depend on conditions of continuity, intimacy, and spontaneity: parental discretion, authentic engagement, and the freedom to express personal values are necessary for these relational goods to emerge. If the state or society were to monitor, standardise, or restrict such practices, the very qualities that make a family morally and developmentally significant would be lost (Gheaus, 2018).

A tension arises from the role of FRGs in producing educational advantage. On the one hand, liberal societies value *meritocracy* (distributing rewards according to talent and effort) and seek *equality of life chances* (ensuring that children's prospects are not unduly shaped by family background). On the other hand, these same societies also aim to protect *family autonomy*, allowing parents to cultivate intimate and constitutive relationships with their children. FRGs lie at the heart of this tension because the same practices that are essential for creating relational goods — such as authoritative guidance and everyday learning interactions — also enhance language, literacy, cognitive skills, and social competencies, thereby producing non-financial advantages that persist into schooling and adulthood (Brighouse & Swift, 2014). Unlike financial inheritance or private tuition — which can in principle be regulated without undermining the family — FRGs are inseparable from the relationship itself. Attempts to equalise opportunity by controlling these practices would destroy the very goods that make a family a family, while permitting them ensures that children enter the educational system with unequal preparation, thereby perpetuating intergenerational advantage. This tension has been formalised as the Equality of Opportunity Trilemma (Fishkin, 1984).

## 1.4 Dissertation Objectives and Layout

Research on educational inequality has traditionally approached the problem from two partial perspectives. Sociological and economic studies focus on material and institutional interventions — such as redistributing resources, equalising school quality, and expanding access to higher education (Blanden et al., 2024). While these strategies are important, they often treat families as "black boxes," emphasising outcomes without considering specific parental practices. Political philosophy, particularly egalitarian traditions, engages more directly with the tension between family autonomy and equality of opportunity, sometimes advocating substantial reductions in parental influence (Gheaus, 2018; Gundersen, 2024). Such interventions, however, risk undermining the relational goods that make families morally, emotionally, and developmentally significant. This dissertation makes an integrated empirical and normative contribution to the debate on educational inequality by addressing a fundamental dilemma: how can a society committed to equality of opportunity accommodate the advantages that arise from family life?

As the preceding discussion suggests, familial relationship goods (FRGs) lie at the heart of this tension. Yet FRGs encompass a rich range of intimate practices — bedtime stories, shared meals, and countless small interactions (Brighouse & Swift, 2014) — that are heterogeneous, context-dependent, and resistant to direct measurement. This dissertation does not isolate any specific FRG practice; rather, it pursues a more aggregate objective: to estimate the portion of intergenerational persistence attributable to the relational dimension of family life. Operating at a macro-level, the dissertation uses behavioural-genetic designs and machine learning to quantify the share of intergenerational transmission that remains after accounting for biological inheritance and socioeconomic background. The transmission effect of this residual provides an empirical estimate for the transmission of FRGs — the portion of parent-child resemblance neither genetically determined nor explained by socioeconomic advantage (Fleury & Gilles, 2018; Holmlund et al., 2011). The transmission of FRGs is operationalised as the environmental spillover of parents' cognitive exposure to randomness on the child's gene–environment system, transmitted through the direct, co-resident family relationship.

The originality of this work lies in its three-part approach: (1) empirically isolating the effect of FRGs using behavioural-genetic designs; (2) constructing a novel normative benchmark ("Fair Progress") that incorporates familial influence; and (3) empirically quantifying the trade-off between protecting family relationships and achieving social mobility. This interdisciplinary synthesis of political philosophy, behavioural genetics, and econometrics moves beyond the stalemate between approaches that either ignore the family or seek to constrain it excessively. The dissertation is structured

Table 1.1: Dissertation layout and chapter roles

| Chapter - Role | Central question | Primary methods |
|---|---|---|
| 1 - General introduction | | Synthesis of literatures; problem framing. |
| 2 - Theoretical foundation | When does the apple fall permissibly? | Integration of variance-components models (behavioural genetics) with political philosophy; methodological review. |
| 3 - Empirical refinement | To what extent do traditional models bias estimates of the transmission of FRGs? | Correction method combining twin and adoption estimators; application to Swedish registry data. |
| 4 - Normative benchmarking | What should perfect mobility look like? | Development of the "Fair Progress" model using transition matrices; application to global mobility data (GDIM). |
| 5 - Empirical quantification | How much limitation on mobility is an inevitable result of the transmission of FRGs? | Empirical analysis using Double/De-biased Machine Learning (DML) with high-dimensional controls. |
| 6 - General conclusion | | Synthesis of findings and discussion of policy pathways. |

around three core, interconnected objectives designed to build this argument cumulatively:

1. *Empirical refinement:* To estimate the contribution of FRGs to intergenerational educational persistence, correcting for methodological biases in traditional behavioural-genetic models.
2. *Normative benchmarking:* To develop and apply the "Fair Progress" benchmark — a standard that treats a portion of intergenerational correlation as permissible, thereby redefining the target for policy.
3. *Empirical quantification:* To quantify the unavoidable inequality, or "cost," imposed on social mobility by preserving the transmission of FRGs, providing the first empirical measure of this trade-off.

The argument unfolds across six chapters, each with a clearly defined role in advancing the dissertation's objectives (see Table 1.1).

- *Objective 1 (Empirical refinement)* is addressed in Chapter 3. Building on the theoretical decomposition developed in Chapter 2, this chapter corrects for gene-environment correlation and interaction in behavioural-genetic models. This correction yields a robust estimate of approximately 0.15 for the transmission effect of FRGs. This estimate serves as the essential empirical input for the subsequent normative analysis.
- *Objective 2 (Normative benchmarking)* is addressed in Chapter 4. Using the corrected estimate from Chapter 3, the chapter critiques the conventional benchmark of "perfect mobility" for treating all intergenerational persistence as problematic. This chapter formally develops the Fair Progress model, in which a 0.15 transmission effect of FRGs is treated as permissible, and derives the Adjusted Mobility metric to assess progress towards this ideal.
- *Objective 3 (Empirical quantification)* is addressed in Chapter 5. This chapter applies the Adjusted Mobility metric within a rigorous framework based on Double and De-biased Machine Learning, isolating the contribution of relational family dynamics to educational transmission. The resulting estimate — a reduction in mobility of approximately 0.24–0.27 standard deviations — provides the first empirical quantification of the cost of preserving the transmission of FRGs.

The chapters are organised as a cumulative sequence, in which each stage provides the analytical or empirical foundation for the next. The dissertation is therefore not a collection of independent studies but a single, integrated argument (see Figure 1.1). Chapter 2 establishes the unifying conceptual framework by defining the transmission of Familial Relationship Goods and decomposing intergenerational educational transmission into distinct channels. Chapter 3 builds directly on this framework: its empirical correction is meaningful only within the framework delineated in Chapter 2. The central output of Chapter 3 — an estimated FRG transmission parameter of approximately 0.15 — is not a stand-alone empirical result but a key parameter that Chapter 4 carries forward into its normative model. Chapter 5 then depends entirely on the metrics developed in Chapter 4 to perform its empirical analysis, thereby closing the loop by quantifying the real-world implications of the theoretical background identified in Chapter 2. Taken together, the chapters trace a coherent arc: from conceptual clarification, to corrected empirical measurement, to normative benchmarking, and finally to a policy-relevant empirical assessment of the family–mobility trade-off.

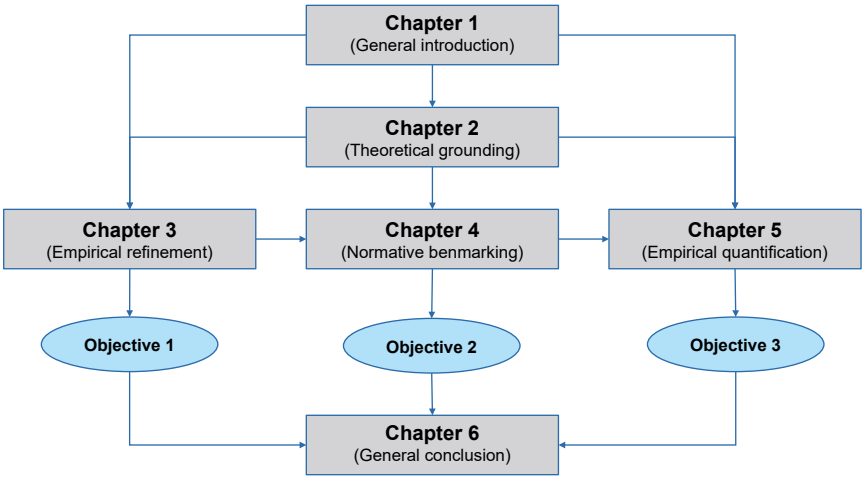



Figure 1.1: Structure of the dissertation

**Notes:** The figure illustrates the logical progression of the dissertation. Chapter 2 establishes the conceptual framework and defines the transmission of Familial Relationship Goods. Chapter 3 provides a corrected empirical estimate of its effects on intergenerational educational persistence. This estimate is used as a key parameter in Chapter 4 to construct the Fair Progress benchmark and the Adjusted Mobility metric. Chapter 5 then applies these metrics to empirically quantify the unavoidable constraint on educational mobility implied by preserving the transmission of familial relationship goods.

# 2

# When Does The Apple Fall Permissibly?

**Abstract**

The strong intergenerational correlation in education is a key metric of social mobility, but its interpretation depends on the underlying causal pathways. This chapter integrates a variance decomposition model from behavioural genetics with political philosophy to analytically separate three distinct channels: genetic inheritance ($G$), shared family environment/socioeconomic background ($F$), and the non-shared residual ($S$). We propose that $S$ captures *familial relationship goods*—the intimate, constitutive practices of family life. Our analysis demonstrates how major research designs estimate different components of this decomposition. The twin design is most effective at isolating $\omega$, the transmission effect of familial transmission. Instrumental variable (IV) approaches can, in principle, identify $\omega$ but rely on strong and often untenable assumptions. Adoption studies capture broad nurture effects but conflate distinct environmental pathways.

Declaration **Author's notes:** The study has been submitted to a journal. **Data and Code Availability:** No datasets or replication code are associated with this study.

## 2.1 Introduction

The apple does not fall far from the tree. As established in Chapter 1, this metaphor captures a robust empirical regularity in social stratification: the strong and persistent resemblance between parents and their children in educational attainment (Black et al., 2005; Corak, 2013). This intergenerational correlation of education (ICE) serves as a primary indicator of social mobility. It summarises the degree to which life chances are shaped by — rather than independent of — social origins (Baier et al., 2022; Jerrim & Macmillan, 2015). A higher correlation suggests that children's prospects remain tethered to their parents' status, a pattern that signals constrained mobility. Yet, as Chapter 1 argued, this raw correlation functions as a "black box" that conceals the mechanisms underlying social mobility (Torche, 2015b). The correlation represents an aggregate of distinct transmission channels — genetic inheritance, financial resources, and non-financial familial practices — each carrying different implications. To assess whether observed persistence reflects problematic structures or permissible processes, we must disentangle these channels. While Chapter 1 introduced this decomposition conceptually, this chapter now operationalises it analytically.

This distinction carries significant empirical weight. In Western Europe and the United States, raw intergenerational correlations average between 0.40 and 0.46 (Fleury & Gilles, 2018). However, when researchers account for genetic inheritance, the estimated *causal* effect of parental education shrinks to about 0.15 — roughly one-third of the observed correlation (Fleury & Gilles, 2018). In some egalitarian settings, direct parental effects nearly vanish once researchers control for heritable traits, a finding that suggests observed resemblance is driven more by genetic transmission than by nurture (Baier et al., 2022; Van Hootegem et al., 2025). This empirical puzzle raises a question: if children resemble their parents mainly due to inherited talents, what are the implications? The answer depends on the theory of justice one adopts. Under liberal theories of opportunity — which align with meritocratic principles — genetic transmission is permissible. Outcomes may reflect individual ability and effort, not socially imposed barriers (Baier et al., 2022; Grätz, 2024). From this view, the "natural lottery" of talents is not itself a problem. In contrast, radical egalitarian or luck-egalitarian theories treat both social background and genetic endowment as sources of concern, since they are unchosen and arbitrary determinants of life chances (Biroli et al., 2026; Grätz, 2024). For these theories, reducing social inheritance only to reveal genetic inheritance represents limited progress.

This divergence extends into the intimate sphere of family life, a sphere where parental practices transmit advantage through non-financial means. Here, the debate centres on what we term familial relationship goods — practices like authoritative

guidance that arise from the intrinsic intimacy of the parent-child bond and are valuable in themselves. Liberal accounts often defend such practices as part of the legitimate exercise of family freedom (Grätz, 2024; Swift, 2005). Egalitarian theories, however, confront a tension: rejecting all partiality may undermine meaningful relationships, while uncritically accepting it can reinforce inequality (Segall, 2011). This tension calls for a framework that distinguishes permissible familial interactions from problematic exercises of social privilege, a framework that addresses the following question:

> When does the apple fall permissibly?

This chapter develops such a framework. We argue that to adjudicate these debates, we must first decompose the intergenerational transmission of education into its constituent pathways, and then evaluate the implications of each pathway. To accomplish this decomposition, we adopt a variance-components model from behavioural genetics. This model expresses a child's educational outcome ($Y$) as the sum of three independent factors: genetic endowment ($G$), shared family environment ($F$), and non-shared or residual factors ($S$). We then map these components onto the categories outlined above. Crucially, we propose that the non-shared residual component ($S$) captures the influence of *familial relationship goods* — the intimate, constitutive practices of family life that are not determined by genetic inheritance (though they may interact with it) and are likewise independent of socioeconomic background (Brighouse & Swift, 2014).

This integration of variance decomposition with political philosophy yields three key contributions. First, it provides a systematic analytical structure for assessing the implications of different transmission channels, moving beyond the monolithic interpretation of intergenerational correlations. Second, it demonstrates that different causal research designs — adoption, twin, and instrumental variable (IV) studies — identify distinct components of this decomposition, each with different implications. Under ideal conditions, twin and IV designs can isolate the component most closely associated with permissible familial influence. Third, it addresses a paradox in equality-of-opportunity theory: a high intergenerational correlation does not necessarily indicate a problematic structure, since it may reflect the transmission of values and attitudes within permissible family relationships.

The chapter proceeds as follows. Section 2.2 first establishes the framework, distinguishing liberal and egalitarian perspectives and their implications for transmission channels (genetic, financial, and non-financial). It then presents the analytical model, decomposing educational outcomes into heritable ($h^2$), shared environmental ($c^2$), and non-shared ($e^2$) variance components based on the linear model $Y = G + F + S$.

Section 2.3 analyses how adoption, twin, and IV research designs, under ideal assumptions, identify specific pathways in this decomposition. Section 2.4 synthesises the findings, discusses their implications for the role of familial relationship goods, and suggests directions for future research. By bridging behavioural genetics and political philosophy, this approach clarifies which aspects of educational inheritance merit concern and which reflect the workings of family life.

## 2.2 Background Theories

### 2.2.1 Normative Framework

Building on the model developed by Jerrim and Macmillan (2015), we trace intergenerational educational transmission through three primary channels: financial resources, genetic transmission, and non-financial investment (see Figure 2.1). Each channel operates through distinct mechanisms and carries different implications (see Table 2.1).

*Financial resources* refer to monetary investments in a child's education, including school quality, tuition fees, private tutoring, and enrichment activities (Jerrim & Macmillan, 2015). These resources are widely considered problematic because their distribution is directly tied to income inequality and credit constraints. Families with higher incomes not only have a greater capacity to invest but also face stronger incentives to do so when the returns to education are high (Jerrim & Macmillan, 2015). In practice, this produces substantial disparities. In the United States, for example, high-income families spend six to seven times more on enrichment activities than low-income families. Moreover, spending by top-income households increased from around $3,500 per child in the early 1970s to nearly $9,000 by the mid-2000s (Corak, 2013). Financial resources also affect educational outcomes indirectly through mechanisms such as residential segregation (Reardon et al., 2024), school funding based on local property taxes (Liu, 2006), and reliance on private schools or tutors in high-inequality settings (Mitnik et al., 2016). From a normative perspective, these investments are often replaceable sources of social advantage. They are not intrinsic to the parent–child relationship and primarily function to entrench social stratification, creating unequal starting points that public programmes may seek to mitigate (Corak, 2013).

*Genetic transmission* involves the intergenerational transfer of abilities and traits, including cognitive skills, IQ, and certain personality characteristics (Piketty, 2000). Its assessment differs across frameworks. Under liberal equality of opportunity —

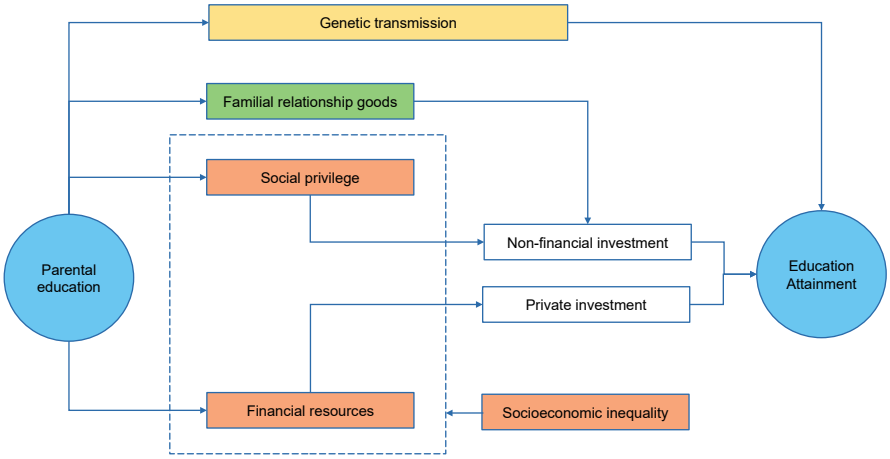



Figure 2.1: Intergenerational transmission of education

**Notes:** Based on the model of Jerrim and Macmillan (2015), we extracted three channels of intergenerational educational transmission: genetic transmission, financial resources, and non-financial investment. Different frameworks assess the implications of these channels differently. Financial resources are widely considered problematic due to credit constraints. Genetic transmission is permissible under liberalism but problematic under egalitarianism. The status of non-financial investment, however, is more nuanced. According to the current framework, non-financial investment can stem from two distinct sources: familial relationship goods (permissible) and social privilege (problematic). Familial relationship goods refer to the intrinsic intimacy of the parent-child bond — what fundamentally constitutes a family. This differs in nature from non-financial investments aimed at preserving the social privilege of a lineage, such as maintaining the status and prestige of wealthy families.

which aligns with Rawlsian fair equality of opportunity and meritocratic principles — genetic transmission is permissible (Grätz & Petrini, 2025; Rawls, 1971). The reasoning is straightforward: individuals with equal abilities and willingness to exert effort should face equal prospects, regardless of social origin. This view accepts the "natural lottery" of abilities while seeking to neutralise socially contingent disadvantages. By contrast, radical or egalitarian equality of opportunity — as articulated in luck egalitarianism — treats genetic transmission as problematic (Arneson, 2018; Cohen, 2008; Dworkin, 2000; Roemer & Trannoy, 2016). Abilities are unchosen and unearned, a characteristic that makes them arbitrary determinants of life outcomes. Under this conception, justice requires neutralising the advantages and disadvantages that arise from innate traits, allowing only inequalities that reflect free choices or effort. Empirical evidence suggests that the impact of genetic transmission on outcomes

is substantial (Rietveld, 2025). Consequently, the scope of inherited advantage is larger under egalitarian standards than under liberal ones.

Table 2.1: When does the apple fall permissibly?

| | **Liberalism** | **Egalitarianism** |
|---|---|---|
| **Genetic transmission** | permissible | problematic |
| **Financial resources** | problematic | problematic |
| **Non-financial investment** | | |
| Familial relationship goods | permissible | permissible? |
| Social privilege | problematic | problematic |

**Notes:** *Liberalism* assesses outcomes mainly through equality of opportunity and merit, allowing inequalities that arise from individual effort, choices, or natural abilities, while correcting only socially imposed disadvantages (Rawls, 1971; Young, 1994). *Egalitarianism* seeks to reduce both social and natural inequalities, treating unearned advantages or arbitrary circumstances as relevant and requiring compensation to ensure access to goods and opportunities (Arneson, 2018; Cohen, 2008; Dworkin, 2000; Roemer & Trannoy, 2016).

*Non-financial investment* includes parental inputs that do not involve direct monetary expenditure, but its status depends on the source. The first source — *familial relationship goods* — is permissible (Brighouse & Swift, 2014). These goods arise from the intimate yet authoritative parent-child bond and include care, attention, and shared practices that constitute family life (Gheaus, 2018; Sypnowich, 2022). They are essential for children's emotional, cognitive, and moral development. A typical example is shared meals, an activity that provides predictable routines, physical and emotional closeness, and reciprocal interaction. Such activities are non-substitutable: no institution can reliably reproduce the intimacy and attentiveness required for these goods (Pedersen & Bøyum, 2020). Luck egalitarians generally seek to neutralise "brute luck" inequalities (Segall, 2011), yet familial relationship goods are often permissible advantages because they protect the free and flourishing internal life of the family. Even if these interactions confer educational or cultural advantages, their intrinsic value may outweigh the resulting inequality (Brighouse & Swift, 2022). Permissibility is further tied to parental motivation: constitutive partiality — interacting for the sake of the relationship itself — is permissible, whereas actions aimed primarily at conferring positional advantage are harder to justify.

The second source — *social privilege* — represents problematic non-financial investment. These activities are designed to preserve the social status and prestige of

a lineage rather than to sustain the parent-child bond. Examples include using social networks to secure internships (Goldthorpe, 2014) and practices such as "Take Our Daughters and Sons to Work Day" when used to transmit advantage (Segall, 2011). Unlike familial relationship goods, these practices are replaceable: they are not required for healthy development or relational intimacy. Social privilege operates through channels that bypass meritocratic processes, including access to elite networks and intergenerational employment in the same firms that confer labour market advantage (Corak, 2013). These practices constitute problematic exercises of parental authority. While the state avoids interfering with intimate family life, it can legitimately regulate external institutions — schools, firms, and recruitment mechanisms — that facilitate these advantages. Mitigating these forms of privilege may be necessary to prevent a child's life chances from being determined by birth and family reputation rather than by effort or talent.

### 2.2.2 Analytical Framework

The analysis starts from the behavioural genetics adaptation model developed by Sacerdote (2007) and applies it to the intergenerational transmission of educational attainment. In this framework, a child's outcome $Y$ is a linear and additive function of three components: genetic endowment $G$, the shared family environment $F$, and unexplained factors (usually the "non-shared" or "unique" environment $S$):

$$Y = G + F + S.$$

Following the standard behavioural genetics framework, we assume independence among components as a simplifying analytical starting point[1]. With $G \perp F \perp S$, total variance is additive:

$$\mathrm{Var}(Y) = \mathrm{Var}(G) + \mathrm{Var}(F) + \mathrm{Var}(S),$$

and the proportional contributions (variance shares) are

$$h^2 = \frac{\mathrm{Var}(G)}{\mathrm{Var}(Y)}, \quad c^2 = \frac{\mathrm{Var}(F)}{\mathrm{Var}(Y)}, \quad e^2 = \frac{\mathrm{Var}(S)}{\mathrm{Var}(Y)}, \quad h^2 + c^2 + e^2 = 1.$$

[1] However, as we discuss in the limitations and in Chapter 3, this assumption is a simplification. In reality, genetic endowment and familial environment are not fully independent; they interact through gene–environment correlation (rGE) and gene–environment interaction (GxE). A child's genetic predispositions may shape how parents respond to them, and parents' own genetics influence the family environment they create. Thus, while the components are conceptually distinct, they are empirically intertwined. We will relax this assumption in Chapter 3.

This decomposition extends across generations. For individual $i$ in family $j$, parental (superscript $p$) and child (superscript $c$) outcomes are

$$Y_{ij}^{p} = G_{ij}^{p} + F_{j}^{p} + S_{ij}^{p}, \quad Y_{ij}^{c} = G_{ij}^{c} + F_{j}^{c} + S_{ij}^{c}.$$

Intergenerational transmission is captured through correlations between corresponding components:

$$\mathrm{Corr}(G^{c}, G^{p}) = \rho, \quad \mathrm{Corr}(F^{c}, F^{p}) = \psi, \quad \mathrm{Corr}(S^{c}, S^{p}) = \omega.$$

Heritability $h^2$ is therefore directly linked to genetic transmission. The analysis then turns to the roles of $c^2$ (the shared family environment) and $e^2$ (the unexplained component), as illustrated in Figure 2.1. The component $c^2$ is constituted by $F_j$, a between-family effect that captures what makes one family differ from another. It reflects family background in terms of socioeconomic inequality, including both monetary and non-monetary dimensions. Although $F_j^p$ in the parent generation cannot equal $F_j^c$ in the child generation, the two are correlated over time. By contrast, the residual component $S$ captures what makes families similar rather than different — namely, familial relationship goods.

To distinguish between $c^2$ and $e^2$, we draw on the distinction between external and internal family goods described by Jonathan (2018). Parents provide their children with "external goods" that have no special connection to family life, are largely impersonal, and are valued broadly in society. These goods include income, other resources, and private education — described as an "impersonal mechanism which equips children with skills, capacities and traits of character important for later study and employment". In the intergenerational transmission of education, such external goods are primary, observable, and naturally associated with $c^2$. By contrast, "families realise internal goods which are valuable in themselves, non-fungible and constitutive of family life". These goods are enjoyed through "parent–child interactions" and include family outings, trips, holidays, games, celebrations, parties, special meals, and religious rituals (Jonathan, 2018). Such "internal goods" are not primarily educational tools. Shared reading is a clear example: a parent reading to a child mainly creates intimacy through shared attention and emotional closeness. Any educational improvements in literacy or language are "incidental benefits" or external by-products of this relational aim. Because familial relationship goods are, in principle, universally accessible and not systematically stratified by socioeconomic status, they remain largely unobserved in standard models of intergenerational educational transmission. In this sense, internal goods — or familial relationship goods — naturally fall under the residual component $e^2$.

Interpreting $e^2$ as familial relationship goods is also consistent with the assumption $G \perp F \perp S$. Familial relationship goods (as an environmental factor) are not determined by[2] — though they do interact with[3] — biological links. As Brighouse and Swift (2014) argue, "It is not the biological relationship that yields the distinctive goods that justify children's being raised in families. Anybody willing to accept that adoptive parents and adopted children can enjoy the kind of relationship we shall describe must acknowledge that what's good about it does not depend on any biological connection between parent and child." This statement supports the claim that such goods are conceptually separate from genetic transmission. Moreover, because familial relationship goods are internal goods, they should also remain independent of external goods such as economic resources or social capital. This distinction is central for identifying which parental practices to protect and which instead undermine a level playing field. It explains why practices such as family gatherings exemplify legitimate constitutive partiality: their value lies in creating shared intimate time, strengthening attachment, and sustaining the parent–child relationship, while any educational gain is incidental. By contrast, practices such as "Take Our Daughters and Sons to Work Day"[4] amount to problematic favouritism, as their main purpose is career advancement, an aim that depends heavily on the parent's social connections and status (Segall, 2011).

One might object that familial relationship goods are unlikely to be entirely independent of genetic factors. This objection relates to the "nature of nurture" literature (Kong et al., 2018), a literature that emerged after these traditional approaches. However, traditional models are still used in economics (Hu et al., 2021; Ulvestad & Markussen, 2023), as evidence suggests gene–environment interactions are modest for wealth, education, and other economic outcomes in Sweden (Black et al., 2020; Brandén, 2018), although recent evidence from the UK shows they account for 15–20% of the treatment effect in education (Biroli et al., 2026). We discuss these issues in Chapter 3. This chapter aims to identify the causal effects of intergenerational transmission that empirical studies cannot explain by biological factors or family background, rather than to critique their key assumptions. We discuss this limitation further at the end of the chapter. It is also important to note that no activity is purely one type. For example, shared reading can also function as a form of private education when parents read with the explicit intention of contributing to literacy skills. Conversely, "Take Our Daughters and Sons to Work Day" may partly

[2] The existence of loving, nurturing relationships in adoptive families demonstrates that these goods do not require genetic ties.

[3] We will address this issue in Chapter 3.

[4] Take Our Daughters and Sons to Work Day is an annual educational programme in the United States where children spend a day at a parent's workplace to explore career possibilities.

reflect relationship goods. In practice, it is difficult to distinguish whether such activities primarily foster family relationship goods or confer social privilege based solely on their stated purpose. Analytically, however, such a distinction is possible. What differentiates them is that social privilege is driven by socioeconomic inequality — since higher-educated parents are better positioned to confer educational advantages — while familial relationship goods are not, as shown in Chapter 5. Moreover, the fixed effects of family background shared by twins — including social privilege as well as financial resources — can be removed in twin studies, as discussed in Chapter 3 and later in this chapter.

Table 2.2: Implications of intergenerational transmission

| Transmission | Content | Analytical framework | Normative framework | Status |
|---|---|---|---|---|
| $\rho$ | $h^2$ | Heritability | Genetic transmission | Neutral |
| $\psi$ | $c^2$ | Family background | Socioeconomic inequality | Problematic |
| $\omega$ | $e^2$ | Residuals | Familial relationship goods | Permissible |

**Notes:** The decomposition follows the linear model $Y = G + F + S$, where $G$ corresponds to $h^2$ (genetics), $F$ to $c^2$ (shared family environment), and $S$ to $e^2$ (non-shared environment or residuals). The status judgement reflects an assessment of each transmission pathway. Genetic transmission is neutral: it is permissible under liberalism but problematic under egalitarianism (see Table 2.1). Heritability is related to, but not identical with, genetic transmission — much as family background is related to, but not exhaustive of, socioeconomic inequality.

Empirically, intergenerational transmission is commonly modelled using the regression

$$Y_i^c = \alpha + \beta Y_i^p + \epsilon_i,$$

where $Y_i^c$ and $Y_i^p$ denote the educational outcomes (or other status measures) of the child and parent in family $i$, and $\beta$ is the intergenerational elasticity. Within the behavioural genetics framework $Y = G + F + S$, this elasticity decomposes as

$$\hat{\beta} = \frac{\mathrm{Cov}(Y_c, Y_p)}{\mathrm{Var}(Y_p)} = \rho h^2 + \psi c^2 + \omega e^2.$$

This decomposition separates overall persistence into three components defined by their content and their transmission effect. The content — $h^2$, $c^2$, and $e^2$ — represents the share of variance in child outcomes attributable to genetics, the shared family environment, and the non-shared environment (or residuals), respectively. The transmission parameters — $\rho$, $\psi$, and $\omega$ — capture the degree to which each component transmits across generations. Together, they describe how genetic inheritance, socioeconomic resources, and relational practices shape child outcomes. Table 2.2 applies

this assessment to the content of each pathway. This clarifies why the observed intergenerational elasticity $\beta$ is not uniform: it combines transmission mechanisms that are neutral (genetic transmission), problematic (socioeconomic advantage), and permissible (familial relationship goods). The decomposition therefore provides a clear analytical structure for identifying and evaluating the status of different channels of intergenerational persistence.

## 2.3 Methodological Review

To clarify what the causal effect of intergenerational educational transmission actually captures, this section examines three causal designs — adoption studies, twin studies, and instrumental variable approaches based on policy reforms — under the assumption of ideal validity. The focus is on conceptual interpretation, setting aside practical concerns of internal and external validity (Holmlund et al., 2011).

### 2.3.1 Adoption Studies

The adoption design offers the most direct way to isolate environmental (nurture) effects by removing genetic transmission. The critical identifying condition is that the genetic correlation between adoptive parents and children is zero:

$$\mathrm{Corr}(G^c, G^p) = \rho = 0.$$

This condition requires random assignment in adoption, a requirement best approximated in studies of international adoptees, such as Korean children adopted into the United States or Norway (Sacerdote, 2007; Ulvestad & Markussen, 2023). Domestic adoption studies often violate this condition due to selective placement, although controlling for the education of biological parents can partially address the issue (Björklund et al., 2006). Early adoption — typically before age three — is also necessary to minimise environmental influences from biological families prior to adoption (Holmlund et al., 2011).

Under these assumptions, the intergenerational transmission equation simplifies to

$$\hat{\beta}_{\text{adopt}} = \psi c^2 + \omega e^2.$$

The adoption estimate therefore captures the combined effect of the adoptive family environment, including family background ($\psi c^2$) — which is generally problematic

— and familial relationship goods ($\omega e^2$) — which may reflect permissible family influence. While adoption studies effectively separate nurture from nature, they cannot distinguish between permissible and problematic transmission, as both components are conflated in the estimate. If the adoption design can eliminate the family fixed effect ($\psi c^2 = 0$), then the estimate becomes a measure of familial relationship goods: $\hat{\beta}_{\text{adopt}} = \omega e^2$.

### 2.3.2 Twin Studies

The twin approach captures the causal effect of intergenerational transmission by exploiting a natural experiment. It compares the children of identical (MZ) or fraternal (DZ) twins. In practice, the method is most credible when applied to MZ or same-sex twins[5], since DZ twins are a weaker comparison group. This limitation arises because DZ twins share only about half of their genes, leaving room for differences due to gene dominance — where certain traits are more strongly expressed from one parent's genes — as well as gene–environment interactions, which can amplify or suppress genetic influences depending on contextual conditions. The central identifying assumption, often called *identical endowments*, is that differences in education between twin parents reflect only their non-shared factors, while their genetic endowments and shared family environment are constant. Although this provides a strong source of identification, some potential biases remain. For example, Behrman and Rosenzweig (2004) find a correlation between birth weight and schooling, a finding that suggests non-random differences even among twins, whereas other studies — such as Black et al. (2007) and Bonjour et al. (2003) — find weak or no such evidence.

A further challenge comes from spousal effects and assortative mating. Because twin parents marry different partners, the spouse's education may confound the estimated effect of the twin's schooling. If the more educated twin marries a more educated or more able spouse, the estimated coefficient may partly reflect the spouse's characteristics rather than the twin's. Controlling for the spouse's education only partially solves this issue, since unobserved endowments such as innate ability or parenting skills are not differenced out in the twin design and may remain correlated with the twin parent's schooling. One common strategy is to use the sum of both parents' education as the key explanatory variable (Oreopoulos et al., 2006). While the sum can be informative, we argue that the average is equally valid and has the advantage of keeping the variances of parent and child education on the same scale, thereby more accurately representing the overall intergenerational transmission process.

[5] as a practical approximation, see Holmlund et al. (2011) and Pronzato (2012)

Formally, consider two twin parents from family $j$. The educational attainment of their children can be modelled as

$$Y_{ij}^{c1} = \alpha + \beta Y_{ij}^{p1} + \gamma X_{ij} + \mu_j + \epsilon_{ij},$$
$$Y_{ij}^{c2} = \alpha + \beta Y_{ij}^{p2} + \gamma X_{ij} + \mu_j + \epsilon_{ij},$$

where $\mu_j$ is a family fixed effect capturing all influences shared by the twin parents. Differencing these equations at the family level eliminates $\mu_j$, leaving a model that exploits only within-twin-family variation:

$$\Delta Y_{ij}^{c} = \beta \Delta Y_{ij}^{p} + \gamma \Delta X_{ij} + \Delta \epsilon_{ij}.$$

The corresponding estimator is

$$\begin{aligned}\hat{\beta}_{\text{twin}} &= \frac{\text{Cov}(\Delta Y_{ij}^{c}, \Delta Y_{ij}^{p})}{\text{Var}(\Delta Y_{ij}^{p})} \\ &= \frac{\text{Cov}(Y^{c1} - Y^{c2}, Y^{p1} - Y^{p2})}{\text{Var}(Y^{p1} - Y^{p2})}.\end{aligned}$$

The identifying variation in parental education ($\Delta Y_{ij}^{p}$) therefore comes exclusively from differences in non-shared environments ($\Delta S^{p}$). Since genetic inheritance and shared family environment are constant within twin pairs, they cannot explain the observed differences. Any association between the differential in parents' schooling and the differential in children's outcomes must operate through the transmission of these non-shared factors.

The twin design often assumes no spillover effects across twins. This assumption may be unrealistic, since twins usually maintain close relationships, and children can be influenced not only by their own parent's schooling but also by that of their aunt or uncle (the co-twin). Such spillovers violate the exclusion restriction because differences in child outcomes may reflect both parents' and co-twins' education. To proceed, most analyses assume no direct spillovers. Under this assumption, the within-pair correlation between parent and child education is

$$\text{Corr}(Y^{c1}, Y^{p1}) = \text{Corr}(Y^{c2}, Y^{p2}) = \rho h^2 + c^2 + \omega e^2.$$

Cross-pair correlations are defined analogously. For genetics, $\text{Corr}(G^{c1}, G^{p2}) = \text{Corr}(G^{c2}, G^{p1}) = \rho$, since $\text{Corr}(G^{p1}, G^{p2}) = 1$ for identical twins. For the shared family environment, $\text{Corr}(F^{c1}, F^{p2}) = \text{Corr}(F^{c2}, F^{p1}) = \psi$; and assuming that family background remains relatively stable across two consecutive generations, then

$\psi \approx 1$. Finally, for non-shared factors, $\mathrm{Corr}(S^{c1}, S^{p2}) = \mathrm{Corr}(S^{c2}, S^{p1}) = \omega\omega'$, with $\omega'$ measuring the similarity of personal life experiences across the twin parents. Using these definitions, the covariance between child and parent differences is

$$\mathrm{Cov}(\Delta Y^c, \Delta Y^p) = 2((1-\psi)c^2 + (1-\omega')\omega e^2)\,\mathrm{Var}(Y).$$

By contrast, the variance of the parental education difference is

$$\mathrm{Var}(\Delta Y^p) = \mathrm{Var}(Y^{p1}) + \mathrm{Var}(Y^{p2}) - 2\,\mathrm{Cov}(Y^{p1}, Y^{p2}),$$

with $\mathrm{Cov}(Y^{p1}, Y^{p2}) = (h^2 + c^2 + \omega' e^2)\,\mathrm{Var}(Y)$. Substituting gives

$$\mathrm{Var}(\Delta Y^p) = 2(1-\omega')e^2\,\mathrm{Var}(Y).$$

Substituting numerator and denominator, the estimator becomes

$$\hat{\beta}_{\text{twin}} = \omega + \frac{(1-\psi)c^2}{(1-\omega')e^2}.$$

This equation shows that the twin design comes close to isolating the transmission effect of familial relationship goods — the form of parental influence often regarded as legitimate — but still includes a bias from family background, which is typically problematic. When family background remains stable between the parent generation (including their siblings) and the child generation, then $\psi = 1$, or $(1-\psi) = 0$. Consequently, the whole bias $\frac{(1-\psi)c^2}{(1-\omega')e^2}$ becomes zero. In this ideal case, the twin estimate provides a measure of the transmission effect of familial relationship goods: $\hat{\beta}_{\text{twin}} = \omega$.

### 2.3.3 IV Approach Using Reforms

The instrumental variable (IV) approach, often implemented through compulsory schooling reforms, provides a way to isolate a specific component of intergenerational transmission. Similar to twin-based designs, it relies on natural experiments to generate exogenous variation in parental education. The instrument $Z$ (e.g., exposure to reform) is assumed to affect child education $Y^c$ only through parental education $Y^p$. Internal validity requires two conditions:

- first, instrument relevance, meaning $Z$ strongly predicts parental schooling;

- second, the exclusion restriction, meaning $Z$ influences child outcomes solely through parental schooling.

The latter assumption is problematic, since reforms may also change teacher quality, alter broader education policies, or shift peer composition[6] (Holmlund et al., 2011). Further complications arise from spousal education. Because partners often match on age and location, reform exposure is correlated within couples. If ignored, this correlation induces bias, while controlling for partner schooling reduces precision[7]. Restricting samples to low-educated parents introduces additional bias, since reforms shift some individuals above the cut-off. Excluding them leaves a negatively selected group of post-reform low-educated parents, a selection that tends to bias estimates downward[8]. Finally, when data on completed schooling are unavailable, researchers rely on proxies such as test scores or grade repetition. These outcomes are not directly comparable to years of schooling and may introduce measurement bias.

Under these conditions, the IV model can be expressed as a system of two equations. The first stage relates parental education $Y^p$ to the reform instrument $Z$:

$$Y^p = \alpha' + \beta' Z + \nu,$$

while the second stage relates child education $Y^c$ to parental education:

$$Y^c = \alpha + \beta Y^p + \epsilon.$$

The IV estimator is then

$$\hat{\beta}_{IV} = \frac{\mathrm{Cov}(Y^c, Z)}{\mathrm{Cov}(Y^p, Z)}.$$

Here, $Z = 1$ if the individual belonged to a birth cohort and municipality where the reform was in effect during their school age, and $Z = 0$ otherwise. When controlling for contextual variables such as municipality fixed effects (which capture time-invariant differences across municipalities) and cohort trends (which capture nationwide changes over time), the instrument is expected to be "as good as random."

[6] For instance, the expansion of schooling increased the demand for teachers, which likely reduced average teacher experience and quality. In addition, reform-induced changes in cohort size and peer composition may have directly shaped educational outcomes, separate from the effects of parental schooling.

[7] If spouses are similar in age and municipality, the reform status of one parent is highly correlated with that of the other. The instrument then partly captures the effect of both parents' education, complicating the interpretation of estimates for a single parent.

[8] For example, if the sample is restricted to parents with less than or equal to nine years of schooling, those who continued to higher education due to the reform are excluded. The remaining group is thus non-random and more negatively selected.

To understand what this estimator captures, we apply the variance decomposition. The instrument $Z$ is not correlated with genetic inheritance ($G^p$), since reforms are assumed independent of genes in the ACE model, implying $\mathrm{Corr}(G^p, Z) = 0$. However, while reforms were motivated by broad goals such as equity and opportunity, their impact disproportionately affected disadvantaged families. This observation implies that $Z$ may correlate with the parental common environment $F^p$, so that $\mathrm{Corr}(F^p, Z) = \lambda \neq 0$. At the same time, $\mathrm{Corr}(S^p, Z) = \sigma$, implying that the reform affects parental experiences and values that may pass to children. Thus, overall,

$$\mathrm{Cov}(Y^p, Z) = \mathrm{Cov}(S^p, Z) + \mathrm{Cov}(F^p, Z) = \lambda + \sigma.$$

A similar decomposition holds for child outcomes:

$$\mathrm{Cov}(Y^c, Z) = \mathrm{Cov}(F^c, Z) + \mathrm{Cov}(S^c, Z),$$

which can be written as

$$\mathrm{Cov}(F^c, Z) = \psi \ \mathrm{Cov}(F^p, Z) + \omega \ \mathrm{Cov}(S^p, Z),$$

under the assumptions that $\mathrm{Var}(S^c) = \mathrm{Var}(S^p)$ and $\mathrm{Var}(F^c) = \mathrm{Var}(F^p)$. This substitution relies on the transmission correlations $\psi$ and $\omega$ as defined in the theoretical model. After controlling for contextual differences between generations, we can assume $\psi = 1$. Substituting into the IV estimator gives

$$\hat{\beta}_{IV} = \frac{\lambda + \omega\sigma}{\lambda + \sigma}.$$

If $Z$ is truly random with respect to the parental environment, then $\lambda = 0$, and the IV estimator simplifies to $\hat{\beta}_{IV} = \frac{\omega\sigma}{\sigma} = \omega$. This means that, under ideal conditions, the IV approach identifies $\omega$ — the transmission effect of familial relationship goods.

From this derivation, it becomes clear why the IV estimator identifies $\omega$ under ideal conditions. A compulsory schooling reform generates exogenous variation in parental education that is, by design, non-selective with respect to both genetic endowments and social stratification. This random exposure transmits to the child through direct, co-resident family relationships rather than through genetic inheritance or structural advantages. The IV estimate therefore captures the spillover of a parent's exposure to randomness via the transmission of familial relationship goods. This aligns with the twin design, where the non-shared environment ($e^2$) — what differentiates identical twins — is likewise real, random (Plomin, 2024), and thus unlinked to genetic inheritance or structural advantages, while the shared environment absorbs all structural inequalities embedded in family, neighbourhood,

school, and institutional environments. Both methods converge on estimating the same permissible pathway. This convergence, however, holds only under ideal conditions. In practice, violations of these ideal conditions (e.g., $\lambda \neq 0$ or $\psi \neq 1$) will bias both estimators, and gene-environment interplay (Biroli et al., 2026) remains a potential confound for the FRG transmission estimate.

## 2.4 Concluding Remarks

This chapter has disaggregated the causal effect of parental education on children's educational outcomes and argued that the transmission of *familial relationship goods* represents a permissible feature of family life. In practice, these goods — bedtime stories, shared meals, family gatherings — are essential to the bonds that make a family a family. Theoretically, they are neither driven by genetic inheritance (evident in adoptive families) nor by socioeconomic background (present even in disadvantaged households). What remains is the intergenerational passage of life values — through non-selective mechanisms unlinked to social stratification — a passage that shapes effort and motivation in education. Indeed, Radl et al. (2026) move beyond traditional effort measures in their "social origins of effort" literature. Instead of relying on residual approaches that control for structural circumstances (Ferreira, 2022), they employ real-effort tasks, avoiding the measurement problems of self-reported or indirect behavioural measures. Their estimate of the intergenerational transmission coefficient from parental effort to child effort is approximately 0.1 — a magnitude provocatively similar to the causal transmission effect of education in Sweden (Holmlund et al., 2011), the focus of Chapter 3. These studies — one using laboratory-based behavioural effort tasks, the other quasi-experimental methods with Swedish administrative data — suggest that the transmission of values and effort dispositions through family relationships is real, though its magnitude still requires de-biasing for gene-environment interplay, as addressed in Chapter 3.

The focus of this chapter — and of the dissertation as a whole — is the *transmission effect* of familial relationship goods, not the goods themselves, nor their contribution to child outcomes (see Figure 2.2). We operationalise the transmission effect of familial relationship goods as:

> the environmental spillover of parents' cognitive exposure to randomness on the child's gene–environment system, transmitted through the direct, co-resident family relationship .

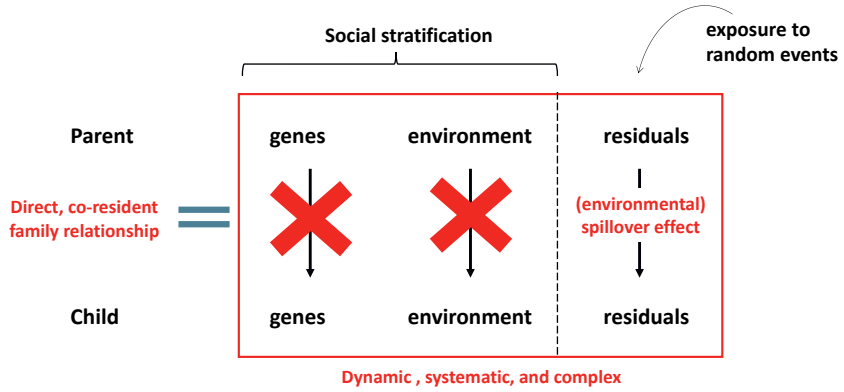



Figure 2.2: The transmission effect of familial relationship goods (FRGs)

**Notes:** We operationalise the transmission effect of familial relationship goods as *the environmental spillover of parents' cognitive exposure to randomness on the child's gene–environment system, transmitted through the direct, co-resident family relationship* . *What is transmitted* is exposure to randomness (e.g., educational reforms) that is non-selective and non-systematic — through cognitive processes — into the dynamic, complex system of gene–environment interplay associated with social stratification. *How this transmission occurs* is through direct, co-resident (with no multigenerational effect) family (not necessarily parental) relationships, such as bedtime stories, shared meals, and family gatherings — relationships that the institution of the family enables. *What this dissertation estimates* is the (environmental, not genetic) spillover effect of exposure to these random events; we do not estimate familial relationship goods themselves, but rather the transmission effect of those goods. Thus, the estimated effect captures the institution of the family in operation.

In essence, we are concerned with the spillover effect of exposure to random events — specifically in the form of values, not the raw events themselves[9] — via family relationships. The values or goods themselves are not stable, but the transmission effect is stable insofar as it operates as a spillover mechanism. These goods and values may pass across generations as accumulative *cultural capital*. But such multigenerational transmission is not what we mean by *familial relationship goods*, which are generated only within direct, co-resident family relationships. Because the child generation obtains these goods and values through a non-random mechanism (intergenerational transmission), the transmission of these goods and values from *child to grandchild* is conceptually different. Moreover, familial relationship goods operate within a direct relationship between an adult and a child. That adult need not be a parent — it could

[9] Random events include *luck* — significant events that immediately create opportunity (e.g., educational reforms) — as well as small, chance occurrences (e.g., Newton's falling apple or stumbling upon an idea in a video). What transmits is not the event per se, but exposure to randomness filtered through cognitive processes.

be a grandparent, uncle, aunt, or adoptive parent who directly raises the child within a living family context, where "family" here is restricted to co-residence, not extended family including ancestors who passed down values across generations. Thus, our theory on family relationships is less relevant to *multigenerational mobility* (Solon, 2018). In addition, these goods may not operate similarly between adults, since adults are already developmentally formed, and such values are less influential than during childhood. In this respect, our argument does not contradict the case for *early childhood interventions* advanced by Heckman et al. (2026) and Heckman (2006). Rather, we emphasise family relationships because they shape children's motivation and effort to acquire skills, without justifying inequalities in resources for skill formation.

The twin design provides a framework for measuring the transmission effect of familial relationship goods. Identical twins share the same gene-environment system. This system includes not only the family environment but also neighbourhood, school, and institutional environments.[10] In short, it captures the entire *dynamic, systematic, and complex* relationship between genes and environment. What differentiates twins is *exposure* to random events — that is, the non-shared environment, which is real and random (Plomin, 2024). The twin estimator therefore captures the transmission effect of exposure to such random events (not measurement errors nor random noise, which are *uncorrelated between individuals* and not transmissible). It excludes all accumulated *cultural capital* — such as family traditions — because these are absorbed into the shared family background (i.e., fixed effects) and therefore do not contribute to the *unshared* component that the twin estimator isolates. What remains is not cultural capital but the transmission of random exposures — experiences that are cultural in content but not accumulated as capital across generations. Similarly, the instrumental variables approach captures this transmission effect using a specific random event — for example, education reforms as a source of random assignment. However, this IV approach is less clear about how gene-environment interplay affects the transmission effect. Twin and IV designs, under ideal conditions, converge on estimating $\omega$. This convergence is empirically supported by the meta-analysis of Fleury and Gilles (2018): there is no statistically significant difference between twin estimates and IV estimates. Chapter 3 extends this framework by directly modelling gene-environment interplay.

[10] This actually strengthens generalisability: by stripping away context-specific factors, what remains is randomness (non-selection) alone.

# 3

# Bias Due to Gene–Environment Interplay

**Abstract**

This study introduces a correction method for bias in estimating the intergenerational transmission of education, addressing a key flaw in twin and adoption designs that ignore gene–environment interplay (including interaction and correlation). Findings show that using standard behavioural genetic models leads to an underestimation of the true effects. Applying the correction to Swedish data — where all design assumptions hold except gene–environment interplay — yields a corrected transmission estimate of 0.15 with a standard error of 0.12. This corrected coefficient represents the the transmission effect of familial relationship goods: the permissible, constitutive practices of family life that generate unavoidable inequality in educational opportunity.

Declaration **Author's notes:** The study has been submitted to a journal. **Data and Code Availability:** No datasets or replication code are associated with this study.

## 3.1 Introduction

Equality of opportunity in education requires distinguishing permissible from problematic channels of intergenerational transmission. While the raw correlation between parental and child educational attainment is large, the component attributable specifically to the transmission of familial relationship goods (Brighouse & Swift, 2014) — the permissible, constitutive practices of family life — appears considerably smaller. As Chapter 2 demonstrates, twin studies currently offer the most reliable method for estimating this permissible component, typically yielding coefficients in the range of 0.10–0.15 (Fleury & Gilles, 2018; Holmlund et al., 2011). These studies generally rely on classical behavioural genetics models such as ACE or ADE, which decompose trait variance into genetic and environmental components but deliberately abstract from gene–environment interplay (Biroli et al., 2026; Horwitz & Neiderhiser, 2011). ACE models partition variance into additive genetics (A), shared environment (C), and non-shared environment (E), while ADE models replace the shared environment component with dominance genetic effects (D). This simplification raises a central question:

> To what extent do traditional models bias estimates of the transmission of familial relationship goods?

This chapter develops a framework that extends beyond ACE and ADE models by incorporating gene–environment interplay, including genotype–environment correlation (rGE) and gene–environment interaction (G×E). The analysis shows that, when such interplay is present, twin studies tend to underestimate the causal effect of intergenerational transmission — an effect interpreted here as the transmission of familial relationship goods. No existing method in the social sciences fully resolves this issue in intergenerational transmission estimates. Rather than relying on direct controls, we propose an indirect approach that combines information from twin and adoption estimators. Adoption studies add leverage on the nature–nurture distinction. This combined approach improves estimation of the true transmission effect and clarifies the relative roles of genetic and environmental factors.

Applying this correction to Swedish estimates (Holmlund et al., 2011) yields a corrected effect of approximately 0.15. Genetic factors explain about 57% of the variance, environmental factors about 40%, with the remaining share attributable to their interplay. This corrected estimate corresponds to the unavoidable inequality generated by the transmission of familial relationship goods. Although this result does not settle normative questions, it provides an empirical lower bound on what policies aimed at equal opportunity can plausibly achieve and identifies the portion of intergenerational transmission that is intrinsically unavoidable.

The remainder of the chapter is organised as follows. Section 3.2 reviews the assumptions underlying twin and adoption studies. Section 3.3 formalises the bias induced by gene–environment interplay. Section 3.4 presents the correction method and applies it to Swedish data. Section 3.5 discusses implications for research on equality of opportunity and the limits of social policy.

## 3.2 Methodological Review

### 3.2.1 Adoption Studies

Adoption studies provide a robust method to control for genetic influences on intergenerational mobility. These studies examine the educational attainment of adoptees who share no genetic relationship with their adoptive parents. This design allows researchers to estimate the impact of parental education and socioeconomic status on child outcomes, a feature that makes adoption studies particularly useful for understanding nurture's role in shaping long-term achievements (Sacerdote, 2007; Sacerdote, 2002). When adoption is random — as in the case of international adoption (Sacerdote, 2007; Ulvestad & Markussen, 2023) — selection biases are minimised, thereby enhancing causal interpretations. This condition is important because selective placement could otherwise inflate estimates of environmental influences (Holmlund et al., 2011). These studies consistently show that parental education has a substantial effect on children's education, while economic outcomes such as labour earnings are also influenced by the adoptive family environment (Plug & Vijverberg, 2003). Recent research by Ulvestad and Markussen (2023) confirms that nurture significantly affects education, labour earnings, and sickness absence but has a negligible effect on the use of disability insurance. These findings align with earlier studies (Björklund et al., 2006; Sacerdote, 2007), demonstrating that environmental interventions can enhance social mobility but may have limited effects on welfare-related outcomes (De Haan & Schreiner, 2025; Hartley et al., 2022).

The relationship between adoptees' outcomes ($Y_c$) and their adoptive parents' outcomes ($Y_p$) is:

$$Y_c = \beta_d \times Y_p + \alpha \times C + \epsilon,$$

where $Y_c$ represents the adoptees' years of schooling, $Y_p$ is the adoptive parents' years of schooling, $C$ includes control variables, $\epsilon$ is the error term, and $\beta_d$ represents the target effect. Adoption studies typically rely on the following key assumptions:

- *Random Assignment of Adoptees*: Adopted children are randomly placed into families, meaning no systematic associations exist between the children's biological backgrounds and their adoptive parents' characteristics. This assumption helps mitigate biases from selective placement[1].
- *No Genetic Transmission*: Adopted children share no genes with their adoptive parents. This assumption allows researchers to attribute any correlation between adoptive parents' education and children's outcomes to environmental factors rather than genetic inheritance.
- *Early Adoption*: Children are adopted at a very young age — ideally at birth or shortly thereafter — thereby minimising the pre-adoption environment's influence. If adoption occurs later, the pre-adoption environment may introduce confounding factors.
- *Similar Parenting Practices*: Adoptive parents treat their adopted children similarly to their biological children. If parenting practices differ significantly, outcomes may be affected independently of the parents' education levels.

In adoption studies, several practical issues challenge these assumptions. One major issue is the random adoption assumption, often violated due to selective assignment based on compatibility between adoptive parents and the child's personality, background, or appearance. While international adoptions are generally closer to random (Sacerdote, 2007; Ulvestad & Markussen, 2023), domestic adoptions often involve selection bias that could affect the results (Holmlund et al., 2011). A potential solution is to include biological parents' education in the model for adopted children (Björklund et al., 2006), an inclusion that would account for some pre-adoption factors. However, this solution risks multicollinearity, especially if biological and adoptive parents' education levels are highly correlated, a situation that makes separating individual effects difficult. Another practical complication arises when a child is raised by both biological and adoptive parents at different developmental stages (Ulvestad & Markussen, 2023). This situation can create heterogeneity in nurturing variables, as the child's environment may change during crucial developmental periods. This heterogeneity complicates estimating the true impact of the adoptive environment on child outcomes. Additionally, some studies may ignore or lack the exact age at adoption (Tsou et al., 2012), a gap that further complicates analysis and potentially introduces bias. These issues highlight the need for careful consideration

[1] Furthermore, in practice, adoption samples are often non-representative, as adoptive families tend to be more stable, educated, and affluent than average, while birth parents may differ in key traits, a pattern that limits the generalizability of findings.

of the adoption process and the child's environment when interpreting results from adoption studies.

### 3.2.2 Twin Studies

Twin studies provide an alternative to adoption studies by comparing the outcomes of children of twin parents (who should be MZ more often than DZ) to estimate intergenerational transmission effects. This design also helps control for shared family background and has been widely used to study the intergenerational transmission of education (Behrman & Rosenzweig, 2002). A key advantage of twin studies is that they allow within-family comparisons, reducing concerns about unobserved bias in traditional OLS estimators (Holmlund et al., 2011). A recent development by Bingley et al. (2023), using Danish Twin Registry data, challenges traditional twin study assumptions. Their findings show that the estimated heritability of education drops from 34% to just 9%, while shared environmental effects explain up to 81% of intergenerational socioeconomic persistence. This suggests that earlier twin-based estimates overemphasised genetic transmission and that educational mobility is more responsive to environmental interventions than previously believed. These results align with adoption study findings, reinforcing that while genetic factors play a role, family environment remains a key determinant of socioeconomic success (Sacerdote, 2007; Ulvestad & Markussen, 2023).

The relationship between the differences in twins' children's outcomes ($Y_{c1} - Y_{c2}$) and the differences in the twin parents' outcomes ($Y_{p1} - Y_{p2}$) is:

$$(Y_{c1} - Y_{c2}) = \beta_w \times (Y_{p1} - Y_{p2}) + \alpha \times C + \epsilon$$

where $Y_{p1}$ and $Y_{p2}$ represent the years of schooling of twin 1 and twin 2, respectively; $Y_{c1}$ and $Y_{c2}$ represent the years of schooling of the children of twin 1 and twin 2, respectively; $C$ refers to control variables; $\epsilon$ is the error term; and $\beta_w$ denotes the target effect. Twin studies typically rely on the following key assumptions:

- *Identical Endowments*: Monozygotic (MZ) twins are genetically identical and share the same upbringing environment[2]. This assumption allows researchers

[2] In genetics, individuals inherit two gene copies, one from each parent. These may combine additively, with each contributing to the trait, or show dominance, where one masks the other (Neale, 2009). Additive models sum effects, but dominant genes can override others, affecting trait expression. In DZ twin studies, ignoring dominance can bias estimates, as twins may inherit different dominant alleles (Bingley et al., 2023). Using only MZ twins helps control for this.

to attribute differences in children's outcomes to differences in the twins' education levels, assuming that other factors (such as innate abilities and shared environment) are controlled for.

- *Random Differences in Schooling*: Differences in schooling levels between identical twins are random and not influenced by other unobserved factors that could affect their children's schooling. This randomness is crucial for identifying causal effects.
- *No Twin Spillover Effects*: One twin's education does not directly affect the other twin's children. In other words, no spillover effects occur whereby one twin's education influences the other twin's children's outcomes.
- *Assortative Mating*: Twin studies often assume that the twins' spouses do not introduce additional bias. If twins with higher education levels tend to marry spouses with higher education levels, this tendency could affect children's outcomes independently of the twins' education levels.

In earlier twin studies, the identical endowments assumption was often violated due to database limitations that did not distinguish[3] between monozygotic (MZ) and dizygotic (DZ) twins (Holmlund et al., 2011; Pronzato, 2012). In studies comparing MZ and DZ twins, researchers typically assume MZ twins share a more similar environment than DZ twins (Bingley et al., 2023). However, differences in parental treatment — even among MZ twins — can violate this assumption. If MZ twins are treated more similarly than DZ twins, this difference could overestimate genetic effects and underestimate environmental influences. Twin studies also frequently face small sample sizes (Amin et al., 2015; Holmlund et al., 2011), especially when examining specific subgroups such as MZ or DZ twins within a particular demographic (with different education outcomes). This limitation can reduce statistical power and lead to unreliable estimates. Small samples also make controlling for a broad range of covariates harder and increase overfitting risk. Assortative mating — where individuals tend to marry someone with similar characteristics (e.g., education level or income) — can bias estimates. If twins with higher education levels marry similarly highly educated spouses, the observed effects of education on outcomes may be confounded by spouse traits (Amin et al., 2015; Hu et al., 2021). Although the spouse's education in the twin parent model does not directly capture transmission effects, including both parents' education can help control for assortative mating, despite multicollinearity concerns. To address these challenges, Oreopoulos et al. (2006) recommend using

[3] However, with the advent of molecular genetic data, most contemporary twin registries have genotyped their participants and accurately confirmed zygosity.

the sum of both parents' schooling as the endogenous regressor, a strategy that both avoids multicollinearity and provides more accurate estimates.

## 3.3 Measuring the Bias

To formalise the bias from gene-environment interplay, we must first engage with behavioural genetics frameworks[4], particularly the ACE/ADE models. These models typically apply to twin and adoption studies (Behrman, 2015; Hübler, 2018; Sacerdote, 2007). The ACE model decomposes a trait's variance into three components: additive genetic effects (A), shared environmental effects (C), and non-shared environmental effects (E). Additive genetic effects capture the cumulative influence of inherited alleles. Shared environment effects reflect factors that make individuals raised in the same family more similar, such as parental education or neighbourhood characteristics. Non-shared environment effects include individual-specific experiences and measurement error. The ADE model, in contrast, replaces the shared environment component with dominance genetic effects (D), which capture interactions between alleles at the same locus. These models are identified using the different degrees of genetic relatedness in twin designs — where monozygotic twins share 100% of their genes and dizygotic twins share on average 50% — and are sometimes extended using adoption data, a practice that separates genetic from rearing effects. The choice between ACE and ADE depends on observed correlation patterns: when the correlation between dizygotic twins is less than half that of monozygotic twins, dominance effects are inferred to be important, favouring the ADE model. Both frameworks offer statistical decompositions that estimate the relative contributions of genes and environments, helping to quantify variation sources in outcomes such as education.

Gene–environment interplay — which includes both genotype–environment correlation (rGE)[5] and genotype × environment interaction (G×E)[6] — is central to behavioural genetics (Biroli et al., 2026; Horwitz & Neiderhiser, 2011). Yet traditional

[4]The field began with Galton's twin studies (Galton, 1889) and later showed substantial heritability for traits like cognition and personality (Plomin, 2018). Criticism over determinism and flawed methods (Gould, 1981; Lewontin, 2006) led to stronger designs. Genome-wide association studies (GWAS) marked a shift by identifying many small-effect variants, enabling polygenic scores as sample sizes grew (Wainschtein et al., 2022; Yengo et al., 2022).

[5]Genotype–environment correlation (rGE) refers to genetic influences on an individual's exposure to specific environments, reflecting genetic control over environmental context. It occurs in three forms: passive rGE, where parents transmit both genes and correlated environments; evocative rGE, where genetically influenced traits elicit environmental responses; and active rGE, where individuals select environments matching their genetic tendencies.

[6]G×E occurs when the environment's effect on an outcome depends on an individual's genetic makeup (or vice versa). It reflects moderation, where genes and environment interact to produce outcomes.

models such as ACE (additive genetic, common environment, unique environment) and ADE (which includes dominance) fail to capture these dynamics adequately. These models often misattribute interaction or correlated effects to additive genetic variance and produce biased estimates, especially when rGE is present or the Equal Environments Assumption[7] is violated (Manuck & McCaffery, 2014; Plomin, 2018; Zyphur et al., 2013). These models assume independent, additive influences and treat genetic and environmental effects as static, overlooking how genetic influences may depend on environmental context (G×E) or how genes may influence exposure to environments (rGE). For example, a child's inherited traits might evoke specific parental behaviours (evocative rGE), or genetic risk for a disorder may manifest only under stress (G×E). To address these limitations, newer approaches have emerged. These include latent interaction models that allow environmental variables to moderate genetic effects (Purcell, 2002; Van Hulle et al., 2013), extended twin family designs (ETFDs) that incorporate data from parents, siblings, and spouses to better identify both G×E and rGE (Keller et al., 2010), and Children-of-Twins (CoT) and Extended CoT (ECoT) designs that separate passive and evocative rGE using intergenerational data (D'Onofrio et al., 2005; Narusyte et al., 2008). While these advanced models offer more accurate representations of gene–environment interplay, they come with challenges such as large data requirements, estimation complexity, and sensitivity to assumptions. As a result, many studies still use classic twin designs (CTDs) for their simplicity despite known limitations[8]. This situation raises a key question:

**Question 3.1.** If economic studies rely on traditional genetic models, to what extent do their estimates of intergenerational transmission effects suffer from bias?

### 3.3.1 Making Sense of Heritability

To answer Question 3.1, we build a new framework — beyond ACE/ADE models — that accounts for gene–environment interplay and makes sense of heritability in behavioural genetics. The analysis revisits *the rectangle analogy*, a concept originally formulated by Hebb and Donderi (1987). This analogy captures the intuitive idea that genes and environment are both essential and jointly contribute to trait development,

[7] The Equal Environments Assumption (EEA) states that monozygotic (MZ) and dizygotic (DZ) twins experience equally similar environments relevant to the trait being studied. This assumption underlies classical twin models (e.g., ACE), allowing researchers to attribute greater trait similarity in MZ twins to genetic factors rather than environmental ones. If violated — such as when MZ twins are treated more similarly than DZ twins — heritability estimates can be biased upward.

[8] Newer methods, including polygenic scores and causal inference techniques like Mendelian randomisation, provide promising tools to better disentangle genetic and environmental influences on behaviour (Plomin, 2018; Smith, 2010); however, they are not yet common in education economics.

analogous to how a rectangle's area depends on both its length and width[9]. The rectangle analogy, though popular and intuitive, oversimplifies the relationship between genes and environment in several ways (Plomin, 2018; Sesardic, 2005). First, it assumes a multiplicative model, where trait development depends on non-additive interaction, although most empirical data are better explained by additive models. Even when interactions exist, transformations such as logarithmic scaling often linearise them[10]. Second, the analogy suggests that gene–environment interaction prevents separating their effects, but quantitative genetics routinely decomposes phenotypic variance into additive, environmental, and interaction components. Third, it focuses on individual-level outcomes, while heritability is defined at the population level; interpreting heritability as individual causation is conceptually flawed[11]. Finally, while the analogy implies individual causal inference is meaningless, structured models can still estimate the relative role of genes and environment in individual deviations from the mean, albeit with some uncertainty.

This chapter develops a new framework based on *the rectangle analogy* to address the conceptual and statistical critiques discussed above, as illustrated in Figure 3.1. In this model, the genetic factor $G$, aligned with the Generalist Genes hypothesis[12], is normally distributed[13], with population mean $G_0$ and genotypic deviation $g$. While genotypic deviation often explains system-level inequalities, $g$ accounts for only about 1% of total genetic variance[14]. The non-genetic factor $N$, representing nurture distinct from gene–environment correlations[15], also follows a normal distribution, where

[9] Hebb's original quote — 'To ask how much heredity contributes to intelligence is like asking how much the width of a field contributes to its area' — emphasises that separating these influences into independent contributions is conceptually flawed if one views their joint effect as a product.

[10] for example, $\log(\text{Area}) = \log(\text{Length}) + \log(\text{Width})$.

[11] Statements like 'height is 70% heritable' refer to the proportion of variance in a population, not to individual causes of height.

[12] Many genetic influences on cognitive traits are non-specific. Plomin and Kovas (2005) showed that genes affecting learning disabilities also influence general learning abilities. Further work by Kovas et al. (2007) found high genetic correlations across reading, math, and science, suggesting that a shared genetic basis explains much observed comorbidity. Similarly, Harlaar et al. (2005) found a genetic correlation of 0.9 between reading familiar and unfamiliar words.

[13] The normal distribution is key to understanding genetic influences on psychological traits. Genetic differences for traits, including disorders, result from many small DNA effects (polygenicity) that combine into a normally distributed polygenic score. This shows genetic risk is continuous and quantitative, meaning disorders lie at the extremes of a normal spectrum — 'the abnormal is normal' (Plomin & Kovas, 2005; Reichenberg et al., 2016).

[14] Heritability is a genetic term that quantifies how much trait variation — between individuals in a specific population at a specific time — is due to inherited DNA differences. The emphasis is on differences, not on individuals or trait levels.

[15] In behavioural genetics, 'environmental influence' is any influence not due to inherited DNA differences, including family, school, peers, prenatal factors, illness, lifestyle, and even non-inherited DNA changes. This broad scope reflects the discovery of 'the nature of nurture' (Kong et al., 2018) — that many

$N_0$ is the population mean and $n$ captures idiosyncratic individual experiences[16]. $N$ acts like a contextual factor, with $N_0$ akin to country or school fixed effects in social research, while $n$ introduces random within-system variation. Since $n$ is random noise, its expected value declines over time through the law of large numbers, whereas genotypic deviation $g$ tends to accumulate, making age a critical control variable[17]. The interaction $g \times n$, representing gene–environment interaction, fades with age as $n$ approaches zero, while the direct environmental effect is $n \times G_0$.

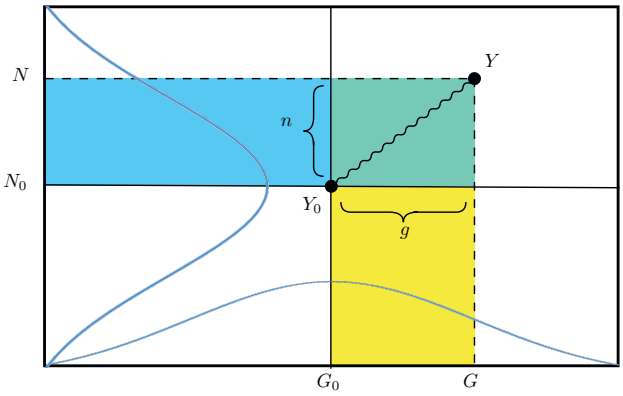



Figure 3.1: Gene–environment interplay

**Notes:** $G$ is the genetic factor with mean $G_0$; $g$ is genotypic deviation, the deviation from $G_0$. $N$ is the non-genetic factor with mean $N_0$; $n$ captures individual random non-genetic variation. $n \times g$ represents the gene–environment interaction; $n \times G_0$ captures direct environmental effects.

To apply this framework to measuring educational outcomes while controlling for

environmental exposures are themselves shaped by genetic propensities. Twin and adoption studies show that individuals partly create or select their environments based on their genetic traits. Thus, this expansive definition is necessary to distinguish non-genetic causes, even when they correlate with inherited DNA through genotype–environment correlation.

[16] Contrary to common assumptions, siblings raised in the same family often show marked differences in psychological traits, with shared environment explaining little of this variation. This finding was termed the 'gloomy prospect' by Plomin and Daniels (2011), reflecting that most environmental influences are non-shared, idiosyncratic, and unpredictable. These influences include chance events, unique experiences, and unstable interactions, which are unsystematic and lack long-term consistency. Since these influences involve many small random effects, their combined impact across individuals approximates random noise and tends toward a normal distribution. Outside the structured family context, non-genetic trait variance is best understood as the cumulative effect of such distributed, stochastic environmental factors.

[17] Genetic influence on psychological traits is a systematic, stable, and long-lasting force throughout life, while environmental influence — particularly the type that makes individuals differ from one another — tends to be unsystematic, random, and unstable, without enduring effects (Plomin, 2018).

age (to avoid genetic amplification[18]), let $Y$ represent years of schooling, $G$ the genetic factor with $G_0$ as the population mean and $g$ as genotypic deviation, and $N$ the non-genetic factor with $N_0$ as the population mean (representing contextual factors such as country environment) and $n$ as random individual experience. The parameter $g$ is a quantitative measure of genotypic deviation, which can be positive or negative, accounting for about 1% of genetic variation, while $G_0$ represents the approximately 99% similarity in DNA across the population. Similarly, $n$ quantifies random deviations from the normal condition $N_0$ in the population and can also be positive or negative. Both $g$ and $n$ are independent and normally distributed around their respective means, with $E[g] = 0$ and $E[n] = 0$. The educational outcome is

$$Y = G \times N = (G_0 + g)(N_0 + n) = Y_0 + nG_0 + gN_0 + ng,$$

where $Y_0 = G_0 N_0$. Given the independence and zero means of $g$ and $n$, the variance of $Y$ decomposes as

$$\mathrm{Var}(Y) = N_0^2 \,\mathrm{Var}(g) + G_0^2 \,\mathrm{Var}(n) + \mathrm{Var}(g) \times \mathrm{Var}(n).$$

Here, $N_0^2 \,\mathrm{Var}(g)$ represents pure nature's contribution, $G_0^2 \,\mathrm{Var}(n)$ pure nurture's contribution, and $\mathrm{Var}(g) \times \mathrm{Var}(n)$ their interplay's contribution. Within this framework, pure nature and nurture contributions depend on contextual factors $N_0$ and $G_0$, which can vary across countries or populations. In other words, pure nature's contribution is sensitive to country fixed effects such as geography and climate, analogous to how allele frequencies vary across populations due to demographic history. Similarly, pure nurture's contribution reflects random experiences of a typical individual with average genetic endowment. The interplay term $\mathrm{Var}(g) \times \mathrm{Var}(n)$ captures G×E, where environmental influences are moderated by genotypic deviation.

In intergenerational transmission (see Figure 3.2), two primary concerns arise for future measurement. First, contextual changes occur across generations, both genetically (e.g., minor genetic evolution) and environmentally (e.g., climate change). As a result, population means shift between parent and child generations by $\lambda_G$ for nature and $\lambda_N$ for nurture, a shift that implies $\mathrm{Var}(Y_p) \neq \mathrm{Var}(Y_b)$ and necessitates stan-

[18] Genetic influence on cognitive traits increases over time. This pattern, first observed in the Louisville Twin Study (Wilson, 1983) and confirmed by the Colorado Adoption Project (Plomin et al., 1997), indicates that heritability for intelligence rises from infancy through adolescence. Meta-analysis by Briley and Tucker-Drob (2013) supports this age-related increase. The process, termed genetic amplification, occurs as individuals increasingly select environments compatible with their genotypes (Plomin & DeFries, 1985).

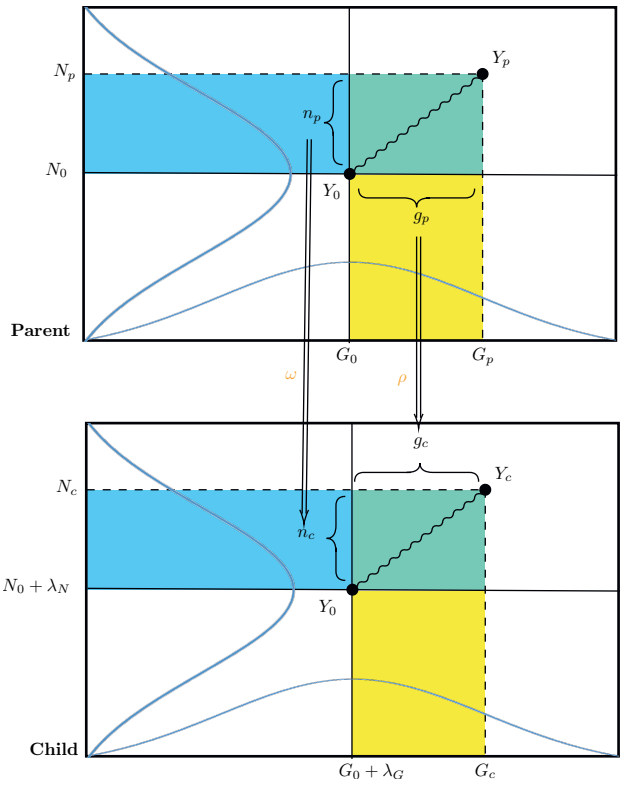



Figure 3.2: Intergenerational transmission

**Notes:** This figure extends Figure 3.1 to intergenerational transmission, showing one distribution for the parent generation and another for the child generation. The population difference between generations is denoted by $\lambda_G$ for the nature factor's mean and $\lambda_N$ for nurture. Intergenerational transmission of nurture is $\omega$, and transmission of nature is $\rho$.

dardisation. Let the standardised education outcome of the parent generation be

$$\tilde{Y}_p = \frac{Y_p - E[Y_p]}{\sqrt{\operatorname{Var}(Y_p)}} = \frac{G_0 n_p + N_0 g_p + g_p n_p}{\sqrt{G_0^2 \operatorname{Var}(n_p) + N_0^2 \operatorname{Var}(g_p) + \operatorname{Var}(g_p)\operatorname{Var}(n_p)}},$$

and that of the child generation be

$$\tilde{Y}_c = \frac{Y_c - E[Y_c]}{\sqrt{\operatorname{Var}(Y_c)}} = \frac{(G_0 + \lambda_G) n_c + (N_0 + \lambda_N) g_c + g_c n_c}{\sqrt{(N_0 + \lambda_N)^2 \operatorname{Var}(g_c) + (G_0 + \lambda_G)^2 \operatorname{Var}(n_c) + \operatorname{Var}(g_c)\operatorname{Var}(n_c)}}.$$

To unify notation, let the standardised outcome $\tilde{Y} = a + u + \lambda(a \cdot u)$, where $a$ and $u$ are orthogonal latent variables of nature and nurture, respectively. Therefore, $E[\tilde{Y}] = E[a] = E[u] = 0$ and $\mathrm{Var}(\tilde{Y}) = \mathrm{Var}(a) + \mathrm{Var}(u) + \lambda^2 \mathrm{Var}(a)\,\mathrm{Var}(u) = 1$. Here, $\mathrm{Var}(a)$ represents the outcome variance proportion attributable to nature, $\mathrm{Var}(u)$ to nurture, and $\lambda^2 \mathrm{Var}(a)\,\mathrm{Var}(u)$ to their interplay, turning the model into a phenotypic form. If we hypothesise that $\mathrm{Var}(a)$ and $\mathrm{Var}(u)$ are consistent[19], then $\lambda$ should be a fixed value across generations:

$$\lambda^2 = \frac{1 - \mathrm{Var}(a) - \mathrm{Var}(u)}{\mathrm{Var}(a)\,\mathrm{Var}(u)} = \left(\frac{1}{\mathrm{Var}(a)} - 1\right)\left(\frac{1}{\mathrm{Var}(u)} - 1\right) - 1$$

Second, the transmission effects between generations can be described using the standardised outcomes of parents and their *biological* children:

$$\tilde{Y}_p = a_p + u_p + \lambda(a_p \cdot u_p), \quad \tilde{Y}_b = a_b + u_b + \lambda(a_b \cdot u_b).$$

Assuming family-level heterogeneity, nurture transmission is $\omega = \mathrm{Corr}(u_p, u_b)$ and nature transmission is $\rho = \mathrm{Corr}(a_p, a_b)$. Since $\mathrm{Var}(\tilde{Y}) = 1$ by standardisation, the intergenerational association is

$$\mathrm{Cov}(\tilde{Y}_p, \tilde{Y}_b) = \rho\,\mathrm{Var}(a) + \omega\,\mathrm{Var}(u) + \lambda^2 \rho\omega\,\mathrm{Var}(a)\,\mathrm{Var}(u),$$

an expression showing that observed intergenerational correlation depends not only on nature and nurture's separate effects but also on their interplay.

### 3.3.2 Biases of Twin and Adoption Studies

In *the adopted-child OLS estimator* framework, let $\tilde{Y}_d$ denote the adopted child's standardised educational attainment, $\tilde{Y}_d = a_d + u_d + \lambda(a_d \cdot u_d)$. By construction, the adopted child shares no genetic link with the adoptive parents, so $\mathrm{Corr}(a_p, a_d) = 0$, while the environmental correlation is retained, $\mathrm{Corr}(u_p, u_d) = \omega$. The intergenerational transmission effect of education, captured by the regression coefficient $\beta_d$ from

[19] If educational attainment is measured as standardised years of schooling and both generations belong to relatively similar cohorts (see the application to the estimates of Holmlund et al., 2011 in Section 3.4.2), then it is reasonable to assume that intergenerational differences in education distribution are captured by shifts in mean and variance rather than by changes in distributional shape. Structural changes such as mass schooling or educational expansion are assumed to shift only the distribution's location (mean) and scale (variance), not its shape.

regressing $\tilde{Y}_d$ on $\tilde{Y}_p$, is

$$\beta_d = \frac{\mathrm{Cov}(\tilde{Y}_d, \tilde{Y}_p)}{\mathrm{Var}(\tilde{Y}_p)} = \omega \,\mathrm{Var}(u).$$

This expression indicates that $\beta_d$ does not reflect the pure environmental transmission parameter $\omega$ alone but is scaled by the nurture component's variance, $\mathrm{Var}(u)$. In this sense, the adopted-child OLS estimator quantifies the nurture share in the total intergenerational association.

For *the twin-parent within-estimator*, let $\tilde{Y}_{p1}$ and $\tilde{Y}_{p2}$ denote the standardised outcomes of the parent twins, $\tilde{Y}_{p1} = a_{p1} + u_{p1} + \lambda(a_{p1} \cdot u_{p1})$ and $\tilde{Y}_{p2} = a_{p2} + u_{p2} + \lambda(a_{p2} \cdot u_{p2})$. Assume genetic correlation $\mathrm{Corr}(a_{p1}, a_{p2}) = \rho'$ and shared environmental correlation $\mathrm{Corr}(u_{p1}, u_{p2}) = \omega'$. Their outcome covariance is

$$\mathrm{Cov}(\tilde{Y}_{p1}, \tilde{Y}_{p2}) = \rho' \,\mathrm{Var}(a) + \omega' \,\mathrm{Var}(u) + \lambda^2 \rho' \omega' \,\mathrm{Var}(a)\,\mathrm{Var}(u).$$

Let $\tilde{Y}_{c1}$ and $\tilde{Y}_{c2}$ denote the standardised outcomes of the corresponding children: $\tilde{Y}_{c1} = a_{c1} + u_{c1} + \lambda(a_{c1} \cdot u_{c1})$ and $\tilde{Y}_{c2} = a_{c2} + u_{c2} + \lambda(a_{c2} \cdot u_{c2})$. Intergenerational correlations are $\mathrm{Corr}(a_{p1}, a_{c1}) = \mathrm{Corr}(a_{p2}, a_{c2}) = \rho = 0.5$ and $\mathrm{Corr}(u_{p1}, u_{c1}) = \mathrm{Corr}(u_{p2}, u_{c2}) = \omega$. Thus, the outcome covariance between each parent and their child is

$$\mathrm{Cov}(\tilde{Y}_{c1}, \tilde{Y}_{p1}) = \mathrm{Cov}(\tilde{Y}_{c2}, \tilde{Y}_{p2}) = \rho \,\mathrm{Var}(a) + \omega \,\mathrm{Var}(u) + \lambda^2 \rho\omega \,\mathrm{Var}(a)\,\mathrm{Var}(u).$$

Assuming a chain rule of correlation, transmission is restricted to biological links. No direct spillover occurs across twin siblings, so $\mathrm{Corr}(a_{p2}, a_{c1}) = \mathrm{Corr}(a_{p1}, a_{c2}) = \rho \cdot \rho'$ and $\mathrm{Corr}(u_{p2}, u_{c1}) = \mathrm{Corr}(u_{p1}, u_{c2}) = \omega \cdot \omega'$. The cross-pair covariance then becomes

$$\mathrm{Cov}(\tilde{Y}_{c2}, \tilde{Y}_{p1}) = \mathrm{Cov}(\tilde{Y}_{c1}, \tilde{Y}_{p2}) = \rho\rho' \,\mathrm{Var}(a) + \omega\omega' \,\mathrm{Var}(u) + \lambda^2 \rho\rho'\omega\omega' \,\mathrm{Var}(a)\,\mathrm{Var}(u).$$

The twin-parent within-estimator is

$$\begin{aligned}
\beta_w &= \frac{\mathrm{Cov}((\tilde{Y}_{c1} - \tilde{Y}_{c2}), (\tilde{Y}_{p1} - \tilde{Y}_{p2}))}{\mathrm{Var}(\tilde{Y}_{p1} - \tilde{Y}_{p2})} \\
&= \frac{(\mathrm{Cov}(Y_{c1}, Y_{p1}) + \mathrm{Cov}(Y_{c2}, Y_{p1})) - (\mathrm{Cov}(Y_{c1}, Y_{p2}) + \mathrm{Cov}(Y_{c2}, Y_{p1}))}{2\,(\mathrm{Var}(Y) - \mathrm{Cov}(Y_{p1}, Y_{p2}))} \\
&= \frac{\rho(1-\rho')\ \mathrm{Var}(a) + \omega(1-\omega')\ \mathrm{Var}(u) + \lambda^2 \rho\omega(1-\rho'\omega')\ \mathrm{Var}(a)\,\mathrm{Var}(u)}{\mathrm{Var}(a)\ (1-\rho') + \mathrm{Var}(u)\ (1-\omega') + \lambda^2\ \mathrm{Var}(a)\,\mathrm{Var}(u)\ (1-\rho'\omega')}
\end{aligned}.$$

For MZ twins, where $\rho' = 1$ and $\rho = 0.5$, this simplifies to

$$\beta_w = \omega \cdot \frac{1 + 0.5\lambda^2 \operatorname{Var}(a)}{1 + \lambda^2 \operatorname{Var}(a)}. \tag{3.1}$$

This expression implies that $\beta_w$ underestimates the full intergenerational transmission effect of nurture, since the ratio $\frac{1 + 0.5\lambda^2 \operatorname{Var}(a)}{1 + \lambda^2 \operatorname{Var}(a)} < 1$. The downward bias magnitude depends on genetic variance $\operatorname{Var}(a)$ and the interplay coefficient $\lambda$. Intergenerational transmission is not affected by shared environment correlation $\omega'$, and twin estimates become more robust as $\lambda$ approaches zero (no gene–environment interplay). Although $\lambda$ may be very small (as shown in the next section), it is never exactly zero, meaning twin estimates still slightly underestimate the true effect.

## 3.4 Corrected Estimate

As discussed in the previous sections, twin studies tend to underestimate the transmission effect of familial relationship goods when gene–environment interplay is involved. To date, no effective method in social science research fully addresses this issue[20]. Although natural sciences sometimes manage this issue through strictly controlled experiments (Smith & Kruglyak, 2008; Wahlsten et al., 2003), such approaches require substantial time and resources. Rather than attempting direct control of gene–environment interplay, this chapter proposes an indirect approach that combines established twin and adoption estimators — methods widely used despite their limitations in accounting for gene–environment interplay — to better estimate the true transmission effect and clarify whether nature or nurture plays the dominant role. We present correction methods grounded in our proposed framework and demonstrate their application using a real-world example. This discussion raises the second question we address:

**Question 3.2.** What is the true effect of intergenerational transmission?

[20] For example, adoption studies like Björklund et al. (2006) use interactions between parent outcomes to separate nature and nurture, addressing non-random assignment (Holmlund et al., 2011) but not gene–environment interplay. In twin studies, Bingley et al. (2023) use a school reform to assess how environment affects heritability, though this approach captures nurture mainly through policy and may overlook interactions between genes and shared environment.

### 3.4.1 The Correcting Method

To answer Question 3.2, we begin with the variance decomposition of the standardised educational outcome into its genetic, environmental, and gene–environment interplay components:

$$\mathrm{Var}(a) + \mathrm{Var}(u) + \lambda^2 \mathrm{Var}(a)\,\mathrm{Var}(u) = 1.$$

Empirical studies typically report three estimators: the adoptive estimate, the biological estimate, and the within-twin estimate:

$$\begin{aligned}
\beta_d &= \omega\,\mathrm{Var}(u) \\
\beta_b &= 0.5\,\mathrm{Var}(a) + \omega\,\mathrm{Var}(u) + 0.5\lambda^2\omega\,\mathrm{Var}(a)\,\mathrm{Var}(u) \\
\beta_w &= \omega\frac{1 + 0.5\lambda^2\,\mathrm{Var}(a)}{1 + \lambda^2\ \mathrm{Var}(a)}
\end{aligned}$$

These equations form a system with four unknowns — $\mathrm{Var}(a)$, $\mathrm{Var}(u)$, $\omega$, and $\lambda$ — that is point-identified under standard assumptions (see the solution in Appendix 3.1). Solving the system yields closed-form solutions:

$$\begin{aligned}
\omega &= 2\beta_w - \beta_d\frac{1 - 2\beta_w}{1 - 2\beta_b} \\
\mathrm{Var}(a) &= \frac{2(\beta_b - \beta_w)}{1 - 2\beta_w} \\
\mathrm{Var}(u) &= \frac{\beta_d(1 - 2\beta_b)}{2\beta_w(1 - 2\beta_b) - \beta_d(1 - 2\beta_w)}
\end{aligned}$$

To estimate the uncertainty around these quantities, we apply the Delta Method (Gold et al., 2017), assuming that $\beta_b$, $\beta_d$, and $\beta_w$ are mutually independent. For any smooth function $f$ of these estimators, the variance is approximated by

$$\mathrm{Var}(f) \approx \left(\frac{\partial f}{\partial \beta_b}\right)^2 \mathrm{Var}(\beta_b) + \left(\frac{\partial f}{\partial \beta_d}\right)^2 \mathrm{Var}(\beta_d) + \left(\frac{\partial f}{\partial \beta_w}\right)^2 \mathrm{Var}(\beta_w),$$

a formula that computes standard errors for all derived parameters (see partial derivatives details in Appendix 3.2).

### 3.4.2 A Real-World Example

Having established that prior studies using different identification strategies have produced varying intergenerational schooling effect estimates, our analysis shows that

the contextual factor $\lambda$ plays a significant role, especially when comparing samples across countries and cohorts. To best align with our correction method, we rely on the estimates from Holmlund et al. (2011). This study was the first to apply all three designs — biological, adoption, and twin — to the same dataset, thereby holding country and cohort effects constant. Their research provided a detailed comparison of the three designs available at the time, although it did not address gene–environment interplay as highlighted in behavioural genetics — a limitation later recognised and still discussed today. They used a large dataset (Swedish Registry data) compiled from multiple Swedish registers administered by Statistics Sweden. Their estimates fully meet all necessary criteria under our methodological framework (see estimate and sampling details in Appendix 3.3). Specifically:

- *Assortative mating*: The sample is restricted to individuals who are married or cohabiting, have children, and live together. The analysis controls for assortative mating by using both parents' average educational attainment.
- *Similar parenting practices*: Biological children are raised by parents who also adopt, a design that holds parenting style constant across biological and adopted children.
- *Random adoption*: Foreign-born adoptees serve as a quasi-random sample, making adoption status as good as random. Sacerdote (2007) and Ulvestad and Markussen (2023) support this assumption for Korean American and Korean Norwegian adoptees, respectively.
- *Early adoption*: Only children adopted no later than six months of age are included, ensuring minimal pre-adoption exposure to biological parents.
- *Measurement error*: Children in the sample are at least 23 years old, reducing the risk that some may still be in school at data collection[21].
- *Identical endowments*: Since distinguishing between monozygotic (MZ) and dizygotic (DZ) twins in the dataset is impossible, only same-sex twins are used as a workaround. To validate this approach, we cross-check with the MZ twin estimator from Amin et al. (2015), who also used Swedish registry data and a similar methodology. The results are highly consistent with Holmlund et al.'s estimates.

[21] Genetic influence on cognitive traits increases over time — genetic amplification — during development as individuals select environments matching their genetic predispositions. However, researchers typically measure years of schooling once formal education is complete (usually in late adolescence or adulthood), so the dynamic process of increasing heritability during development does not apply to it in the same way. Years of schooling is more a cumulative endpoint than a developing trait, a characteristic that makes the rising genetic influence pattern less relevant.

Table 3.1: Estimates from the study of Holmlund et al. (2011)

| | $\beta'_f$ | $\beta'_m$ | $\beta_f$ | $\beta_m$ | $\ddot{\beta}$ |
|---|---|---|---|---|---|
| **1. Adoptee sample**: 912 own-birth children and 4,893 adopted children born abroad (foreign-born adoptees). At least one of the parents is born 1943–55. $\sigma_f = 2.89;\ \sigma_m = 2.54;\ \sigma_c = 1.86$ | | | | | |
| 1.1. OLS estimates based on own-birth children who have foreign-born adoptive siblings | 0.19<br>(0.03) | 0.22<br>(0.03) | 0.13<br>(0.04) | 0.15<br>(0.04) | 0.14<br>(0.02) |
| 1.2. OLS estimates based on foreign-born adoptees who have own-birth siblings | 0.04<br>(0.01) | 0.04<br>(0.01) | 0.04<br>(0.01) | 0.03<br>(0.01) | 0.03<br>(0.01) |
| **2. Twin sample:** 2,110 twin fathers and 2,940 twin mothers (where at least one is) born 1943–55 with 9,947 children. $\sigma_f = 2.82;\ \sigma_m = 2.52;\ \sigma_c = 2.01$ | | | | | |
| 2.1. Difference estimates using the twin design | 0.12<br>(0.03) | 0.06<br>(0.03) | 0.11<br>(0.03) | 0.04<br>(0.03) | 0.07<br>(0.02) |

**Notes:** $\sigma_f$, $\sigma_m$, and $\sigma_c$ denote the standard deviations of educational attainment for the father, mother, and child, respectively. $\beta'_f$ is the regression coefficient of the father's education on the child's education without controlling for assortative mating, while $\beta_f$ is the corresponding coefficient when controlling for assortative mating. $\beta_m$ is the analogous coefficient for the mother. $\ddot{\beta}$ represents the pooled parental effect under the constraint $\beta_f = \beta_m = \ddot{\beta}$, with controls for assortative mating. More details in Appendix 3.3.

Table 3.1 reports estimates from Holmlund et al. (2011) on intergenerational transmission using both the adoptee and twin samples. The variables are: $\sigma_f$, $\sigma_m$, and $\sigma_c$ represent the sample standard deviations of educational attainment for the father, mother, and child, respectively. The coefficient $\beta'_f$ is the regression coefficient of father's education on child's education without controlling for assortative mating, while $\beta_f$ adjusts for assortative mating. The corresponding estimate for the mother is $\beta'_m$ and $\beta_m$, respectively. Assuming equal effects from both parents and controlling for assortative mating, they estimate a pooled coefficient $\ddot{\beta}$ under the restriction

$\beta_f = \beta_m = \ddot{\beta}$. The corresponding regression specifications are:

$$Y_c = \beta_f' Y_f + \varepsilon, \quad Y_c = \beta_m' Y_m + \varepsilon,$$
$$Y_c = \beta_f Y_f + \beta_m Y_m + \varepsilon,$$
$$Y_c = \ddot{\beta} Y_f + \ddot{\beta} Y_m + \varepsilon, \quad \text{with the constraint } \beta_f = \beta_m = \ddot{\beta}.$$

However, two issues arise when adapting Holmlund et al. (2011)'s estimates to our correcting method. First, the dependent variable $Y$ in their regressions is not standardised. This can bias estimates due to contextual differences — such as shifts in environmental, health, or institutional factors — between parent and child generations. Standardisation is necessary for interpretable, scale-free measures. To accomplish this standardisation, we rescale their original (unstandardised) coefficient estimates $\widehat{\beta}_i$ using the ratio of parent and child outcome standard deviations:

$$\beta_i = \widehat{\beta}_i \cdot \frac{\sigma_p}{\sigma_c}, \quad \text{SE}(\beta_i) = \text{SE}(\widehat{\beta}_i) \cdot \frac{\sigma_p}{\sigma_c},$$

where $i \in \{b, d, w\}$, corresponding to the biological (row 1.1), adoptee (row 1.2), and twin (row 2.1) design. The child's standard deviation $\sigma_c$ is from Appendix C.1, while the parent's standard deviation $\sigma_p$ must be derived, as explained below.

The second issue concerns the 'parent' definition in estimation. Using only the father or mother introduces gender sensitivity, a bias that could distort interpretation or limit generalisability. To avoid this issue, we follow Oreopoulos et al. (2006) and use the average[22] education of the two parents, $Y_p = \frac{Y_f + Y_m}{2}$, as the single measure of parental education. The model specification becomes: $Y_c = \beta_i Y_p + \varepsilon$, a specification that implies the coefficient associated with average parental education is $\beta_i = 2\ddot{\beta}_i$, where $\ddot{\beta}_i$ is the pooled estimate under the constraint $\beta_f = \beta_m$, with assortative mating controlled. Before using this coefficient in our method, we again need to standardise it. The standardised coefficient and standard error are:

$$\beta_i = 2\ddot{\beta}_i \cdot \frac{\sigma_p}{\sigma_c}, \quad \text{SE}(\beta_i) = 2\text{SE}(\ddot{\beta}_i) \cdot \frac{\sigma_p}{\sigma_c}.$$

To calculate $\sigma_p$, we apply variance decomposition to average parental education:

$$\text{Var}\left(\frac{Y_f + Y_m}{2}\right) = \frac{1}{4}\left(\text{Var}(Y_f) + \text{Var}(Y_m) + 2\text{Cov}(Y_f, Y_m)\right).$$

[22] Oreopoulos et al. (2006) use the sum of parental schooling to reduce multicollinearity — thus, the regression coefficient in that case equals $\ddot{\beta}_i$. Here, we use the average of parental schooling instead to maintain the same scale as the child's schooling while preserving validity.

The covariance $\text{Cov}(Y_f, Y_m)$, reflecting assortative mating, is not directly available. However, we can derive it using the difference between unadjusted and adjusted paternal coefficients:

$$\beta'_f - \beta_f = \beta_m \cdot \frac{\text{Cov}(Y_f, Y_m)}{\text{Var}(Y_f)} \quad \Rightarrow \quad \text{Cov}(Y_f, Y_m) = \frac{\beta'_f - \beta_f}{\beta_m} \cdot \text{Var}(Y_f).$$

Substituting this expression into the variance formula yields:

$$\text{Var}\left(\frac{Y_f + Y_m}{2}\right) = \frac{1}{4}\text{Var}(Y_m) + \frac{1}{2}\left(\frac{\beta'_f - \beta_f}{\beta_m} + \frac{1}{2}\right)\text{Var}(Y_f),$$

or in standard deviations:

$$\sigma_p^2 = \frac{1}{4}\sigma_m^2 + \frac{1}{2}\left(\frac{\beta'_f - \beta_f}{\beta_m} + \frac{1}{2}\right)\sigma_f^2.$$

After applying standardisation and correction procedures, the estimates are $\beta_d = 0.0621$ (SE = 0.0207), $\beta_b = 0.349$ (SE = 0.0498), and $\beta_w = 0.149$ (SE = 0.0425) for adoptee, biological, and twin data, respectively. Our corrected intergenerational transmission effect is $\omega = 0.154$ (SE = 0.123), with variance components of $\text{Var}(a) = 0.570$ (SE = 0.151) for nature and $\text{Var}(u) = 0.404$ (SE = 0.396) for nurture. These results align with a U.S. study using polygenic scores that shows a direct nurture effect near 0.050 (Verweij & Keizer, 2022) — an effect that closely matches our estimate of $\omega\,\text{Var}(u) = 0.0621$ — and a meta-analysis reporting a transmission effect around 0.15 (Fleury & Gilles, 2018). Our nature estimate also matches Dutch studies attributing 55–70% of educational variance to genetics (Knigge et al., 2022; Plug & Vijverberg, 2003), supporting our corrections' validity. Consistent with prior literature (Black et al., 2020; Brandén, 2018) in Sweden, gene–environment interaction ($G \times E$) accounts for a small share (<3%) of education outcome variance in our calculation. As a confounding bias not addressable through an interaction term, gene–environment correlation ($rGE$) is not separately identified by our method but is absorbed into natural attributes' overall contribution in the framework[23]. We also demonstrate that the residual or non-shared environment does not include $r$GE, but rather $G \times E$, in Appendix 3.4.

It is important to note that $\beta_w$ remains valid as a measure of the transmission effect of familial relationship goods, as discussed in Chapter 2. Our model, developed in

[23] If $rGE$ holds, then $E = \gamma_0 + \gamma_G G + u$, where $\gamma_0$ corresponds to $N_0$ in our framework — the equalised environmental context. This expression implies that all systematic environmental variation is genetic in origin, while only the residual $u$ is non-genetic — what Plomin (2024) describes as "real but random."

Figures 3.1 and 3.2, assumes that genetic and non-genetic factors are independently generated but jointly contribute to educational outcomes through their interactions. Familial relationship goods transmission is therefore entirely non-genetic — as observed in adoptive families without biological children — but these goods' effects can combine with biological links within families raising their own birth children. Our approach also separates family background (social privilege and financial resources) from familial relationship goods transmission, as it relies on within-estimates from twin parents, a design that removes the twins' shared family background. What our model does is adjust familial relationship goods transmission to its pure value, and adoption estimates provide additional information to do so. Importantly, because our framework isolates gene–environment interaction (G×E) but absorbs gene–environment correlation (rGE) into the genetic component $\mathrm{Var}(a)$, any portion of familial relationship goods transmission arising from rGE — for example, when genetically influenced parental traits shape the family environment — is excluded from our estimate of $\omega$. The corrected $\omega$ therefore captures only the purely non-genetic component of familial relationship goods transmission, a focus consistent with our core claim: these goods are not determined by genes, though their transmission may interact with them.

One might misinterpret familial relationship goods transmission as a spillover of parental "luck", where luck refers to random, non-genetic events. This misinterpretation would weaken their claim to permissibility, since such advantages are often seen as arbitrary. We argue otherwise. Even when parental educational attainment is shaped by such shocks ($n_p$), these experiences typically stabilise into enduring values before transmission. They reshape the parent's lived experience and consolidate into narratives conveyed to their children. At transmission, they no longer act as "luck" in an environmental sense; instead, they form part of family practices and relationship goods (Brighouse & Swift, 2014). We can write the child's non-genetic component as

$$n_c = \text{luck} + \text{parental transmission of values}.$$

A child's own luck refers to random events that happen directly to them and should be uncorrelated with parents' luck. Therefore, no intergenerational transmission of luck occurs. What transmits are the effects of parental personal experiences that were initially random. These effects are not originally linked to family background or genes, since they occur directly to parents. However, if they persist across generations, they can become stable family values and thus part of family background. Once that happens, these effects would be "removed" in a model that controls for family background. Therefore, intergenerational transmission of the "residual" — the component beyond genes and family background — reflects only the parent–child relationship, not systematic advantage. By focusing on the correlation, we isolate relationship

goods transmission from one-off luck, a component the model already excludes.

A critical qualification concerns the external validity of estimates derived from Swedish registry data. One might argue that the non-shared environment's transmission effect is modulated by family bond intensity (e.g., contact frequency, parent–child interaction), a modulation that may vary across regimes. However, this concern does not undermine our approach for two reasons. First, family bond intensity and warmth are not exogenous; they are embedded within the existing gene–environment system, as behavioural traits and the shared family environment may co-determine them. Second, traditional twin estimates are indeed context-sensitive because they are conditional on $\lambda \operatorname{Var}(a)$ of a specific population (see expression (3.1)), a condition that expands or contracts depending on a country's opportunity structure. Our bias-correction framework directly addresses these conventional limitations. Moreover, because the non-shared environment consists of non-systemic randomness (twin similarity already captures all systematic environment, including institutional effects; see Chapter 2), it has no inherent macro-institutional footprint, so the corrected parameter $\omega$ should theoretically remain invariant across contexts. Nevertheless, this theoretical invariance remains an empirical question. We therefore explicitly encourage future research to replicate and recalculate $\omega$ for other institutional settings — using the novel bias-correction method presented here — before applying the broader framework to new populations or policy contexts.

## 3.5 Conclusion and Discussion

This chapter proposes a method to correct bias from gene–environment interplay when estimating intergenerational education transmission from twin studies. The method combines twin studies with adoption studies drawn from the same population. The focus is on identifying the transmission effect of familial relationship goods, as defined in Chapter 2. We apply the method to the estimates in Holmlund et al. (2011) using Swedish administrative data. Sweden provides a setting where the standard assumptions underlying twin and adoption designs are largely satisfied, except for gene–environment interplay. After correction, the estimated intergenerational transmission effect is 0.15 with a standard error of 0.12. This estimate is close to those using polygenic scores, suggesting external consistency across methods. The analysis further indicates that genetic factors account for 57% of educational attainment variance, with a standard error of 0.15. This estimate aligns with earlier findings, including Knigge et al. (2022) and Plug and Vijverberg (2003), who report genetic contributions in the 55% to 70% range. It is also consistent with Arpawong et al. (2023), who document heritability estimates for educational attainment between 23% and 80%,

depending on context and design. These results motivate a new social mobility measure in which the intergenerational transmission component attributable to familial relationship goods transmission is preserved, rather than setting the parent–child link to zero. The appropriate magnitude of this preserved link is around 0.15, a magnitude that corresponds to the true intergenerational transmission effect after correcting for gene–environment interplay. As a result, social mobility should not be defined mechanically as one minus the transmission coefficient. We develop this alternative measure in Chapter 4.

The proposed correction allows education economists to obtain consistent estimates even when gene–environment interplay is present. A key limitation is that the method relies on strong assumptions and requires specific research design conditions. This concern is valid, but the design is feasible in practice. It only requires a structure similar to that in Holmlund et al. (2011), where twin and adoptee samples are drawn from the same administrative population. Moreover, if the main objective is to estimate the genetic contribution, $\mathrm{Var}(a)$, to educational attainment, the adoption design is not strictly necessary. Identifying $\mathrm{Var}(a)$ does not depend on $\beta_d$, the OLS estimate based on adopted children. A design using twins and biological children alone is sufficient to identify $\mathrm{Var}(a)$ consistently, even with gene–environment interplay. In this framework, nature includes all genetic effects, including genetic influences operating through the environment. Nurture is primarily non-genetic random variation, similar to non-shared environmental effects. Shared environment is also a nurture component, but it operates through fixed effects at the family or school level.

One might be concerned that the proposed correction assumes specific functional forms for gene–environment interplay (rGE and G×E), and question how sensitive the results are to these assumptions — particularly if the true interaction is non-linear. We argue that this concern is not serious for two reasons. First, the twin design already captures the systematic and complex relationship between genes and environments; what is estimated is the unshared environment's transmission effect, which is real and random (Plomin, 2024). This approach is analogous to the partialling-out framework in Chapter 5, where the linear component is simply a regression on residuals after predictive analysis using machine learning (understood as capturing a complex system). Second, we directly compare linear prediction (using Lasso) with non-linear prediction (using machine learning) in Chapter 5, and find no statistically significant difference. Heritability estimates in these models are fundamentally based on twin similarity. Moreover, current economics and econometrics practice continues to rely predominantly on linear models, and no strong evidence yet shows that non-linear models are required or substantially outperform linear models (Biroli et al., 2026).

Several future research directions emerge from this analysis. First, while the cur-

rent study focuses on years of schooling, the method can extend to other socioeconomic outcomes — such as cognitive ability (Grönqvist et al., 2017), health (Thompson, 2014), or crime (Hjalmarsson & Lindquist, 2013) — provided they can be described by genetic–behavioural models and measured comparably across generations. However, treating discrete outcomes as continuous may introduce measurement bias. Future work should apply the method to a wider set of outcomes to assess its general applicability, especially given evidence that nature and nurture's relative importance varies across domains (Ulvestad & Markussen, 2023). Educational attainment is discrete and censored, yet z-score transformations assume continuity — ceiling effects may bias estimates. This limitation is field-wide, as most research uses years of schooling, and future work will need methods to correct for it. Second, the Swedish focus raises generalisability questions. However, the bias is not serious as we theoretically demonstrate at the end of Section 3.4.2. Replication in other settings would further strengthen this claim. Third, existing studies are limited by small numbers of twins and adoptees, a limitation that reduces precision and contributes to large standard errors, as reflected in our corrected estimates' uncertainty. Future research should prioritise larger samples or methods that reduce small sample size sensitivity.

Despite these limitations, the corrected estimate of $\omega = 0.15$ suggests that even under ideal conditions — where all financial and social privilege is equalised — some parent-child similarity would remain. This residual similarity reflects familial relationship goods transmission that constitutes family life. Chapter 4 develops a mobility measure that preserves this component rather than setting the parent-child link to zero, offering an alternative to conventional intergenerational elasticity.

# 4

# What Should Perfect Mobility Look Like?

**Abstract**

This chapter revisits perfect mobility — children's outcomes independent of their parents' — and examines whether it is truly achievable or simply a statistical benchmark. Standard measures treat mobility as a flat landscape, ignoring the obstacles and uneven terrain of real opportunities. We identify three observations: downward mobility can reflect structural barriers, intergenerational persistence is not always problematic, and upward mobility is not additive, since the difficulty of climbing educational rungs varies. To address this, we propose fair progress, which accounts for legitimate family influence and uneven transition difficulties, and derive adjusted mobility, capturing the gap between observed outcomes and fair progress, providing an alternative map of social mobility worldwide.

Declaration **Author's notes:** The study has been submitted to a journal. **Data and Code Availability:** The data (DOI: 10.6084/m9.figshare.30574931) and replication code (DOI: 10.6084/m9.figshare.30574934) that support this study are openly available.

## 4.1 Introduction

"Every day, nearly 400,000 babies are born around the world. None of them choose their gender, race, place of birth, or the social and economic conditions of their families — life begins as a lottery. But the future need not be left to chance," said Kristalina Georgieva, Chief Executive Officer of the World Bank, in a report on global intergenerational mobility (Narayan et al., 2018). All parents, particularly those in the poorest segments of society, hope their children will have better lives. Children themselves aspire to break free from the constraints of their birth — a vision once called the "American Dream" but now a universal ideal of intergenerational mobility. Yet, as the World Bank report shows, upward mobility remains elusive for the poor, especially in developing countries (Narayan et al., 2018). Even in the "land of opportunity," the United States, the distribution of opportunity remains highly uneven (Chetty et al., 2014). This uneven distribution raises a fundamental question: Is current progress fair? The concern is reinforced by the "Great Gatsby curve," a relationship that shows existing inequalities deepen disparities and suppress mobility (Durlauf et al., 2022).

Intergenerational mobility can be measured through earnings, occupation, or education, each metric carrying distinct trade-offs. Earnings-based measures, while precise, face challenges of lifecycle bias, short-term volatility, and limited availability outside high-income countries (Blanden, 2013; Clemente-Casinhas et al., 2025; Deutscher & Mazumder, 2023). Occupational measures are easier to collect but suffer from inconsistencies in cross-country comparability (Blanden, 2013). Given these limitations and the need for a globally comparable metric, this chapter operationalises intergenerational mobility through educational attainment. Education-based mobility tables offer several advantages: they provide a stable, clearly ordered metric that is fixed in early adulthood, closely reflect social stratification (van der Weide et al., 2024), and are widely available internationally through frameworks like ISCED (Narayan et al., 2018). These tables support detailed analysis of mobility patterns and inequality-sensitive indices (Apouey et al., 2023), a combination that makes education the most practical approach for international comparisons (Narayan et al., 2018).

We acknowledge that a similar analytical framework could be applied to class mobility, and that educational mobility may be influenced by credentialism. However, evidence from labour economics suggests the importance of credentialism is often overstated (Groot & Oosterbeek, 1994). Education continues to signal productive potential and trainability — qualities that employers value (Goldthorpe, 2014). In contrast, class mobility is profoundly biased by technological and structural economic changes, changes that can create an illusion of progress without a genuine improvement in equality of opportunity (Torche, 2015a). This discrepancy arises because the

occupational structure — the "job queue" — is not infinitely malleable to the supply of educated labour but is exogenously shaped by factors like deindustrialisation. These exogenous factors create structural mobility that obscures the underlying fairness of opportunity (Goldthorpe, 2014; Torche, 2015a). The primary rationale for focusing on education is that it captures a formative life stage where outcomes are more directly determined by individual choices and effort, before later-life labour market mediations such as employers' use of social background as a screening signal (Goldthorpe, 2014) or the growing importance of within-class income variation for children's outcomes (Blanden et al., 2013). Therefore, barriers in the educational pipeline provide a more fundamental measure of the initial distribution of unequal opportunity, a measure that makes education a necessary precondition for understanding broader social mobility.

Yet even within educational mobility (as well as other quantitative forms of social mobility), a key problem persists: the conventional notion of perfect mobility. Defined as the statistical independence of children's educational outcomes from their parents' background, perfect mobility is often treated as a neutral or ideal benchmark. This notion has faced foundational criticism from Swift (2004), who — notably as one of the two scholars who established the concept of familial relationship goods (Brighouse & Swift, 2014) — argued that "no sociologist has been foolish enough to endorse such an extreme view." Building on this critique and his conceptual work, we argue that the conventional benchmark is problematic for three reasons. First, it treats downward mobility as harmless. Second, it assumes all upward moves are equally difficult. Third, and most critically, it ignores the legitimate and justifiable influence of those very familial relationship goods (see Chapter 2). As quantified in Chapter 3, these goods account for a baseline intergenerational transmission effect of approximately 0.15. By framing mobility as a flat landscape, perfect mobility conceals structural barriers and the real, unequal challenges children face in advancing educationally. This chapter therefore addresses a central question: what should a benchmark of mobility look like if it accounts for both legitimate family influence and the unequal difficulty of educational transitions?

We critique "perfect mobility" for ignoring structural forces. While these forces are most obvious in class mobility (e.g., deindustrialisation), they are equally potent in education, primarily in the form of educational expansion. Expansion is the engine of absolute mobility, but it does not automatically produce fairness. The Maximally Maintained Inequality (MMI) hypothesis provides the crucial mechanism (Raftery & Hout, 1993): expansion only reduces class-based inequality at a given educational level after the demand from the privileged class is saturated. This means the structural shift of expansion systematically benefits the advantaged first, often creating an 'illusion of progress' while maintaining relative advantage. Our "fair progress" model

is specifically designed to account for this dynamic. It uses the actual structural constraints of a society's educational distribution to create a benchmark for expansion that is not captured by the privileged classes under the MMI logic. Our adjusted mobility measure then reveals which countries have managed their educational expansion in a way that distributes opportunity more fairly, and which have allowed structural growth to mask deeply unequal opportunities.

The chapter proceeds as follows. Section 4.2 reviews the literature on intergenerational mobility and education-based mobility tables, highlighting the strengths and limitations of existing measures. Section 4.3 develops the conceptual model, critiques the notion of perfect mobility, and introduces fair progress as a more realistic benchmark. Using education-based mobility tables from the GDIM for the 1980s birth cohort in 153 countries, Section 4.4 applies this framework to derive adjusted mobility, capturing the gap between observed outcomes and fair progress. The results show substantial variation: Africa and South Asia display low adjusted mobility, developed countries perform better, and Latin America achieves educational gains that do not fully translate into opportunity. Comparisons with conventional mobility measures and the Social Progress Index suggest that adjusted mobility provides a clearer view of both progress and fairness. Section 4.5 concludes with limitations, policy implications, and directions for future research.

## 4.2 Literature Review

### 4.2.1 Opportunity and Mobility Table

Intergenerational mobility refers to the movement of individuals across social or economic positions relative to their parents, including both upward and downward shifts (Bukodi et al., 2019). It captures the extent to which family background shapes children's outcomes in adulthood — such as occupational class, education level, or income bracket (Blanden, 2013). A society is considered more mobile when this link is relatively weak, a condition that means inherited advantages or disadvantages have less influence on where people end up. Intergenerational mobility can be conceptualised as a discrete game: while individuals start in different positions, fairness depends on whether outcomes are determined by inherited starting points or by personal choices and effort.

Absolute mobility measures the observed movement of individuals across discrete social categories, such as parental and children's occupational classes, rather than continuous outcomes (Van De Gaer et al., 2001). In mobility tables, absolute mobility is

recorded as the total mobility rate — the share of individuals whose social position differs from that of their parents — and can be broken down into upward, downward, and horizontal moves (Bukodi & Goldthorpe, 2022; Bukodi et al., 2019). Among these, upward mobility is most commonly used in practice, as it directly reflects the proportion of individuals who have improved their social or occupational status relative to their parents. This measure is often the focus of research on social progress and inequality. While economists sometimes operationalise absolute mobility in terms of income, mobility tables focus on categorical changes. Importantly, absolute mobility does not distinguish changes due to increased fairness from those driven by structural shifts in the system (Deutscher & Mazumder, 2023; Torche, 2015a). For example, the expansion of white-collar occupations or the decline of agricultural work can generate observed movement in mobility tables without reflecting greater equality of opportunity. In other words, absolute mobility captures how many individuals change categories, but not whether those changes occur impartially (Bukodi & Goldthorpe, 2022).

Relative mobility, or social fluidity, emphasises *opportunity equality* in mobility tables (Bukodi et al., 2019). It quantifies how strongly parental positions constrain children's destinations, controlling for structural changes in the distribution of categories (Torche, 2015a). In other words, relative mobility asks whether individuals from different origins face similar chances of reaching higher-status categories once the opportunity structure is accounted for. High relative mobility indicates that outcomes in mobility tables are less tied to family background and more to individual effort and choices (Bukodi & Goldthorpe, 2021). Statistically, relative mobility can be assessed using transition matrices and analysed through odds ratios or log-linear models (Torche, 2015a), a method that isolates the effect of origin on destination independently of overall structural changes. In contrast, for earnings, intergenerational elasticity is a commonly used approach. Unlike absolute mobility, relative mobility focuses on fairness within the system, not total movement.

Structural mobility highlights the *opportunity structure* itself, showing how shifts in the distribution of positions affect observed mobility (Schluter & Van de gaer, 2011). Unlike exchange mobility — where individuals simply swap categories within a fixed distribution — structural mobility occurs when the system of positions changes, such as when industrialisation increases professional jobs and reduces agricultural positions (Beckfield, 2020; Torche, 2015a). In mobility tables, structural mobility explains why upward or downward moves may result from changing category frequencies rather than from changes in opportunity equality (Bukodi et al., 2019). In sum, absolute mobility measures overall categorical movement, relative mobility measures fairness in how positions are attained, and structural mobility measures how the system of positions evolves. Together, these three dimensions

show that intergenerational mobility in mobility tables depends on both opportunity equality and opportunity structure.

### 4.2.2 Model of Intergenerational Mobility

While absolute, relative, and structural mobility emphasise different dimensions of intergenerational mobility, log-linear models provide a unified framework to capture all three within *mobility tables*. For a two-way origin-destination table, the basic specification is (Blanden, 2013; Bukodi & Goldthorpe, 2021)

$$\log F_{ij} = \mu + \lambda_i^O + \lambda_j^D + \lambda_{ij}^{OD}, \tag{4.1}$$

where $F_{ij}$ is the expected frequency in cell $(i, j)$, $\mu$ is a normalising constant, $\lambda_i^O$ and $\lambda_j^D$ describe the marginal distributions of origins and destinations, and $\lambda_{ij}^{OD}$ captures the net association between them. Absolute mobility corresponds to the total observed flows in the table — that is, the proportion of individuals who move from their origin class to a different destination class, including both upward and downward moves. The fitted counts $F_{ij}$ reproduce these observed flows, directly capturing absolute mobility. However, absolute mobility does not separate movements due to structural changes in the class distribution from those reflecting individual-level opportunities, which are captured in the interaction term $\lambda_{ij}^{OD}$. The decomposition of the log-linear model separates these components. The marginal terms $\lambda_i^O$ and $\lambda_j^D$ reflect *structural mobility*, describing how the distribution of social positions shifts across generations. In contrast, the association term $\lambda_{ij}^{OD}$ captures *relative mobility*, representing the extent to which children's destinations depend on their origins once structural shifts are accounted for. This distinction allows mobility tables to quantify both the fairness of opportunity and the impact of changing social structures.

For comparisons across countries, cohorts, or time periods, the model can be extended to a three-way table

$$\log F_{ijk} = \mu + \lambda_i^O + \lambda_j^D + \lambda_k^C + \lambda_{ik}^{OC} + \lambda_{jk}^{DC} + \lambda_{ij}^{OD}, \tag{4.2}$$

where $k$ indexes the third dimension (e.g., cohort, country, or time period). The Common Social Fluidity (CmSF) model assumes that the association term $\lambda_{ij}^{OD}$ is constant across all $k$, while the UNIDIFF model introduces a log-multiplicative structure (Bukodi et al., 2019):

$$\lambda_{ij}^{OD}(k) = \beta_k \cdot \phi_{ij}, \tag{4.3}$$

with $\phi_{ij}$ representing a baseline pattern of origin–destination association and $\beta_k$ scaling its strength. Larger values of $\beta_k$ indicate lower relative mobility (stronger dependence of destinations on origins), while smaller values indicate higher mobility.

### 4.2.3 Perfect Mobility

In the context of intergenerational mobility, *perfect mobility* represents the highest possible degree of mobility, whereas total persistence (or complete immobility) represents the lowest. Perfect mobility is defined as a situation where an individual's outcome is entirely independent of their origin (Swift, 2004). Statistically, this condition implies that origin and destination are independent random variables:

$$P(D = j \mid O = i) = P(D = j) \quad \text{for all } i, j,$$

so that every row of the transition matrix is identical to the marginal distribution of destinations. In economic models using intergenerational income elasticity, perfect mobility corresponds to $\beta = 0$, a condition that means parental outcomes provide no information about children's outcomes. Recent research on mobility measurement similarly suggests that mobility rises as the correlation between incomes across generations ($\rho$[1]) declines, reaching its maximum when incomes in the two periods are independent — a condition equivalent to perfect mobility (Cowell & Flachaire, 2018).

In log-linear terms, perfect mobility implies $\lambda_{ij}^{OD} = 0$ for all $i, j$, indicating no net association between origins and destinations. Under this condition, Equation (4.1) simplifies to

$$\log F_{ij} = \mu + \lambda_i^O + \lambda_j^D.$$

By setting $\lambda_i^O = \log P_i$, $\lambda_j^D = \log C_j$, and $\mu = \log s$, the expected cell frequencies become

$$F_{ij} = sP_iC_j.$$

When $P_i$ and $C_j$ are expressed as percentages, the scaling constant is $s = \frac{1}{100}$, so that

$$F_{ij} = \frac{P_iC_j}{100}.$$

Thus, under perfect mobility, each cell in the transition table equals the product of the marginal distributions (see Table 4.1).

[1] The parameter $\rho$ represents the correlation between incomes in period 0 and period 1.

Table 4.1: Perfect mobility table

| | C1 | C2 | C3 | C4 | C5 | Total |
|---|---|---|---|---|---|---|
| **P1** | $\frac{C_1 \times P_1}{100}$ | $\frac{C_2 \times P_1}{100}$ | $\frac{C_3 \times P_1}{100}$ | $\frac{C_4 \times P_1}{100}$ | $\frac{C_5 \times P_1}{100}$ | $P_1$ |
| **P2** | $\frac{C_1 \times P_2}{100}$ | $\frac{C_2 \times P_2}{100}$ | $\frac{C_3 \times P_2}{100}$ | $\frac{C_4 \times P_2}{100}$ | $\frac{C_5 \times P_2}{100}$ | $P_2$ |
| **P3** | $\frac{C_1 \times P_3}{100}$ | $\frac{C_2 \times P_3}{100}$ | $\frac{C_3 \times P_3}{100}$ | $\frac{C_4 \times P_3}{100}$ | $\frac{C_5 \times P_3}{100}$ | $P_3$ |
| **P4** | $\frac{C_1 \times P_4}{100}$ | $\frac{C_2 \times P_4}{100}$ | $\frac{C_3 \times P_4}{100}$ | $\frac{C_4 \times P_4}{100}$ | $\frac{C_5 \times P_4}{100}$ | $P_4$ |
| **P5** | $\frac{C_1 \times P_5}{100}$ | $\frac{C_2 \times P_5}{100}$ | $\frac{C_3 \times P_5}{100}$ | $\frac{C_4 \times P_5}{100}$ | $\frac{C_5 \times P_5}{100}$ | $P_5$ |
| **Total** | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | **100%** |

*Notes.* The table shows the cross-classification of children's and parents' educational attainment. Rows ($i = 1, \ldots, 5$) correspond to parents' education levels (P1 – P5), and columns ($j = 1, \ldots, 5$) correspond to children's education levels (C1 – C5), based on ISCED categories: ISCED 0 = less than primary, ISCED 1 = primary, ISCED 2 = lower secondary, ISCED 3 – 4 = upper secondary, and ISCED 5 – 8 = tertiary. Each cell $\frac{C_j \times P_i}{100}$ represents the expected share of children at education level $j$ given parents at level $i$ under the assumption of independence between parents' and children's education. Row totals (P1 – P5) indicate the share of parents in each educational category, column totals (C1 – C5) indicate the share of children in each category, and the bottom-right cell sums to 100%.

However, as Swift (2004) ask, "would perfect mobility be perfect?" We take up his views and present three main critiques of the concept of perfect mobility within the framework of equality of opportunity.

- *First*, perfect mobility treats downward movement as harmless, framing it as freedom of choice. Yet rational choice models of education suggest that people are more motivated to avoid falling than to climb higher, a pattern that reflects parental loss aversion. While some children may voluntarily accept downward paths, systematic downward mobility across social groups signals structural barriers rather than free choice. Even when voluntary, downward trajectories in education can limit the opportunities of the next generation. For this reason, downward mobility is not neutral from a policy perspective.
- *Second*, persistence across generations is not always problematic. Inheriting wealth may raise fairness concerns, but genetic endowment — something beyond human control — raises a different issue, as also noted in Chapter 2. This distinction underscores the boundary between radical and liberal views of equality of opportunity (Grätz & Petrini, 2025). The idea of a "lottery of birth" highlights that outcomes are partly determined by chance. Luck egalitarianism rejects advantages from natural inheritance, while meritocracy accepts

differences in talent, with heritability sometimes used as an indicator of opportunity equality once social inequalities are reduced (Plomin, 2018). Moreover, non-material family influences — such as shared meals and everyday interactions — are inescapable in cohabitation. Ceiling effects in education can also constrain further upward mobility at the highest levels, a constraint where such persistence is not necessarily unfair.

- *Third*, upward mobility should not be treated as additive, particularly when using absolute measures. For example, a child who enters university while their parents completed only primary school is not equivalent to a child who completes only high school with the same parental background, even though both experience upward mobility. Similarly, attaining secondary-level education when parents had only primary schooling is not equivalent to attaining a university degree when parents completed only high school. These examples demonstrate that the difficulty of transitions between educational stages is unequal. The key point is not whether parental background matters, but that mobility should be assessed in relation to meritocracy and legitimate family influence.

The critique of perfect mobility — notably by Swift (2004) — was indeed developed in the context of class mobility. However, the core philosophical questions it raises — regarding the desirability of downward mobility, the legitimacy of family influence, and the additive nature of progress — are equally, if not more, acute in the domain of education. Education is a primary mechanism for both social reproduction and mobility, and it is a sphere where the state interacts directly with family influence through public policy (e.g., compulsory schooling, tuition subsidies). It is true that a one-to-one correspondence between an educational move and a class move cannot be assumed. As noted by theories of credential inflation (Collins, 1979), the value of educational qualifications can depreciate as they become more common. Conversely, privileged families can deploy economic, social, and cultural capital to ensure their children secure favourable class positions despite ordinary educational performance (Lareau, 2003).

Nevertheless, for a global study, educational mobility tables provide an indispensable — if imperfect — tool. Occupational schemas are difficult to standardise across agrarian, industrial, and post-industrial economies, and income data are plagued by lifecycle bias and non-comparability in low-income countries (Blanden, 2013). Educational categories, based on ISCED, offer a consistent ordinal scale. More importantly, from the perspective of fair progress, the focus on education allows us to isolate and evaluate the fairness of a critical, state-influenced life stage. If the educational

system is rife with inequality, it is a powerful indicator of a failure in equality of opportunity, regardless of subsequent compensatory mechanisms in the labour market. Therefore, while occupational mobility reveals outcomes in the labour market, educational mobility reveals the structure of opportunity in the formative years, a focus that makes it highly relevant for a study on fairness.

Therefore, this chapter seeks to reframe the idea of perfect mobility by asking the following question:

What should perfect mobility look like?

In the existing literature, perfect mobility is typically defined as a theoretical extreme in which origins and destinations are entirely independent. This benchmark is neither realistically attainable nor normatively desirable, yet it has often served as the implicit standard against which actual societies are judged. The contribution of this chapter is to propose a redefined benchmark of perfect mobility that reflects a condition of genuine equality of opportunity: one that recognises legitimate family influence while excluding problematic forms of advantage or disadvantage. By comparing observed mobility patterns across countries to this redefined benchmark, the analysis identifies the gap between real societies and an attainable ideal that incorporates both structural realities and human agency. In this way, the proposed benchmark provides a more meaningful standard for evaluating mobility regimes and serves as a valid measure of "fair progress" in intergenerational mobility.

## 4.3 What Should Perfect Mobility Look Like?

To address the first question, we construct a new mobility table, a table we call *fair progress*. We begin with the original educational distribution of the parent generation. The goal is to define the destination distribution for the child generation while preserving the overall distribution. The expected matrix is divided into three areas: downward, persistent, and upward. Downward mobility is excluded, as discussed in the previous section, because of *loss aversion* (Malloy, 2015). A small degree of downward movement among individuals may reflect choice, but systematic downward mobility of an entire group signals structural problems. Therefore, the fair progress table assigns zero probability to these cells. Intergenerational persistence is kept minimal to reflect legitimate family influence, especially when parents and children live together. This influence is non-monetary, such as passing down unique life experiences. For example, a child may be inspired by a parent's career in pottery — an area where higher education provides little benefit. This kind of persistence is

considered permissible and does not require correction, since it reflects preferences rather than constraints.

Genetic transmission, however, is treated differently. It is a matter of chance and is not classified as persistence, but rather as the baseline for assessing upward mobility. Genes do not fully determine outcomes, since effort still plays a role (Plomin, 2018). While aspirations from a parent's career shape individual preferences, genetic endowment only sets the initial base. Effort, combined with this base, determines progress, and long-distance upward mobility should be weighted more heavily than short-distance moves. This discussion also connects to the claim that outcomes should be independent of family background, a claim that makes the issue more complex. Here, "family background" is seen as another type of birth lottery and should be understood as a fixed effect that parents and children share within the same family environment (see more in Chapter 2). What is legitimate in "family" is the transmission of unique parental life experience to children through parenting — also called *familial relationship goods*. This transmission is both natural and socially recognised as a moral responsibility of parents toward their children. In short, persistence should be the transmission effect of *familial relationship goods*. The key question is how much persistence can be considered a legitimate form of family influence. To address this question, we rely on the corrected estimate of the strength of familial relationship goods from Chapter 3, namely $\omega = 0.15$. This estimate implies a 15% probability that children remain at the same education level as their parents.[2]

Considerable concern might arise about what value of $\omega$ should be considered acceptable. First, $\omega$ certainly cannot be zero, as this would be entirely impossible if the institution of the family still exists — or, more precisely, if what makes a family a family — namely the transmission of FRG, as discussed in Chapter 2 — still exists. If $\omega = 0$, this would imply the abandonment of all family values, a consequence that contradicts natural law (as observed in wildlife) and social ethics (parental rights and duties). Preserving the institution of the family does not conflict with reducing inequality in resources for children; it merely affects children's motivation and effort. One of the most advanced recent studies, conducted by Radl et al. (2026), attempted to measure the social origin of effort — that is, the intergenerational effect of effort — which they estimated to be $0.1$ (interestingly similar in magnitude to the causal effect of intergenerational transmission in education using Swedish data in the twin-based approach of Holmlund et al., 2011). Their results go beyond simply measuring effort through real tasks rather than through so-called residuals (that is, what remains

[2] Within the education goal matrix, a similarity score of $0.15$ is empirically derived from parent–child relationship bonds. Operationally, this value equates to a retention rate of $0.15$ (15% probability of staying in the same category) for categorical data, and a Pearson correlation of $r = 0.15$ for continuous data. Despite mathematical differences, both represent the same conceptual transmission effect of FRG.

unexplained after controlling for observable inequalities). This finding suggests that the transmission of values through family relationships is real, with approximately $\omega = 0.1$. However, both of these measurements are biased by gene–environment interplay, since environmental factors — including random events and interventions — inevitably interact with genetic predispositions in shaping behaviour and outcomes within estimates of intergenerational transmission (Holmlund et al., 2011), particularly given that Radl et al. (2026) adopted a measure of cognitive effort. We corrected for this bias in Chapter 3, obtaining $\omega = 0.15$. We recognise that the choice of $\omega$ is sensitive; therefore, we also compare the research results for the two cases ($\omega = 0.1$ and $\omega = 0.15$) in Appendix 4.3 (the results show no significant difference between them). For other possible values of $\omega$, we have no scientific basis. Hence, although our correction approach to twin estimates in Chapter 3 theoretically removes institutional effects, we encourage future research to recalculate $\omega$ for the applied context based on the method presented in Chapter 3, in order to apply the proposed framework for measuring intergenerational mobility introduced in this current chapter.

For upward mobility, two factors matter: the original base (innate ability, derived from genetic transmission) and effort, which is inversely related to the difficulty of moving between levels. The gap between levels differs — for example, moving from primary to secondary education is not the same as moving from high school to university. Thus, upward mobility for children from disadvantaged backgrounds is modelled as cumulative probabilities across levels. The principle here is that disadvantaged children should not be expected to reach the same absolute education levels as advantaged children; both innate ability and effort must be taken into account. Less fortunate children may attain lower levels, but on the same scale of progress, compared to more advantaged peers. This approach aligns with the theory of *cumulative (dis)advantages* in education (Walberg & Tsai, 1983).

To formalise this approach, let $a$, $b$, $c$, and $d$ represent the probabilities of transitioning from one education level to the next. Using these definitions, we express the fair progress in Table 4.2. Applying the law of total probability to this structure, the constraints on the transition probabilities can be written as:

$$\begin{cases} a + a \times b + a \times b \times c + a \times b \times c \times d = (1-\omega)P_1 < 1, \\ b + b \times c + b \times c \times d = (1-\omega)P_2 < 1, \\ c + c \times d = (1-\omega)P_3 < 1, \\ d = (1-\omega)P_4 < 1. \end{cases}$$

Solving for $a$, $b$, $c$, and $d$, we obtain:

Table 4.2: The fair progress table

| | **C1** | **C2** | **C3** | **C4** | **C5** | **Total** |
|---|---|---|---|---|---|---|
| **P1** | $\omega P_1$ | $a$ | $a \times b$ | $a \times b \times c$ | $a \times b \times c \times d$ | $P_1$ |
| **P2** | 0 | $\omega P_2$ | $b$ | $b \times c$ | $b \times c \times d$ | $P_2$ |
| **P3** | 0 | 0 | $\omega P_3$ | $c$ | $c \times d$ | $P_3$ |
| **P4** | 0 | 0 | 0 | $\omega P_4$ | $d$ | $P_4$ |
| **P5** | 0 | 0 | 0 | 0 | $P_5$ | $P_5$ |
| **Total** | | | | | | **100%** |

*Notes*. The table presents the *adjusted mobility table* of children's education conditional on parents' education. Rows (P1 – P5) correspond to parents' education levels, and columns (C1 – C5) correspond to children's education levels, based on ISCED categories. The diagonal elements $\omega P_i$ represent the probability that children remain in the same education category as their parents. The off-diagonal elements ($a$, $b$, $c$, $d$ and their products) represent upward transitions between consecutive education levels. Each row sums to the share of parents $P_i$, and the bottom-right cell sums to 100%.

$$\begin{cases} a = \dfrac{(1-\omega)P_1}{1+(1-\omega)P_2} < 1, \\ b = \dfrac{(1-\omega)P_2}{1+(1-\omega)P_3} < 1, \\ c = \dfrac{(1-\omega)P_3}{1+(1-\omega)P_4} < 1, \\ d = (1-\omega)P_4 < 1. \end{cases} \tag{4.4}$$

Equation (4.4) shows that all transition probabilities remain below one, confirming that the upward allocation is valid. Figure 4.1 provides real examples from Burkina Faso and Uzbekistan, where observed mobility is compared with perfect mobility and fair progress. In Burkina Faso, nearly 90% of parents have less than primary education. Under perfect mobility, about 70% of children would also remain below primary education. The difference between observed mobility and perfect mobility is therefore very small. This finding might suggest that the country has already achieved good progress. But this conclusion is misleading. From the perspective of fair progress, more than 70% of children should at least reach primary education. This goal is realistic, given that most of the population has not yet completed primary school, and it is more meaningful than expecting equal chances for children to reach all education levels at once. Uzbekistan shows the opposite case. Most of the population is

already well educated. In such contexts, the absence of further upward mobility does not imply a lack of progress, but rather reflects a ceiling effect.

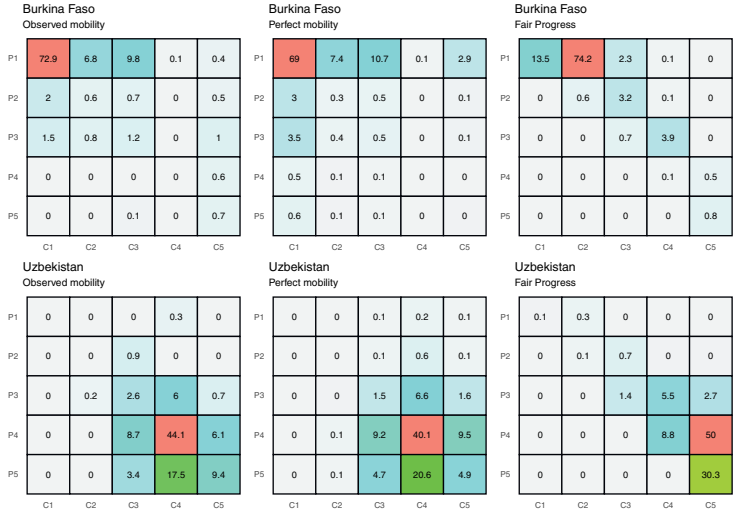



Figure 4.1: Examples of fair progress

*Note.* Defined the adjusted mobility based on the education distribution of the parent generation and compared it with the observed mobility.

It is worth noting that our model of fair progress is designed with the specific nature of educational mobility in mind. The exclusion of systematic downward mobility is justified because in the educational domain, such movement rarely reflects free choice and more often signals a failure of the system to support students. Furthermore, by defining a benchmark that accounts for the uneven difficulty of educational transitions (e.g., the greater challenge of progressing to tertiary versus secondary education), our model directly addresses the ordinal nature of educational data that is central to our analysis. While credential inflation may change the absolute value of a degree, it does not negate the relative difficulty and resource requirement of attaining it — a difficulty that is precisely what our transition probabilities $(a, b, c, d)$ capture.

## 4.4 How Do Countries Differ From this Benchmark?

To answer our second research question — how do countries differ from the fair progress benchmark? — we require a dataset with broad coverage across diverse

economic and institutional settings. The Global Database on Intergenerational Mobility (GDIM) provides this coverage, encompassing 153 countries and 97% of the global population for the 1980s cohort. A focused comparison of a few countries, while valuable, would be insufficient to map the global landscape of educational opportunity and identify the macro-structural factors that shape it. The global scale is not merely a convenience; it is essential for understanding how fair progress varies with a nation's level of development, educational infrastructure, and social policies. Our use of educational data makes this ambitious comparison feasible and methodologically consistent.

We quantify the difference between the observed mobility $Q(x)$ and the fair progress $P(x)$, a difference we call *adjusted mobility*. Adjusted mobility for a country $r$ can be expressed in a single formula by combining upward and non-upward moves:

$$\text{Adjusted mobility}_r = \sum_{i>j}(Q_r(i,j) - P_r(i,j)) - \sum_{i\leq j}(Q_r(i,j) - P_r(i,j)),$$

where $i$ indexes the child's education level, $j$ indexes the parent's education level, $Q_r(i,j)$ is the observed mobility table, $P_r(i,j)$ is the adjusted mobility table, the first sum runs over upward moves ($i > j$), and the second sum runs over non-upward moves ($i \leq j$). In this framework, downward and persistent mobility are treated as "negative" outcomes, whereas upward mobility is treated as "positive." In simpler terms, a country's score increases when upward mobility exceeds the fair progress benchmark and decreases when persistence or downward mobility is higher than expected. To enable cross-country comparisons of both absolute and relative mobility, we apply a max-min normalisation. This approach provides a measure that is less sensitive to arbitrary assumptions and suitable for comparing fair progress internationally.

The analysis draws on the Global Database on Intergenerational Mobility (GDIM), a database that has been widely used in research across the world (Clemente-Casinhas et al., 2025; Duong, 2024; Leone, 2019; Nybom, 2018; van der Weide et al., 2024), including studies focused on South Asia (Khan & Patra, 2024) and Latin America (Torche, 2021). We ensure consistency by focusing on the 1980s birth cohort, using the maximum parental education, including all children (gender-neutral), and applying the same normalisation procedures for absolute mobility (CAT) and relative mobility (1-BETA) as in the original database. Adjusted mobility is calculated after cleaning the GDIM data to ensure each transition matrix sums to 1, preserving the original structure. A full list of countries with their absolute, relative, and adjusted mobility scores is provided in Appendix 4.1.

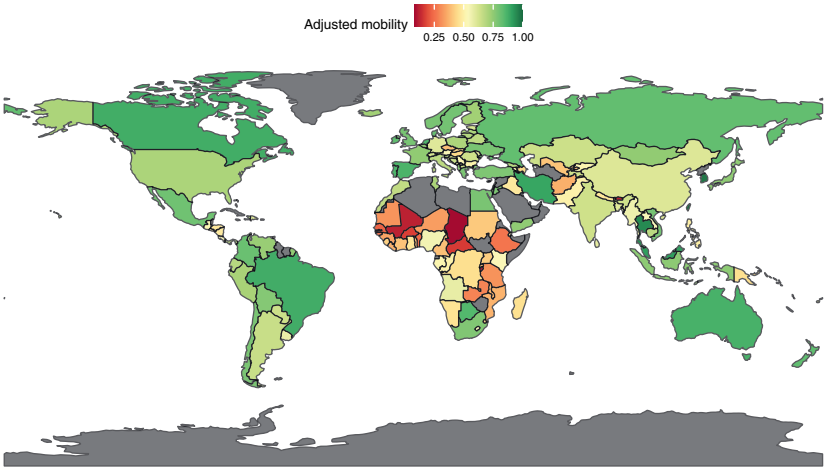



Figure 4.2: World map of adjusted mobility

*Note.* The authors calculated the data from the Global Database on International Mobility (GDIM) 2023, filtered for the 1980 cohort, maximum parent education, and all children. A full list of countries is provided in Appendix 4.1.

Figure 4.2 presents adjusted mobility[3] globally, highlighting regional differences. Africa and South Asia exhibit lower mobility, while most developed countries show higher progressiveness. Latin America shows significant educational gains that do not fully translate into economic advancement, a pattern that reflects a mismatch between education and labour market outcomes (Busso et al., 2012). Consistent with their historical trajectories of economic development (Morris, 1996), South Korea and Taiwan rank highest, whereas the Central African Republic and Zambia rank lowest. Structural factors remain critical: the United States performs better than expected due to accessible tertiary pathways (Bailey & Dynarski, 2011). In contrast, the UK and Switzerland underperform — a pattern attributable to institutional rigidities, including early tracking in Switzerland and persistent elite bias in the UK (Boliver, 2013; Buchmann & Park, 2009). China presents a distinct case: rapid educational expansion has been achieved, but the hukou system and urban-rural divides continue to

[3] Adjusted mobility measures education-based mobility for cohorts born in the 1980s, framing progress in terms of fairness by isolating structural conditions. This measure complements, rather than replaces, conventional metrics, providing a clearer view of how opportunities are distributed across countries.

limit intergenerational mobility (Wu, 2019). Finland and France exceed expectations, likely benefiting from strong public education and progressive redistribution (Maurin & McNally, 2008; Sahlberg, 2011).

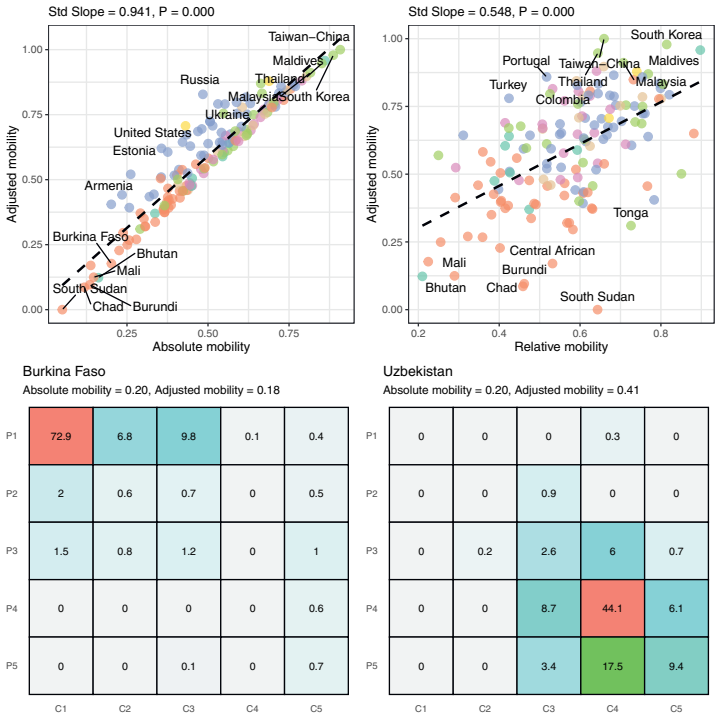



Figure 4.3: Compared to absolute and relative mobility

*Note.* The data are from the Global Database on International Mobility (GDIM) 2023, filtered for cohort 1980, maximum parent education, and all children. Absolute (mobility) is measured as $CAT$, Relative (mobility) as $1 - BETA$, and the Adjusted (mobility) refers to a newly defined measure introduced in this chapter. The slope is standardised for comparison. Along with Figure 4.1, we illustrate two cases where adjusted mobility better captures progress, even when absolute mobility has the same value.

To illustrate how our adjusted mobility better captures "fair progress" in intergenerational mobility, we compare it with absolute and relative mobility. We expect adjusted mobility to align more closely with absolute mobility, as both measures reflect "progress." We then show how adjusted mobility more accurately reflects opportunity and access to advanced education, a pattern we interpret as "fairness." Thus, adjusted mobility can serve as a measure of fair progress in intergenerational mobility.

First, we examine its relationship with absolute and relative mobility (see Figure 4.3), both derived from the GDIM. Adjusted mobility captures characteristics of both absolute and relative mobility, as indicated by significant positive statistical relationships. However, it reflects social progress more than social fluidity, aligning more closely with absolute mobility (standardised slope = 0.941) than with relative mobility (standardised slope = 0.548). We further demonstrate that adjusted mobility captures "progress" better than absolute mobility in a comparison between Burkina Faso and Uzbekistan, which have the same absolute mobility (0.2). Uzbekistan shows limited upward mobility due to ceiling effects, whereas Burkina Faso has more room for upward mobility, yet more than 70% of the population remains in the same status.

Second, we compare adjusted mobility with another related measure — the Social Progress Index (SPI)[4]. We focus on the SPI's Opportunity dimension, a dimension that includes personal rights, personal freedom and choice, tolerance and inclusion, and access to advanced education. Absolute, relative, and adjusted mobility all show significant positive relationships with Opportunity, and even stronger relationships with access to advanced education, a sub-dimension of Opportunity (see Figure 4.4). Compared with absolute and relative mobility, adjusted mobility aligns better, with standardised slopes of 0.542 for opportunity and 0.670 for access to advanced education. This finding suggests that adjusted mobility is more closely aligned with fairness.

[4] The SPI is grounded in Amartya Sen's theoretical contributions on social development, particularly drawing from the "Mismeasuring Our Lives" report by the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz et al., 2010). The SPI is a composite index (see details in Appendix 4.2) averaging scores across three dimensions: Basic Human Needs, Foundations of Wellbeing, and Opportunity (Krylova et al., 2026). Within each dimension, weights are assigned using principal component factor (PCF) analysis.

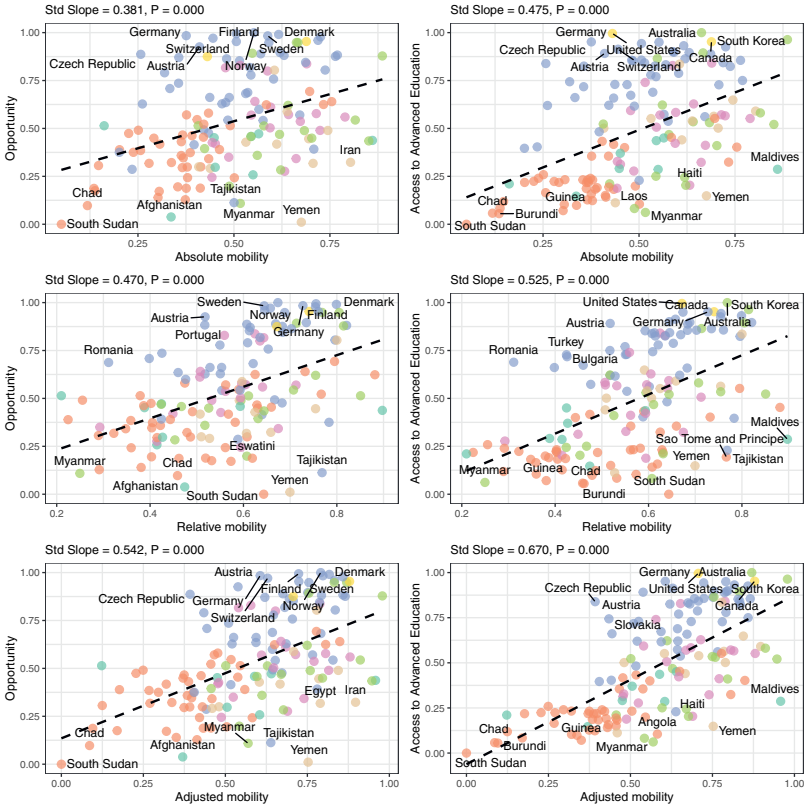



Figure 4.4: Compared to Social Progress Index

*Note.* Each panel shows the relationship between one of the three mobility measures — absolute mobility, relative mobility, and adjusted mobility — and either the Opportunity dimension or its sub-dimension Access to Advanced Education. Mobility measures and SPI indicators are normalised. Adjusted mobility aligns more closely with Opportunity and Access to Advanced Education compared with absolute and relative mobility, as indicated by stronger standardised slopes, a pattern that suggests adjusted mobility better captures fairness in intergenerational opportunity.

## 4.5 Conclusion, Limitations, and Future Research

Intergenerational mobility has long been regarded as a test of a society's commitment to equal opportunity. Yet the conventional benchmark of "perfect mobility" — which envisions a world where children's outcomes are statistically independent of their parents' — reduces a complex, uneven landscape of opportunity into a flat and

misleading abstraction. This chapter has argued that this benchmark is neither a realistic target nor a normatively desirable one, as it misinterprets systematic downward mobility, dismisses all forms of intergenerational persistence, and ignores the varying difficulty of educational ascents. To move beyond this impasse, we introduced a new normative standard: the fair progress mobility table. This benchmark is "fair" because it acknowledges legitimate family influences — what Brighouse and Swift (2014) term familial relationship goods — and the unequal challenge of upward educational transitions. It embodies "progress" because it is consistent with a society's overall educational expansion. From this principled ideal, we derived an adjusted mobility measure that quantifies the gap between observed outcomes and this attainable benchmark, thereby providing a more nuanced map of global opportunity.

Applying this framework to GDIM data reveals a stratified world. Nations in Africa and South Asia exhibit low adjusted mobility, a pattern that indicates their observed educational flows fall short of a fair distribution of progress. Latin American countries, despite significant educational expansion, display patterns in which growth has not fully translated into equitable opportunity. Developed nations, while performing better overall, still confront ceiling effects and institutional rigidities that limit further advancement. Although this analysis draws on global educational data, its conceptual contribution extends further. The framework of fair progress and adjusted mobility can be applied to any ordinal transition table, an extension that opens avenues for future research into mobility in domains such as health (Halliday et al., 2021) or well-being (Molina et al., 2011).

We conclude by acknowledging several critical limitations. Educational attainment is an imperfect proxy for human capital, vulnerable to distortions from credential inflation and the global "learning crisis" (Narayan et al., 2018; World Bank, 2018). Moreover, structural expansion can inflate schooling statistics without generating real gains in human capital (Mueller, 2021; Van de Werfhorst & Andersen, 2005; van der Weide et al., 2024). Most importantly, educational mobility does not automatically equate to socioeconomic advancement, as parents may compensate for their children's educational shortfalls and labour markets may not reward qualifications equally (Busso et al., 2012). Nonetheless, our fair progress benchmark is specifically designed to address a core issue: it separates the fairness of opportunity from the scale of educational expansion. It is less concerned with how much a country's education level has risen and more concerned with who benefits from that rise. This focus makes adjusted mobility a more robust measure of whether new opportunities are broadly shared or captured by the already advantaged. An unjust educational system represents a fundamental failure of equality of opportunity in its own right.

This framework sets the stage for a critical new line of inquiry that directly ad-

dresses the tension identified by Brighouse and Swift (2014): "The family, even when kept within its genuinely valuable bounds, is more threatening to the prospects for equality of opportunity, even of the conventional kind, than many egalitarians might hope." While Chapter 3 measured the strength of familial relationship goods in transmission, this measurement alone is insufficient, as social mobility concerns not only fairness but also progress. The effects of the transmission of familial relationship goods on social mobility will be estimated in the next chapter (Chapter 5), an analysis that will allow us to examine how legitimate family influences interact with broader structural changes in educational opportunity. More broadly, the framework of fair progress and adjusted mobility can be extended to any ordinal transition table, opening avenues for future research into mobility in domains such as health (Halliday et al., 2021) or well-being (Molina et al., 2011). This extension offers a promising foundation for a richer, multidimensional understanding of opportunity across generations.

# 5

# How Much Limitation On Educational Mobility?

**Abstract**

This chapter explores the tension between families' role in producing familial relationship goods — the unique benefits arising from intimate-yet-authoritative relationships between parents and children, such as small practices like bedtime stories or shared routines — and their contribution to intergenerational inequality. While families transmit socioeconomic advantage, these goods cannot be replicated by the state. Their intimate practices also pass on cultural capital, making some inequality unavoidable. The chapter quantifies this trade-off by estimating how familial relationship goods affect educational mobility using a residualisation strategy with double/debiased machine learning. Results show these goods reduce mobility by 0.24–0.27 standard deviations, not explained by biological ties and socioeconomic inequality. This suggests that intergenerational inequality is a structural feature of family-protecting societies.

Declaration **Author's notes:** The study has been submitted to a journal. **Data and Code Availability:** The data (DOI: 10.6084/m9.figshare.31145920) and replication code (DOI: 10.6084/m9.figshare.31145959) that support this study are openly available.

## 5.1 Introduction

Societies committed to meritocracy face a fundamental tension. Families — celebrated as the cornerstone of social life — are also the primary mechanism through which intergenerational inequality persists (Gheaus, 2018). They transmit not only wealth and social connections, but also cultural knowledge, skills, and cognitive habits that shape life outcomes (Kraaykamp & van Eijck, 2010). A common policy response is to try to weaken this transmission, insulating opportunity from the so-called "accident of birth" (Grusky & Cumberworth, 2010). Yet this approach rests on a conceptual issue: it treats a by-product of family life as if it were its central purpose. Philosophically, families exist not merely to transmit resources, but to generate what can be called "familial relationship goods" (Brighouse & Swift, 2014). These are the irreplaceable benefits — emotional security, moral formation, and the capacity for autonomy — that emerge uniquely from the intimate, authoritative, and partial bonds between a child and caring adults. No state programme or institutional design can reproduce these goods without destroying the discretion, particularised care, and spontaneity that make them valuable (Gheaus, 2018).

The family operates as a primary vehicle for the transmission of social advantage through the formation of embodied cultural capital, understood as durable dispositions of mind and body acquired through prolonged socialisation and experienced as natural rather than socially produced. This capital is generated through relational goods embedded in everyday practices such as shared meals, bedtime stories, and routine conversation (Gheaus, 2018; Jonathan, 2018). These practices shape values, aspirations, linguistic competence, and reasoning styles that are later rewarded in educational settings (Kraaykamp & van Eijck, 2010). Advantaged parents are more likely to engage in concerted cultivation and to provide educational resources that support navigation of complex institutions, a pattern that further reinforces these dispositions (Bukodi & Goldthorpe, 2013; Roksa & Potter, 2011). This constitutive role of the family creates a structural conflict with meritocratic ideals, since schools routinely translate class-based cultural capital into credentials attributed to individual talent and effort (Kraaykamp & van Eijck, 2010). As Rawls (1971) argued, "the principle of fair opportunity can be only imperfectly carried out, at least as long as the institution of the family exists." Achieving a fully level playing field would therefore require the standardisation of child-rearing or the replacement of families with institutional care (Gheaus, 2018). Such solutions would eliminate familial relationship goods essential to human flourishing (Sypnowich, 2022), while still failing to remove arbitrary inequalities arising from differences in care and unavoidable human partiality (Gheaus, 2018).

Society therefore faces a basic choice. Familial relationships unavoidably conflict

with the aim of perfect meritocratic parity, yet their moral value outweighs the case for full equality of opportunity (Brighouse & Swift, 2014). Even under highly egalitarian conditions, inequality would persist through everyday micro-interactions that constitute parent–child intimacy and transmit cultural and embodied capital beyond the reach of policy (Gheaus, 2018). Partial parenting is therefore not a flaw but a moral necessity. It implies structural limits on social mobility and makes some intergenerational persistence inevitable. Achieving perfect equality of opportunity would require breaking the parent–child link, but this would undermine the development of the autonomous agents that meritocracy seeks to reward. The appropriate response is a strategy of decoupling: reducing the material stakes of family advantage through progressive taxation (Kraaykamp & van Eijck, 2010), strong and equal public education, and wage compression (Jerrim & Macmillan, 2015), while preserving the private sphere in which familial attachment and its distinctive goods are produced (Brighouse & Swift, 2014).

This chapter examines this tension through empirical analysis, using the new measure of social mobility introduced in Chapter 4 and comparing it with traditional mobility indicators. Drawing on the concept of familial relationship goods, we pose a measurable question: how much limitation on educational mobility is unavoidable as a consequence of the transmission of these goods? The chapter's main contribution is to shift the debate from theory to quantification. A novel identification strategy isolates the component of educational transmission that arises purely from relational family dynamics, distinct from genetics, socioeconomic status, or institutional factors. The analysis estimates that the transmission of these relational goods reduces educational mobility by approximately 0.24–0.27 standard deviations. This effect — not explained by biological and socioeconomic influences — provides an empirical benchmark for the unavoidable "cost" of preserving meaningful family life.

The analysis proceeds in four parts. Section 5.2 formalises the problem using an extended Origin-Education-Destination (OED) model, decomposing intergenerational transmission and highlighting the transmission of familial relationship goods as the irreducible core of non-financial transmission. Section 5.3 explains the identification strategy, employing a partially linear model and Double/De-biased Machine Learning (Chernozhukov et al., 2018) to isolate the key variable. Section 5.4 presents the estimate and robustness checks, quantifying the mobility constraint imposed by the transmission of relational goods. Finally, Section 5.5 synthesises the findings, framing the quantified effect as a necessary trade-off and outlining implications for a realistic understanding of equality of opportunity. The structure moves from conceptual tension to theoretical formalisation, empirical isolation, and synthesis, offering an assessment of the unavoidable trade-off at the heart of the family-mobility relationship.

## 5.2 Theoretical Framework

The theoretical framework underpinning this chapter is anchored in the sociological and economic tradition of the *intergenerational transmission of advantage*, drawing directly on foundational theories from Becker and Tomes (1986), Blau et al. (1978), and Breen and Jonsson (2005). At its core, the model argues that parental resources — both financial and non-financial — function as crucial inputs into a child's development, ultimately shaping educational attainment and later labour-market outcomes. Building on the work of Corak (2013) and Solon (2009), Jerrim and Macmillan (2015) proposes a key macro-level relationship: in societies with higher income inequality, disparities in these parental resources are more extreme, a condition that leads to stronger intergenerational persistence of socioeconomic status. This central proposition is formalised through an analytical model rooted in the classic *Origin-Education-Destination (OED) triangle* of social stratification research (Breen & Luijkx, 2004; Goldthorpe, 2013).

The model first establishes the total intergenerational association. Let $E^{\text{parent}}$ represent parental education and $Y^{\text{child}}$ represent offspring's earnings. For a country $K$, this association $\beta_K$ is estimated as:

$$\log(Y^{\text{child}}) = \alpha + \beta \cdot E^{\text{parent}} + \phi \cdot C + \epsilon$$

where $C$ is a vector of demographic controls and $\epsilon$ is the error term. This coefficient $\beta$ captures the raw earnings gap between individuals from high and low parental education backgrounds.

Following the methodological approach of Gregg et al. (2017), we decompose the total association $\beta$ to isolate the mediating role of education:

$$\beta = \gamma \cdot \lambda + \delta$$

In this decomposition, the *intergenerational correlation of education* $\lambda$ measures the link between parent and child's educational attainment. This concept is informed by Becker's (2009) human capital theory, a theory that suggests such a correlation stems from a family's combined *capacity* (based on its resources) and *incentive* (based on the anticipated returns to education, $\gamma$) to invest in a child's schooling. Here, $\gamma$ represents the *labour-market returns to education*, and $\delta$ is the *residual effect* — capturing the portion of parental advantage that operates through channels other than the child's formal education. This residual reflects theories of social and cultural capital (Bourdieu, 2018) and direct labour-market sponsorship (Lin, 1999).

The framework posits that income inequality amplifies $\beta$ by intensifying each

component of this equation through distinct, yet interconnected, mechanisms. First, income inequality strengthens the *intergenerational correlation of education ($\lambda$)*. Drawing on models of parental investment (Becker & Tomes, 1986; Duncan & Murnane, 2011), greater dispersion in financial resources in unequal societies means affluent, highly-educated parents can make vastly larger investments in their children's human capital — from early childhood enrichment (Cunha et al., 2006) and high-quality schooling (Mayer, 2002) to private tutoring — compared to poorer families. This disparity widens the socioeconomic gradient in educational achievement, directly increasing $\lambda$. While non-financial resources and heredity[1] also contribute, Jerrim and Macmillan (2015) argues they are less systematically tied to national income inequality, a claim that positions financial disparities as the primary driver of cross-national variation in $\lambda$ (Solon, 2009).

Second, income inequality increases the *returns to education ($\gamma$)*. According to human capital and labour market theory (Becker, 2009), a more dispersed earnings distribution — characteristic of high-inequality countries — mechanically inflates the wage premium for educational credentials. As Corak (2013) summarises, this creates a feedback loop: not only do wealthier families have a greater *capacity* to invest in education, but the higher economic payoff ($\gamma$) in unequal societies gives them a stronger *incentive* to do so. This dual effect multiplicatively boosts the "through education" component $\gamma \cdot \lambda$.

Third, income inequality enlarges the *residual effect ($\delta$)* — the influence of family background that goes around formal education. This channel is supported by theories of social capital (Bourdieu, 2018; Coleman, 1990) and direct resource transfer. Wealthier parents can leverage financial resources to support unpaid internships, provide housing during job searches, or fund relocation — advantages that directly affect labour-market entry and success (Goldthorpe, 2013). They can also utilise social networks to secure opportunities for their children (Lin, 1999). While non-financial networks and hereditary traits also contribute to $\delta$, the framework hypothesises that the financial mechanism is most strongly correlated with macro-level income inequality, a hypothesis that underscores the pervasive role of economic resources.

Finally, the model incorporates an *institutional dimension* concerning educational systems (Jerrim & Macmillan, 2015). It posits that in high-inequality countries, public investment in education is often lower, while private, family-funded investment is higher. This institutional context minimises the state's role in levelling the playing

[1] Heredity is the biological process of passing traits from parents to offspring through genes (the actual transfer of DNA). Heritability is a statistical metric used to measure how much of the variation in a specific trait across a population is caused by genetic differences, as opposed to environmental factors.

field, thereby reinforcing the centrality of private family wealth in the intergenerational transmission process. The theoretical framework thus synthesises human capital theory, models of familial investment, social capital theory, and institutional analysis to argue that income inequality reinforces intergenerational persistence primarily by exacerbating disparities in *financial resources*, disparities that in turn magnify both educational inequalities ($\lambda$) and their economic rewards ($\gamma$), while also exerting a direct, non-educational influence on life chances ($\delta$).

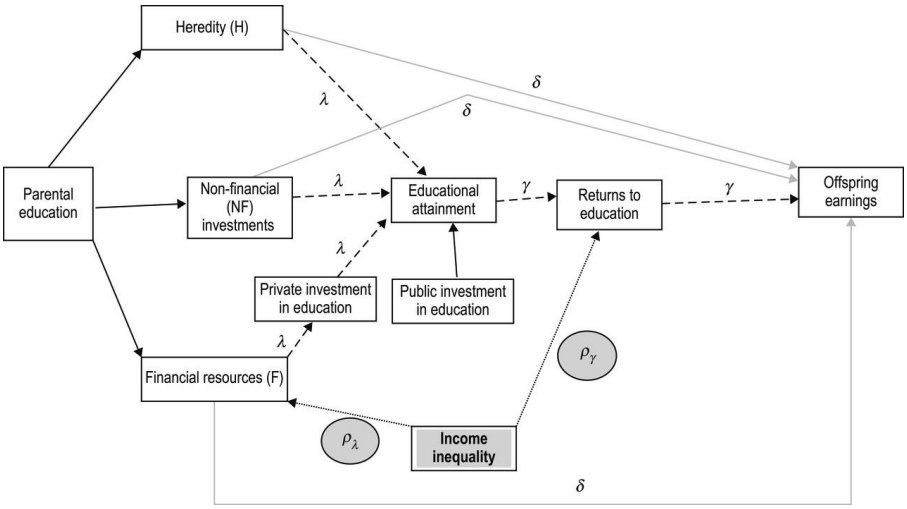



Figure 5.1: The role of education

**Notes:** The model posits two primary channels for the transmission of advantage: (1) a through-education pathway, $(\gamma \cdot \lambda)$, in which parental background influences offspring educational attainment $(\lambda)$, which in turn affects earnings through labour-market returns $(\gamma)$; and (2) a residual pathway, $(\delta)$, whereby parental resources affect offspring earnings directly, net of offspring education. The strength of both pathways is amplified under higher income inequality and weaker public investment. Sourced from Jerrim and Macmillan (2015).

Jerrim and Macmillan (2015) identify the intergenerational correlation of education, $\lambda$, as a key mechanism linking higher income inequality to lower social mobility. Using cross-national Programme for International Assessment of Adult Competencies (PIAAC) data from 24 countries, they show that education is more strongly transmitted from parents to children in more unequal societies. This pattern is reflected in strong correlations between national income inequality and $\lambda$, reaching 0.74 for gaps in university completion and 0.59 for differences in years of schooling. They further decompose $\lambda$ into three channels. Differences in *financial resources* between high-

and low-educated families are strongly associated with income inequality (Spearman's $\rho \approx 0.73$), a finding that makes this the dominant source of cross-national variation in $\lambda$. In contrast, *non-financial resources* such as cultural capital, parental involvement, and social networks show only a weak association with inequality (Spearman's $\rho \approx 0.20$), indicating a limited role. *Genetic transmission* is assumed to be invariant across countries and therefore does not explain cross-national differences in $\lambda$, although it may still contribute to educational persistence within countries.

From this perspective, reducing intergenerational inequality requires weakening the transmission of education, a transmission that reflects genetic factors as well as financial and non-financial resources. Reducing the transmission of financial resources through lower income inequality is relatively straightforward. Genetic transmission, however, raises questions. It reflects natural rather than social inequality and is generally treated as part of personal identity under liberal views, while egalitarian perspectives see it as a "lottery of birth" for which compensation may be warranted. The focus here is therefore on non-financial resources. According to Jerrim and Macmillan (2015), non-financial resources include social capital (such as social networks) and cultural capital (such as tastes and knowledge) (Bukodi & Goldthorpe, 2013). These resources are commonly understood as part of family background — not simply as sources of advantage. The issue is not that these forms of "capital" are inherently problematic, but whether the process through which they are acquired is acceptable. When labelled as "capital," they can carry a sense of concern, yet many of these resources are also vehicles for relational goods that are central to family life. As Brighouse and Swift (2014) argues, such familial relationship goods may matter more than formal equality of opportunity. Unlike the transmission of capital aimed at preserving social privileges, these practices are expressions of family bonds — intimate, caring, and loving relationships — not driven by wealth, social status, inherited advantage, or even biological ties, as they occur in adoptive families as well.

The concept of familial relationship goods (FRGs) challenges conventional thinking about reducing the transmission of education. While these goods — shared activities, emotional support, and nurturing interactions — matter more for well-being than strict equality of opportunity, they nonetheless have negative implications for social mobility (Brighouse & Swift, 2014). The tension between the transmission of familial relationship goods and social mobility manifests in several ways. Many interactions that generate relationship goods inadvertently confer competitive advantages. For instance, family conversations at dinner foster intimacy and emotional regulation, but they also function as cultural capital, enhancing a child's performance in education and, ultimately, the labour market (Baderin, 2023). Brighouse and Swift (2014) note that fully achieving equality of opportunity would require abolishing the family, as inequality arises from processes inherent to family life. Yet intimate par-

ent–child relationships are essential for human flourishing and cannot be sacrificed without serious social and ethical costs. The unavoidable implication is that intergenerational inequality is, to some degree, inevitable: the very practices that sustain family well-being and relational goods also perpetuate differences in opportunity and outcomes across generations. This conclusion raises the central question addressed in this chapter:

> How much limitation on mobility is an inevitable result of the transmission of FRGs?

## 5.3 Data and Methods

### 5.3.1 Identification Strategy

We restate the research question as identifying the negative effect of the transmission of familial relationship goods — defined as the component of educational transmission not attributable to biological or social inheritance — on educational mobility. The empirical challenge lies in isolating the variation in educational transmission that arises from relational family dynamics, separate from genetic factors, family background, and institutional investments. To address this challenge, we employ a partially linear model that explicitly separates the role of observable confounders from the treatment of interest. The model specifies educational transmission $D$ as a function of observed controls $X_i$ — which include genetic factors, family background, private investments, and public investments — and an orthogonal residual $V$, a residual that represents the transmission of familial relationship goods:

$$D = f(X_i) + V, \quad E[V|X_i] = 0.$$

Educational mobility $M$ is then modelled as a function of $D$, the same controls $X_i$, and an idiosyncratic error $\zeta$:

$$M = D\theta + g(X_i) + \zeta, \quad E[\zeta|X_i, D] = 0,$$

where $\theta$ is the parameter of interest. Substituting the first equation into the second yields a representation where $M$ depends linearly on $V$ and non-linearly on $X_i$:

$$M = V\theta + \underbrace{f(X_i)\theta + g(X_i)}_{m(X_i)} + \zeta.$$

To identify $\theta$, we employ an orthogonalisation approach that residualises both outcome and treatment with respect to $X_i$. Taking conditional expectations, we have

$$E[M|X_i] = E[D|X_i]\theta + g(X_i),$$

which allows us to solve for $g(X_i)$ and substitute back into the original equation, yielding

$$M - E[M|X_i] = (D - E[D|X_i])\theta + \zeta.$$

Defining $\tilde{M} = M - E[M|X_i]$ and $\tilde{D} = D - E[D|X_i]$, we obtain the residual-on-residual regression

$$\tilde{M} = \tilde{D}\theta + \zeta,$$

which we estimate via ordinary least squares, giving the estimator

$$\hat{\theta} = (\tilde{D}^\top \tilde{D})^{-1} \tilde{D}^\top \tilde{M}.$$

This approach effectively purges both outcome and treatment of their predictable components given $X_i$, thereby isolating variation attributable to the transmission of familial relationship goods. Identification rests on the assumptions of conditional exogeneity ($E[\zeta|X_i, D] = 0$), first-stage orthogonality ($E[V|X_i] = 0$), sufficient overlap in treatment conditional on covariates, and adequate flexibility in modelling the conditional expectations $E[M|X_i]$ and $E[D|X_i]$. The estimated $\theta$ represents the local average treatment effect of the transmission of familial relationship goods on educational mobility, capturing the influence of relational dynamics — such as emotional support and parenting quality — that are not reducible to genetic or socioeconomic factors.

### 5.3.2 Variables and Data Sources

We integrate three core datasets capturing distinct dimensions of intergenerational dynamics. The first dataset contains the novel mobility measure developed in Chapter 4. The second contains genetic heritability[2] estimates obtained from Engzell and Tropf (2019). The third provides cohort-averaged socioeconomic indicators drawn from three public international repositories: (i) public education expenditure as a percentage of GDP, sourced from the Our World in Data compilation of UNESCO Institute for Statistics and World Bank records; (ii) GDP per capita in 2011 international dollars, obtained from the Maddison Project Database via Our World in Data; and (iii)

[2] We use heritability as a proxy for heredity, employing machine learning to predict this genetic component in intergenerational transmission.

pre-tax income Gini coefficients, derived from the World Inequality Database (WID). We compile these indicators for ten countries (Australia, Germany, Denmark, Spain, Finland, the United Kingdom, Italy, Norway, Sweden, and the United States) across the cohorts 1940s–1980s.

The construction of socioeconomic indicators (the third source) employs a cohort-based analytical framework aligned with the Global Database on Intergenerational Mobility (GDIM) approach. Each cohort represents a 10-year birth window followed by a 22-year observation period to capture formative socioeconomic conditions from birth through typical completion of formal education (approximately age 22). For example, the 1940 cohort includes individuals born between 1940–1949 and tracks relevant socioeconomic indicators through the year 1962 (1940 + 22), 1963 (1941 + 22), up to 1971 (1949 + 22). Mathematically, for each cohort starting year $c \in \{1940, 1950, 1960, 1970, 1980\}$, we define the observation period as years $t \in [c, c+31]$, where $c+31$ represents the maximum year in which the youngest cohort member (born in $c+9$) reaches age 22. Within each country–cohort combination, we compute the arithmetic mean of each socioeconomic indicator:

$$\bar{X}_{i,c} = \frac{1}{n_{i,c}} \sum_{t=c}^{c+31} X_{i,t}$$

where $X_{i,t}$ represents one of the socioeconomic indicators for country $i$ in year $t$, and $n_{i,c}$ is the number of non-missing observations within the 32-year window. This approach captures the socioeconomic environment during critical developmental years when educational investments, economic opportunities, and income distribution most significantly influence human capital formation and subsequent life outcomes.

Table 5.1: Key variables and operational definitions

| Variable name | Source | Operational definition |
|---|---|---|
| Adjusted Mobility | 1 | Fairness-adjusted progress gap measure developed in Chapter 4, defined as the difference between observed upward mobility and a counterfactual benchmark representing equitable intergenerational progress. |

*Continued on next page*

| Variable name | Source | Operational definition |
|---|---|---|
| Absolute Mobility | 1 | Probability that a child attains a higher educational category than the parent, conditional on the parent having less than tertiary education: $\Pr(C > P \mid P < \text{tertiary})$. |
| Transmission | 1 | Intergenerational persistence measured by the coefficient $\beta$ from the regression child_edu $= \alpha + \beta \cdot$ parent_edu $+ \epsilon$. |
| Heritability | 2 | Genetic variance component from behavioural genetic models, representing the share of variance in educational attainment attributable to genetic factors. |
| Educational Expansion | 1 | Intergenerational difference in mean years of schooling: $(\text{MEAN}_c - \text{MEAN}_p)$, capturing average educational growth across generations. |
| Educational Inequality | 1 | Standard deviation of parental education $(\text{SD}_p)$, measuring dispersion in educational attainment within the parent generation. |
| Income Inequality | 3 | Cohort-averaged Gini coefficient of pre-tax income, ranging from 0 (perfect equality) to 1 (perfect inequality). |
| Public Spending | 3 | Cohort-averaged government expenditure on education as a percentage of GDP. |
| GDP per Capita | 3 | Cohort-averaged economic output per person in 2011 international dollars, adjusted for purchasing power parity (PPP). |

*Notes:* The table draws on three integrated sources: (1) fairness-adjusted mobility measures (see Chapter 4); (2) genetic heritability estimates from Engzell and Tropf (2019); and (3) cohort-averaged socioeconomic indicators constructed from UNESCO, World Bank, Maddison Project, and World Inequality Database sources. These indicators cover ten countries (Australia, Germany, Denmark, Spain, Finland, the UK, Italy, Norway, Sweden, and the US) across five birth cohorts (1940–1980). Following the GDIM framework, each cohort captures average conditions from birth to age 22 using a 32-year observation window. All three datasets are merged on country, cohort, child gender, and parent type. All continuous variables are standardised to z-scores for analysis.

We merge all datasets from the three sources using exact matches on country codes, birth cohorts (1940, 1950, 1960, 1970, 1980), child gender categories, and

parent type categories. Key variables are constructed using precise operational definitions (see Table 5.1). All continuous variables are standardised as $z$-scores, defined as $z = (x - \mu)/\sigma$, to ensure comparability of effect sizes across variables measured on different scales. Categorical variables are coded using explicit reference categories for regression analysis:

- *Child gender* consists of three categories. The combined group ("Mixed") is used as the reference category, while "Sons" and "Daughters" are included as comparison groups. This specification allows identification of gender-neutral and gender-specific mobility patterns.
- *Parent education type* includes four categories. The reference category is the average of both parents' education. Alternative categories are the highest-educated parent, father only, and mother only, a design that allows analysis of different measurement approaches.
- *Countries and cohorts* are modelled using full fixed effects. Country indicators cover the United States, Australia, the United Kingdom, Norway, Sweden, Finland, Denmark, Germany, Spain, and Italy, based on the data availability reported in Engzell and Tropf (2019). Cohort indicators correspond to birth cohorts from 1940 to 1980, following the Global Database on Intergenerational Mobility (GDIM) framework. We retain all indicators without omitting a baseline category, a strategy that avoids arbitrary reference choices while fully absorbing country- and cohort-specific effects.

## 5.4 Results and Discussion

Table 5.2: Descriptive Statistics

| Variable | $n$ | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Adjusted mobility | 620 | 0.00 | 1.00 | -3.88 | 1.96 |
| Absolute mobility | 620 | 0.00 | 1.00 | -3.45 | 1.84 |
| Educational transmission | 620 | 0.00 | 1.00 | -2.52 | 4.35 |
| Heritability | 124 | 0.00 | 1.00 | -2.64 | 2.04 |

*Continued on next page*

Table 5.2: Descriptive Statistics (continued)

| Variable | $n$ | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Educational expansion | 620 | 0.00 | 1.00 | -2.33 | 2.89 |
| Educational inequality | 620 | 0.00 | 1.00 | -1.99 | 2.43 |
| Income inequality | 524 | 0.00 | 1.00 | -2.11 | 2.10 |
| Public spending | 620 | 0.00 | 1.00 | -2.58 | 2.05 |
| GDP per capita | 620 | 0.00 | 1.00 | -1.82 | 2.97 |
| Child: Sons | 620 | 0.34 | 0.47 | 0.00 | 1.00 |
| Child: Daughters | 620 | 0.34 | 0.47 | 0.00 | 1.00 |
| Parent: Highest education | 620 | 0.25 | 0.43 | 0.00 | 1.00 |
| Parent: Father only | 620 | 0.25 | 0.43 | 0.00 | 1.00 |
| Parent: Mother only | 620 | 0.25 | 0.43 | 0.00 | 1.00 |
| Country: United States | 620 | 0.13 | 0.34 | 0.00 | 1.00 |
| Country: Australia | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: United Kingdom | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: Norway | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: Sweden | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: Finland | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: Denmark | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: Germany | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: Spain | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Country: Italy | 620 | 0.10 | 0.30 | 0.00 | 1.00 |
| Cohort: 1980s | 620 | 0.19 | 0.40 | 0.00 | 1.00 |

*Continued on next page*

Table 5.2: Descriptive Statistics (continued)

| Variable | $n$ | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Cohort: 1970s | 620 | 0.19 | 0.40 | 0.00 | 1.00 |
| Cohort: 1960s | 620 | 0.19 | 0.40 | 0.00 | 1.00 |
| Cohort: 1950s | 620 | 0.19 | 0.40 | 0.00 | 1.00 |
| Cohort: 1940s | 620 | 0.23 | 0.42 | 0.00 | 1.00 |

Table 5.2 presents descriptive statistics for the 620 observations used in the analysis. Both mobility measures and the key independent variable are standardised (mean = 0, SD = 1), allowing for immediate interpretation of effect sizes in the regression results. The substantial variation in *Adjusted mobility* (ranging from $-3.88$ to 1.96) highlights significant cross-national and inter-cohort differences in intergenerational educational persistence — variation that this chapter seeks to partially attribute to the by-products of the transmission of familial relationship goods. The control variables confirm that the sample composition is well-suited for isolating these effects. Socioeconomic and institutional covariates — including *Public spending*, *GDP per capita*, and *Income inequality* — are also standardised, ensuring comparability across diverse national contexts. Critically, the categorical indicators for child gender and parent education type are evenly distributed, with sons and daughters each comprising 34% of the sample and each parental education measure (*Parent: Highest education*, *Father only*, *Mother only*) representing approximately one-quarter of observations. This balance ensures that the analysis is not improperly influenced by a particular demographic subgroup or measurement approach. Country and cohort representation is similarly well-distributed, with each nation (except the United States at 13%) accounting for roughly 10% of observations and each birth cohort (1940s–1980s) representing approximately one-fifth of the sample. This balanced panel structure provides a robust foundation for isolating the component of educational transmission orthogonal to observed confounders, thereby enabling a credible estimate of the mobility constraint imposed by the transmission of familial relationship goods.

The correlation analysis in Figure 5.2 reveals several notable relationships. As expected, the two mobility measures are very strongly correlated ($r = 0.96, p < 0.001$), confirming that the adjustment preserves the underlying persistence ranking. Educational expansion correlates strongly with both mobility measures ($r = 0.73$ and $0.62$, both $p < 0.001$), supporting the view that broader access promotes mobility, though

its correlation with educational inequality ($r = 0.67$, $p < 0.001$) reflects the tension that expansion may simultaneously increase disparity. Consistent with the theoretical framework, educational transmission shows modest negative correlations with adjusted mobility ($r = -0.21$, $p < 0.001$) and absolute mobility ($r = -0.12$, $p < 0.01$), confirming that stronger parent-child persistence is associated with lower mobility. Its stronger negative associations with public spending ($r = -0.46$, $p < 0.001$) and GDP per capita ($r = -0.42$, $p < 0.001$) suggest that in less affluent contexts with lower educational investment, family background plays a more decisive role. Notably, heritability is distinct from both adjusted and absolute mobility, displaying no significant correlation with either. However, it exhibits strong negative correlations with income inequality ($r = -0.53$, $p < 0.001$) and intergenerational transmission ($r = -0.20$, $p < 0.05$). This pattern suggests that genetic endowments are more strongly expressed in egalitarian societies, where environmental barriers are less likely to constrain their realisation. Conversely, in more unequal societies, family background and economic resources appear to override genetic potential (Engzell & Tropf, 2019; Selita & Kovas, 2019).

### 5.4.1 Naive Approach

Table 5.3 reports OLS regression results for two measures of intergenerational mobility: Adjusted Mobility (columns 1–2) and Absolute Mobility (columns 3–4). Columns (1) and (3) are based on 524 observations, while columns (2) and (4) are analogous to (1) and (3) but include Heritability[3], using a smaller sample of 84 observations due to missing heritability data. Country and cohort fixed effects are included in all regressions but are not reported. The regression results in Table 5.3 provide a descriptive but methodologically naive model of intergenerational mobility determinants. The specification suffers from conceptual mixing, treating "Transmission" — the regression coefficient from a child–parent educational attainment model — as a unitary variable. This measure bundles biological inheritance, socioeconomic advantage, and unobserved transmission of familial relationship goods, obscuring the distinct mechanisms at play. The correlation between Transmission and Heritability is modest ($r = -0.2$, $p < 0.05$), and the coefficient on Transmission is sensitive to specification, as shown by the sharp change when Heritability is added ($-0.054$ in column 1 versus $-0.196$ in column 2 for Adjusted Mobility; $-0.145$ versus $-0.182$ for Absolute Mobility).

[3] It is worth noting that while the heritability data used in this chapter are derived from traditional twin estimates and are therefore sensitive to context, our correction method is not (see Chapter 3). Consequently, controlling for country and cohort fixed effects in this current chapter is helpful.

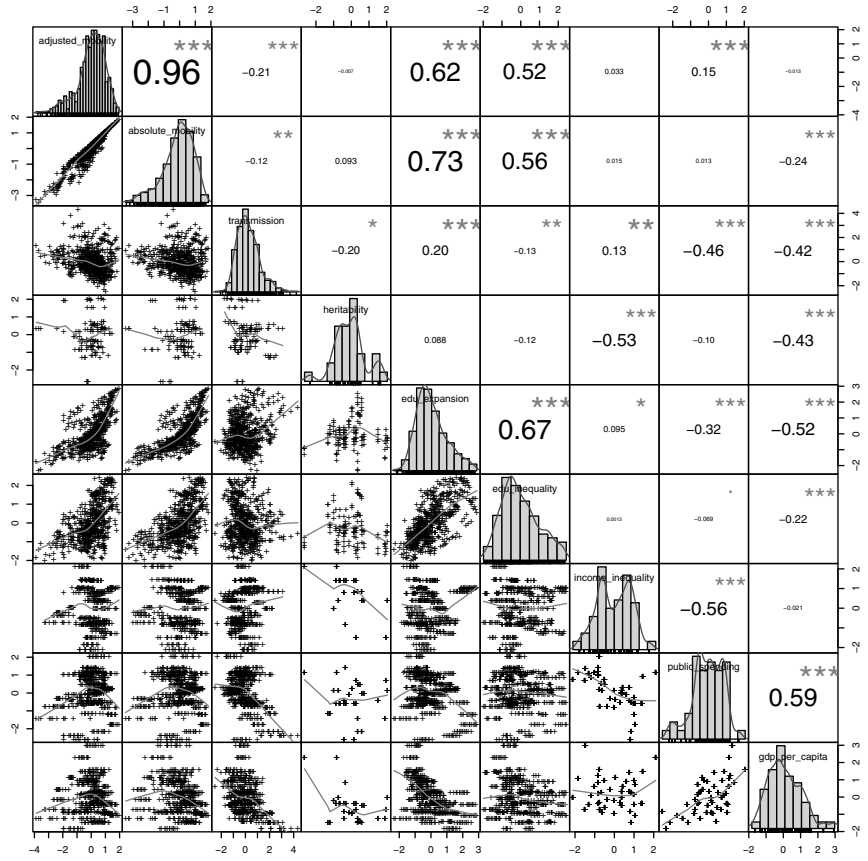



Figure 5.2: Correlation matrix

**Notes:** $n = 620$ for most correlations; heritability correlations $n = 124$; income inequality correlations $n = 524$. Significance levels: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, and $^{\cdot}p < 0.10$.

The pattern of coefficient signs and statistical significance largely aligns with theoretical expectations. Educational Expansion has a strong positive effect (1.230–1.460, significant at the 1% level), suggesting that broader educational access promotes intergenerational progress. In contrast, Income Inequality exerts a negative effect ($-0.297$ to $-0.413$ in the full sample). This pattern implies that unequal economic structures may directly constrain mobility. Heritability shows

a modest negative effect ($-0.098$ for Adjusted Mobility, $p < 0.05$; $-0.118$ for Absolute Mobility, $p < 0.01$). Its inclusion substantially amplifies the estimated effect of Transmission and alters the coefficients of Income Inequality and GDP per capita, including a sign reversal for GDP per capita in Absolute Mobility (from $-0.174$, $p < 0.01$, to $0.748$, $p < 0.05$). This reversal suggests that genetic variance interacts with economic and institutional factors. Parental education indicators (Highest, Father, Mother) have consistently positive coefficients, though statistical significance varies across specifications: "Parent: Highest" remains significant at the $1\%$ level, while "Father" and "Mother" weaken in the smaller sample that includes Heritability. Despite high model fit ($R^2 = 0.824$–$0.925$), the specification does not overcome the fundamental identification problem: Transmission is a reduced-form measure correlated with multiple observed and unobserved mechanisms. These results reinforce the need for the residualisation strategy employed in the main analysis, a strategy that isolates the component of Transmission orthogonal to genetic, socioeconomic, and institutional factors as a cleaner measure of the transmission of familial relationship goods.

The reduction in sample size from 524 to 84 observations upon introducing heritability estimates warrants attention. Following Jenkins and Quintana-Ascencio (2020), who demonstrate that regressions and meta-regressions require $N \geq 25$ for stable inference in the presence of meaningful variance, the 84 country-cohort observations available for this cross-country study comfortably exceed this minimum threshold, supporting confidence in the estimates reported. Furthermore, the heritability data used in this study, as described in Table 5.2, are based on the full sample of Engzell and Tropf (2019) published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS). Nevertheless, we attempt to mitigate this issue. First, the primary identification strategy using Double/De-biased Machine Learning residualises transmission using the full observations, with heritability as a control rather than a sample-restricting condition; the correlation between heritability and transmission ($r = -0.2$, $p < 0.05$) confirms that genetic factors capture distinct variation from the family processes of interest, validating their inclusion. Second, we adopted flexible non-linear estimation using machine learning to capture complex relationships, contrasting with linear approaches, across two measures of educational mobility, supplemented by two robustness checks.

Table 5.3: Regression Results for Intergenerational Mobility Measures

| | **Adjusted Mobility** | | **Absolute Mobility** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Transmission** | -0.054 | -0.196** | -0.145*** | -0.182*** |
| | (0.039) | (0.075) | (0.036) | (0.060) |
| **Heritability** | | -0.098** | | -0.118*** |
| | | (0.048) | | (0.038) |
| **Education Expansion** | 1.230*** | 1.450*** | 1.150*** | 1.460*** |
| | (0.068) | (0.166) | (0.062) | (0.132) |
| **Education Inequality** | -0.139*** | 0.017 | -0.051 | 0.088 |
| | (0.047) | (0.125) | (0.043) | (0.100) |
| **Income Inequality** | -0.297*** | -1.610* | -0.413*** | -2.040*** |
| | (0.090) | (0.855) | (0.082) | (0.681) |
| **Public Spending** | 0.007 | -0.163 | -0.046 | -0.247 |
| | (0.058) | (0.236) | (0.052) | (0.188) |
| **GDP per Capita** | 0.030 | 0.872** | -0.174*** | 0.748** |
| | (0.074) | (0.384) | (0.067) | (0.305) |
| **Child: Sons** | 0.007 | 1.010 | -0.010 | 1.070* |
| | (0.039) | (0.763) | (0.036) | (0.608) |
| **Child: Daughters** | 0.011 | 0.732 | 0.031 | 0.838 |
| | (0.039) | (0.755) | (0.036) | (0.601) |
| **Parent: Highest** | 0.584*** | 0.637*** | 0.318*** | 0.433*** |
| | (0.068) | (0.139) | (0.062) | (0.111) |
| **Parent: Father** | 0.408*** | 0.259* | 0.301*** | 0.174 |
| | (0.060) | (0.132) | (0.055) | (0.105) |
| **Parent: Mother** | 0.239*** | 0.153 | 0.252*** | 0.160** |
| | (0.049) | (0.094) | (0.045) | (0.075) |
| **Constant** | -0.451** | -0.667*** | -0.083 | -0.639*** |

Continued on next page

**Table 5.3 – continued from previous page**

| | Adjusted Mobility | | Absolute Mobility | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | (0.190) | (0.200) | (0.173) | (0.159) |
| **Observations** | 524 | 84 | 524 | 84 |
| **$R^2$** | 0.854 | 0.824 | 0.892 | 0.925 |
| **Adjusted $R^2$** | 0.847 | 0.782 | 0.887 | 0.907 |
| **Residual Std. Error** | 0.361 (df = 499) | 0.270 (df = 67) | 0.328 (df = 499) | 0.215 (df = 67) |
| **F Statistic** | 122.000*** (df = 24; 499) | 19.600*** (df = 16; 67) | 172.000*** (df = 24; 499) | 51.800*** (df = 16; 67) |

**Notes:** Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. For the analysis, 'Mixed' child households and 'Average' parental education serve as reference groups. All country and cohort categories are explicitly included in the model; their coefficients are not reported in the table to conserve space.

### 5.4.2 De-biased Effect

To estimate the effect of the transmission of familial relationship goods on intergenerational mobility, we implement a residualisation strategy that isolates the component of educational transmission orthogonal to observed biological, socioeconomic, and institutional factors. As mentioned in Section 5.3.1, the method is grounded in a partially linear model:

$$D = f(X_i) + V, \quad E[V|X_i] = 0$$
$$M = D\theta + g(X_i) + \zeta, \quad E[\zeta|X_i, D] = 0$$

where $M$ is educational mobility (either adjusted or absolute), $D$ is educational transmission, $X_i$ is a vector of controls (including heritability, educational expansion, inequality measures, public spending, GDP per capita, and demographic indicators), $V$ denotes the transmission of familial relationship goods (the residual variation in transmission unexplained by $X_i$), and $\theta$ is the parameter of interest. It is worth noting that $V$ in this model corresponds to $S$ (the non-shared environment discussed in Chapter 2); both function as the transmission of familial relationship goods and are thus captured in the residual term during intergenerational transmission, rather than as individual-specific random luck, which is uncorrelated across family members.

We employ two complementary estimation approaches to ensure robustness. First, we apply Double/De-biased Machine Learning (DML), via the 'DoubleML' package in R, using random forest learners to flexibly estimate the nuisance functions $m(X_i)$ and $g(X_i)$ while maintaining valid inference on $\theta$. The DML estimator uses cross-fitting with 5 folds to prevent overfitting and the "partialling out"[4] score. To assess stability, we repeat the estimation across 25 different random seeds (spaced by 40 from 1 to 961) and synthesise the results via a random-effects meta-analysis using the 'metafor' package. Second, we estimate a penalised high-dimensional linear model via the 'rlassoEffect' function in the 'hdm' package, which applies the Lasso method with the option of partialling out. We formally compare the two approaches using a Wald test of the difference between the meta-analysed DML estimate and the Lasso-based partialling–out estimate; the results confirm they are statistically comparable.

The results reveal a robust negative effect of the transmission of familial relationship goods on both mobility measures (see Figure 5.3). For adjusted mobility, the 25 DML estimates range from $-0.240$ to $-0.274$ with standard errors between $0.031$ and $0.034$. The random-effects meta-analysis yields a pooled estimate of $\hat{\theta} = -0.263$ with a substantially reduced standard error of $0.007$. The Lasso-based partialling-out estimate is $\hat{\theta} = -0.250$ (SE = $0.083$). The Wald test shows no statistically significant difference between the methods (difference = $-0.013$, p = $0.876$), confirming methodological convergence despite the partialling–out estimate having a wider confidence interval due to its larger standard error. For absolute mobility, the 25 DML estimates range from $-0.220$ to $-0.248$ with standard errors between $0.029$ and $0.032$. The meta-analysed DML estimate is $\hat{\theta} = -0.239$ (SE = $0.006$), while the partialling-out estimate is $\hat{\theta} = -0.272$ (SE = $0.076$). The difference between methods ($0.034$) is not statistically significant (p = $0.659$), again indicating robust convergence across estimation strategies.

The consistency across all 25 random seeds — with very small variations for both adjusted and absolute mobility — demonstrates exceptional algorithmic stability. The meta-analysis reduces uncertainty dramatically, yielding standard errors approximately five times smaller than individual DML runs. The close alignment between the flexible non-linear DML approach and the regularised linear partialling-out method, despite their different modelling assumptions, indicates that the estimated negative relationship is not an artifact of functional form specification. These findings indicate that the transmission of familial relationship goods — the component of educational transmission unexplained by genetic, socioeconomic, and institutional factors — reduces educational mobility by approximately $0.24$–$0.27$ standard deviations

[4] Partialling out statistically isolates the unique relationship between two variables by removing the shared influence of confounding variables.

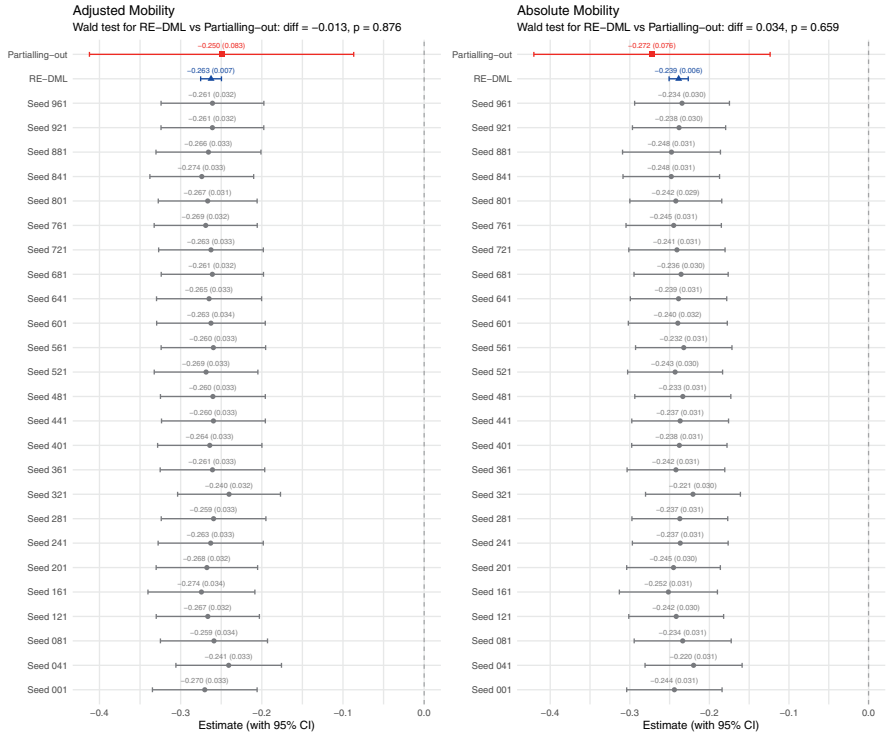



Figure 5.3: The effect of the transmission of familial relationship goods

**Notes:** The left panel shows results for adjusted mobility, the right panel for absolute mobility. Each point represents a separate Double/De-biased Machine Learning (DML) estimate from a different random seed, with horizontal bars indicating 95% confidence intervals. The "RE-DML" point shows the random-effects meta-analysis (estimated using the `metafor` package) of the 25 DML estimates. The "Partialling–out" point shows the Lasso-based linear estimate. A Wald test shows no statistically significant difference between the meta-analysed DML and Lasso-based estimates for adjusted mobility (difference = $-0.013$, $p = 0.876$) or absolute mobility (difference = $0.034$, $p = 0.659$). All estimates are negative, tightly clustered, and statistically significant, confirming that the result is robust to algorithmic randomness, functional-form assumptions, and estimation method.

(all variables are standardised). This substantial constraining effect is not explained by biological inheritance and socioeconomic inequality, a finding that highlights the distinct role of relational family dynamics in shaping intergenerational educational persistence.

### 5.4.3 Robustness

#### Sensitivity Analysis

To assess the robustness of our estimates to potential outliers and influential observations, we implement a comprehensive leave-one-out sensitivity analysis. For a sample of size $n$, this procedure involves re-estimating the parameter $\theta$ $n$ times, each time excluding one observation $i$ from the dataset. Formally, for each $i = 1, \ldots, n$, we compute:

$$\hat{\theta}_{(-i)} = f(\mathcal{D} \setminus \{i\})$$

where $f(\cdot)$ represents our Double/Debiased Machine Learning estimator and $\mathcal{D}$ is the full dataset. The primary estimator is defined using the partialling-out approach:

$$\hat{\theta} = \arg\min_{\theta} \mathbb{E}_n \left[ (\tilde{Y}_i - \tilde{D}_i \theta)^2 \right]$$

where $\tilde{M}_i = M_i - \hat{g}(X_i)$ and $\tilde{D}_i = D_i - \hat{f}(X_i)$ are the residualised outcome and treatment variables, with $\hat{g}(X_i)$ and $\hat{f}(X_i)$ estimated via random forest learners with constrained complexity (500 trees, maximum depth of 5, and minimum node size of 2) to prevent overfitting in our modest sample.

The distribution of these leave-one-out estimates $\{\hat{\theta}_{(-i)}\}_{i=1}^{n}$ provides valuable diagnostic information. We compute several influence statistics for each observation $i$:

$$\Delta_i = \hat{\theta}_{(-i)} - \hat{\theta}, \quad \Delta_i^{\text{abs}} = |\Delta_i|, \quad \Delta_i^{\text{std}} = \frac{\Delta_i}{\widehat{\text{SE}}(\hat{\theta}_{(-i)})}$$

where $\hat{\theta}$ is the full-sample estimate. Observations with large values of $\Delta_i^{\text{abs}}$ or $\Delta_i^{\text{std}}$ are flagged as potentially influential. We identify the most influential observations based on absolute deviation from the full-sample estimate and calculate the proportion of observations whose exclusion changes the estimate by more than 10% of the full-sample magnitude: $\Pr(|\Delta_i| > 0.1|\hat{\theta}|)$.

We visualise the results through a point-and-interval plot of each leave-one-out (LOO) estimate with the full-sample confidence band (see Figure 5.4). The leave-one-out sensitivity analysis confirms the robustness of our estimates. The full-sample estimate is $\hat{\theta} = -0.264$ (SE = 0.0328). Excluding any single observation yields estimates tightly clustered around this value, with a mean LOO estimate of $-0.263$ and a standard deviation of only 0.0074. The range of LOO estimates is 0.0483, spanning from $-0.288$ to $-0.240$. The five most influential observations alter the estimate by approximately ±0.023–0.025. Critically, no observation (0 out of 620)

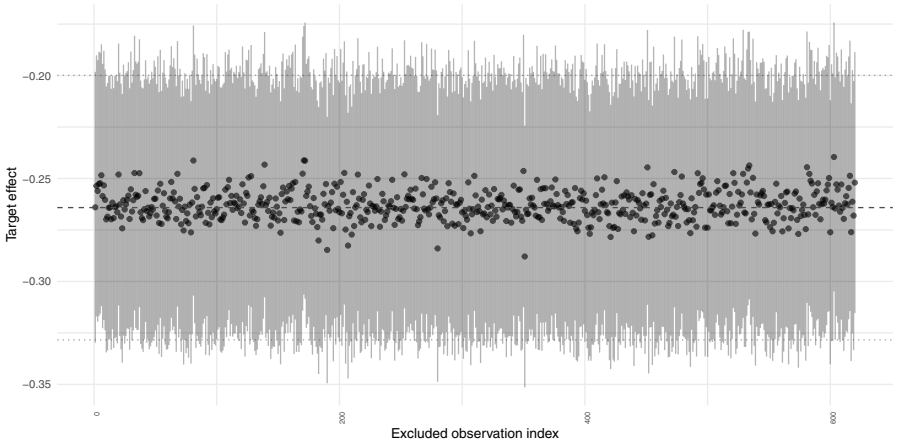



Figure 5.4: Sensitivity analysis

**Notes:** Each point shows the estimated effect $\hat{\theta}$ when excluding the corresponding observation, with vertical bars indicating 95% confidence intervals. The solid red line indicates the full-sample estimate, while the dashed red lines show its 95% confidence interval. The tight clustering of estimates around the full-sample value indicates robustness to the exclusion of any single observation. Random seed = 401.

alters the estimate by more than 10% of the full-sample magnitude. This demonstrates that our results are not driven by any single influential point, reinforcing confidence in the stability and reliability of the estimate.

### Permutation Test

To assess whether our estimated effect could arise by chance alone, we implement a permutation test that evaluates the statistical significance of our estimate under the null hypothesis of no treatment effect. The test constructs a reference distribution by randomly reassigning the treatment variable $D$ across observations while preserving the joint distribution of all other variables. Formally, for each permutation $b = 1, \ldots, B$ (with $B = 500$), we generate a permuted treatment vector $D^{(b)}$ where $D_i^{(b)} = D_{\pi_b(i)}$ and $\pi_b$ is a random permutation of the indices $\{1, \ldots, n\}$. We then re-estimate the parameter using our Double/Debiased Machine Learning estimator:

$$\hat{\theta}^{(b)} = \arg\min_{\theta} \mathbb{E}_n \left[ (\tilde{Y}_i - \tilde{D}_i^{(b)} \theta)^2 \right],$$

where $\tilde{M}_i = M_i - \hat{g}(X_i)$ and $\tilde{D}_i^{(b)} = D_i^{(b)} - \hat{f}(X_i)$ are the residualised outcome and permuted treatment. This yields a null distribution $\{\hat{\theta}^{(b)}\}_{b=1}^{B}$ of placebo estimates under the assumption of no relationship.

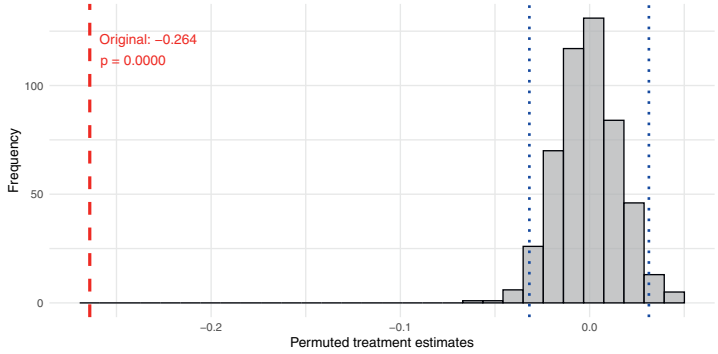



Figure 5.5: Permutation test

**Notes:** The histogram shows the distribution of 500 placebo estimates obtained by randomly permuting the treatment variable. The dashed red line indicates the original estimate ($\hat{\theta} = -0.264$), which lies far in the extreme left tail of the null distribution (permutation $p < 0.001$). The permutation distribution is centred near zero (mean $= -0.0006$, SD $= 0.0163$), demonstrating that our observed effect is highly unlikely to occur by chance alone. Random seed = 401.

The permutation test, as shown in Figure 5.5, provides decisive evidence against a spurious association. Our original estimate is $\hat{\theta} = -0.264$. The permutation distribution is centred near zero (mean $= -0.0006$, SD $= 0.0163$), consistent with the null hypothesis. Our observed estimate falls far in the left tail of this distribution; none of the 500 permutations produced an effect as extreme. We compute the one-sided p-value. This indicates that the probability of observing such a large negative effect by random chance alone is $p < 0.001$, providing strong statistical evidence that our result reflects a genuine relationship rather than a spurious association.

## 5.5 Conclusion, Limitations, and Future Research

This chapter has sought to link a long-standing philosophical dilemma with empirical measurement. It began with the widely recognised critique that families are a primary engine of intergenerational inequality, transmitting advantages that undermine meritocratic ideals (Gheaus, 2018). The logical, if radical, prescription has often been to weaken the parent-child link. Drawing on the work of Brighouse and Swift

(2014), however, this chapter argued that such an approach overlooks the family's essential function: the production of "familial relationship goods." These goods — emotional security, moral development, and the capacity for autonomy — arise from intimate, partial, and discretionary bonds and are fundamental to human flourishing (Sypnowich, 2022). The central tension is that the very interactions which generate these irreplaceable goods — shared meals and conversations about values — are simultaneously the primary channels through which social and cultural advantage is transmitted (Baderin, 2023; Kraaykamp & van Eijck, 2010).

The empirical analysis aimed to quantify the consequences of this tension, using the new measure of social mobility introduced in Chapter 4 and comparing it with traditional mobility indicators. By isolating the component of educational transmission not explained by genetic factors, socioeconomic background, and institutional investments, we identified a residual representing the transmission of familial relationship goods. The de-biased estimate shows that this relational transmission component reduces educational mobility by roughly 0.24 to 0.27 standard deviations. This effect is substantial and operates independently of more commonly cited drivers of persistence, such as wealth or heritability. It provides an empirical benchmark for the unavoidable constraint that intimate family life places on perfect social mobility.

Two main conclusions emerge. Empirically, a significant portion of intergenerational persistence is not a flaw in the social system that can be engineered away, but a feature of the relational system that is essential to human development. The practices that nurture a person intrinsically shape their trajectory in ways that create unequal starting points. This conclusion necessitates a recognition: preserving the family as a protected sphere of close, partial love requires accepting a foundational limit to equality of opportunity. Achieving perfect equality of opportunity cannot be pursued through severing the parent-child link, a pursuit that would trade human flourishing for an empty and lifeless version of fairness. Instead, the appropriate response is "decoupling": mitigating the material consequences of familial advantage through progressive policy while safeguarding the private space where relational goods are cultivated.

Several limitations suggest avenues for further work. First, the interpretation of the residual as purely the "transmission of familial relationship goods" depends on adequately measuring and controlling for all other relevant genetic, socioeconomic, and institutional factors. Unobserved variables — such as subtle differences in school quality (Jennings et al., 2015), peer effects (Fruehwirth, 2014), or neighbourhood characteristics (Patacchini & Zenou, 2011) — could potentially bias the estimates. However, they do not invalidate the interpretation, as these factors are not constitutive of the parent-child relational link that is the focus of this analysis. The transmis-

sion of familial relationship goods is operationalised as the environmental spillover of parents' exposure to randomness on the child's gene-environment system, transmitted through the direct, co-resident family relationship (see Chapter 2). School quality, peer effects, and neighbourhood characteristics operate outside this relationship; they shape educational outcomes through socioeconomic channels already captured in the model, rather than through the parent-child bond itself. Second, while the cross-national, cohort-based design captures broad patterns, it may conceal important heterogeneity. The effect of the transmission of FRGs (which have not been de-biased using the correction method in Chapter 3) could vary across cultural contexts, welfare regimes, or levels of economic development. Future research could use more detailed, longitudinal data to explore these dynamics within specific countries or social subgroups over time, particularly in non-Western contexts where data on intergenerational processes remain scarce. Finally, the analysis focused on educational mobility as the outcome. While education is a key mediator of socioeconomic status, future work should examine whether and how the transmission of familial relationship goods influences other life outcomes, such as occupational status, health, or subjective well-being.

# 6

# General Discussion

## 6.1 The Apple Does Not Fall Far From the Tree

The foundational tension motivating this inquiry is the conflict between the empirically observed strength of the Intergenerational Correlation of Education (ICE) and the ideal of equality of opportunity. This tension often finds capture in the metaphor that "the apple does not fall far from the tree." The ICE measures the persistent statistical link between the educational attainment of parents and their children (Black et al., 2005; Jerrim & Macmillan, 2015). In a fully open and meritocratic society, a person's life chances would not depend on their social origins. Yet the high ICE levels observed across advanced economies reveal a different reality: children's prospects remain closely linked to their birth, pointing to a rigid opportunity structure (Narayan et al., 2018).

This dissertation moves beyond treating this correlation as a simple number that hides the mechanisms of social reproduction. Its core objective is to separate and evaluate the different channels of intergenerational persistence: genetic inheritance, financial and material resources, and non-financial family investments (Jerrim & Macmillan, 2015). Central to this effort is a focus on the family as more than a channel for genes, money or power. By examining the concept of familial relationship goods developed by Brighouse and Swift (2014) — the intimate and everyday practices of family life — the dissertation draws a clear distinction between two types of educational persistence. On one side are the parts that reflect social disadvantage that policy

may address; on the other are those that arise from inevitable, and *even valuable*, family processes. The dissertation does not estimate the goods themselves, but rather their transmission effect — the environmental spillover of parents' cognitive exposure to randomness on the child's gene–environment system, transmitted through the direct, co-resident family relationship . The foundational question, therefore, is not simply *how much* advantage is passed on, but *in what form*, and with *what implications* for a society committed to both opportunity and the privacy of family life.

## 6.2 The Tripartite Synthesis

The dissertation is structured as three investigations, each building on the previous one. The main research question — how a society committed to equality of opportunity can accommodate advantages arising from family life — is pursued through three core objectives. The first objective is *empirical refinement*: to estimate the transmission effect of familial relationship goods while correcting for methodological bias. The second is *normative benchmarking*: to develop a realistic standard that treats part of the ICE as permissible. The third is *empirical quantification*: to measure the unavoidable cost imposed on mobility by preserving the transmission of familial relationship goods. These objectives were put into practice across chapters (see Table 1.1), built on the conceptual groundwork of Chapter 2 ("When does the apple fall permissibly?"). From this foundation come three findings: *what is*, *what it means*, and *what is to be done*.

What is. The first finding meets the objective of *empirical refinement* by answering: "To what extent do traditional models bias estimates of the transmission effect of familial relationship goods?" Chapter 2 combined behavioural genetics with political philosophy to break down the ICE into separate channels: financial resources, genetic transmission, and non-financial family investment. This latter channel divides further into social privilege and relational goods — the intimate, everyday practices essential for human flourishing (Sypnowich, 2022). Using a linear model ($Y = G + F + S$), Chapter 2 proposed that familial relationship goods are distinct from genetic endowment ($G$) and the shared family environment ($F$). Chapter 3 then used twin studies to isolate the family transmission effect, moving beyond the confusion inherent in standard adoption and twin models. This analysis showed that approximately 0.15 standard deviations of the ICE can be empirically attributed to the transmission effect of familial relationship goods. This finding provides an empirical estimate of the family's "relational work" in motion, thereby meeting the objective of correcting methodological bias and measuring this transmission channel.

What it means. The second finding meets the objective of *normative benchmarking* by redefining the standard addressed in Chapter 4: "What should perfect mobility look like?" The finding of a 0.15 transmission effect demonstrates that a high ICE does not, by itself, indicate a problematic structure. Instead, this persistence reflects the unavoidable cost of keeping the family as a private sphere of partial love — a sphere within which the transmission of familial relationship goods is both permissible and morally valuable. Chapter 4 therefore argues that the goal should shift away from the ethically unrealistic benchmark of "perfect mobility" (a correlation of zero) and towards the framework of "Fair Progress." This new benchmark formally treats part of the ICE as permissible and changes the question. The question is no longer whether *all* advantage has been removed, but whether new social opportunities are taken by the already advantaged or shared more widely. In doing so, the chapter develops and applies a new and more realistic standard.

What is to be done. The third finding meets the objective of *empirical quantification* by answering: "How much mobility loss is unavoidable from the transmission of familial relationship goods?" Combining the first two findings leads to the proposed *decoupling* strategy. A society seeking to balance mobility and family life requires two things: accepting the private transmission of relational goods while using public institutions to limit the conversion of other advantages — financial resources and genetic endowments — into fixed inequality (as discussed in Chapter 2). The empirical analysis in Chapter 5 shows that preserving the transmission of familial relationship goods imposes a measurable limit on social mobility, corresponding to a reduction of between 0.24 and 0.27 standard deviations. This estimate provides an empirical measurement of the cost described in the equality of opportunity trilemma (Fishkin, 1984), thereby completing the final objective of the thesis.

## 6.3 Implications and Contributions

### 6.3.1 For the measurement of mobility

A main implication of this dissertation is a basic re-evaluation of how social mobility is measured and judged (van der Weide et al., 2024). The usual benchmark of "perfect mobility" — zero intergenerational correlation — is a flawed and undesirable abstraction: a 'statistical illusion' that hides the uneven terrain of real-world opportunity (Swift, 2004). Building on Chapter 4, this illusion fails in three ways. First, it ignores the harms of downward mobility, treating systematic downward movement as

healthy mobility rather than a potential structural signal. Second, it is blind to the difficulty of transitions, treating the educational landscape as flat when moves between different stages require very different resources. Third, and most fundamentally, it is incompatible with the family: achieving a zero correlation would require destroying the familial relationship goods essential for human flourishing (Sypnowich, 2022).

In its place, the dissertation offers the "Adjusted Mobility" / "Fair Progress" framework as a better diagnostic tool. This framework changes the basic question from "Has all influence been removed?" to "Who benefits from societal growth and educational expansion?" Its strength comes from two innovations. First, it sets a realistic baseline for a society by including the 0.15 transmission parameter (from Chapter 3), accepting this baseline as the cost of family life. Second, it derives the "Adjusted Mobility" measure from this baseline, measuring the gap between observed outcomes and the fair-progress ideal. This measure depends on context: it sees genuine upward mobility as desirable and flags too much persistence or downward mobility as problematic. As a result, the framework separates opportunity from simple expansion, testing whether new opportunities are shared widely or captured by the already advantaged. By providing a detailed, usable standard, "Adjusted Mobility" replaces a statistical fantasy with a philosophically grounded tool for evaluating social mobility.

### 6.3.2 For social theory

This dissertation intervenes in political philosophy by providing a workable compromise and important empirical grounding for the long-standing debate about the family and equality of opportunity (Gheaus, 2018). It addresses the basic tension between family autonomy and social mobility by building an empirical and normative bridge between two opposing theoretical sides. On one side is *Liberal Equality of Opportunity*, which tries to neutralise social disadvantages but often ignores how the family can be a source of non-financial, relational advantage (Brighouse & Swift, 2014). On the other side is *Radical Egalitarianism*, which sees both social background and genetic endowments as arbitrary, thereby suggesting that a truly level playing field might require abolishing the family or standardising child-rearing (Grätz, 2024). This dissertation rejects the first side's comfort with family partiality and the second side's extreme, impractical solution — a solution that would destroy the very relational goods needed for human flourishing.

Instead, the dissertation proposes a sustainable and empirically defined balance, called *Fair Progress*. This balance has two non-negotiable parts. First, it protects the value of *familial relationship goods*. These are the "internal goods" of family life —

practices such as shared meals, bedtime reading, and authoritative guidance — which are valued for the intimacy, emotional security, and moral formation they provide, not as tools for social competition (Brighouse & Swift, 2014). State intrusion into these spontaneous, private interactions would destroy the qualities that make the family a morally significant institution (Gheaus, 2018; Gundersen, 2024). Second, and with equal strength, the balance must actively reduce the *extrinsic advantages* that unavoidably accompany these same family practices. The goal is to stop these intimate goods from turning into engines of rigid social reproduction. This is *decoupling*.

Decoupling directly targets the mechanisms described by the *Great Gatsby Curve* (Corak, 2013; Durlauf et al., 2022), which shows how economic inequality amplifies intergenerational persistence. Public policy must close the *capacity gap* — the large difference in financial and non-financial resources available for educational investment — and reduce the *incentive effect*, whereby high inequality raises the stakes of success and pushes advantaged parents to invest heavily in protecting their children's status (Jerrim & Macmillan, 2015). The Fair Progress framework does not leave this theoretical compromise as a mere abstraction. It is anchored by a central empirical finding: the 0.15 baseline of the ICE, derived from the isolated transmission effect of familial relationship goods.

This number is the key to the contribution to social theory. It represents the measured "acceptable" level of ICE — the price a society pays for family intimacy. This 0.15 transmission effect is not a problem to be removed, but the smallest possible amount of intergenerational continuity arising from family life. By identifying this benchmark, the dissertation moves the philosophical debate from abstract principle to grounded, discussable reality. It offers a clear standard for what makes a *reasonable* — rather than a perfectly equal — starting point in life. A society seeking balance, on this view, accepts this baseline as the necessary cost of a rich private sphere, while using all its public institutions to ensure that this baseline does not become a ceiling for some or a destiny for all.

### 6.3.3 For public policy

The implications of this dissertation suggest a basic shift in the policy approach to social mobility — from criticism to construction. This shift rests on a simple insight: the transmission of family relationship goods is both necessary for human flourishing and a cause of inequality (Sypnowich, 2022). These intimate, everyday practices arise from unique, partial bonds that no state programme can replicate without destroying their value. Policy must therefore abandon the impossible project of creating perfect mobility and instead manage the unavoidable trade-offs that family life entails. The

guiding idea is *decoupling*: preserve the intrinsic goods of family relationships while preventing their extrinsic advantages from becoming inherited destiny (Brighouse & Swift, 2014).

Decoupling operates through two mechanisms. First, it lowers the rewards for advantage so that family background matters less. Where returns to elite credentials are high, advantaged parents invest heavily to protect their children's status (Doepke & Zilibotti, 2019). Progressive taxation, wage compression, and reduced premiums for selective credentials all lower these stakes. The most powerful tool, however, is universal, high-quality childcare and education from early childhood onward (Kalil & Ryan, 2024; Kotera & Seshadri, 2017). When every child has access to a good developmental environment regardless of home background, disparities in parental investment shrink. Second, decoupling builds alternative supports for children who receive less at home. Public mentoring programmes, community centres, after-school activities, and libraries provide other sources of adult guidance and enrichment (Brighouse & Swift, 2014). These programmes do not replace the family; they add a developmental floor. This approach respects family autonomy while ensuring that no child is left behind.

These two mechanisms align with how family influence changes across childhood. In early childhood, family influence operates through *direct influence* — the intimate practices needed for flourishing. The state's role at this stage is *enabling*: universal supports help all families cultivate relational goods without prescribing how. As children grow, family influence increasingly works through *accumulated advantage* — early relational goods contribute to learning resources and educational paths (Mastekaasa & Birkelund, 2023). The state's role here shifts from enabling to *interrupting*. Changes to school tracking, admissions systems, and wage compression stop accumulated advantage from becoming rigid reproduction.

To clarify, decoupling cannot neatly separate intrinsic goods from extrinsic advantages. A family dinner that nurtures love and belonging simultaneously conveys vocabulary, knowledge of social institutions, and cultural habits. Decoupling therefore does not cut these connections — that is impossible. Instead, it reduces the *stakes* of their unequal distribution. When rewards for advantage are lower and public alternatives are strong, the same unequal transmission does less harm. Decoupling, properly understood, is not a surgical separation but a political and economic context in which the consequences of unequal family resources are greatly reduced.

The research shows what is at stake: preserving the transmission of family relationship goods reduces educational mobility by about 0.24 to 0.27 standard deviations (Brighouse & Swift, 2014; Gundersen, 2024). This reduction is not a policy failure to be eliminated. It reflects the price of family intimacy. A society seeking balance

names this trade-off honestly instead of pretending it away. Decoupling does not sever the parent-child link. It flattens the slope described by the Great Gatsby Curve (Corak, 2013; Durlauf et al., 2022). The apple may not fall far from the tree, but every child has fair ground to roll as far as their own effort and talent can take them. A balanced society is found not in removing the tree, but in carefully tending the ground around it.

### 6.3.4 The case of Finland

Finland serves as an ideal case for the decoupling strategy, as it runs both defamilisation (via universal Early Childhood Education and Care, ECEC) and familisation (via the Home Care Allowance, HCA) simultaneously (Kangas & Niemelä, 2026). The first pillar, ECEC, is a universal right: since 1985, municipalities must provide a daycare spot for all children under three whose parents apply. The system is heavily subsidized (customer payments covered only 8% of costs in 2022), with a maximum monthly fee of €295 for the oldest child and free access for low-income families (Laaninen, 2025). The second pillar, the Home Care Allowance (HCA), serves as the primary alternative to ECEC. Available for children under three not in municipal care, the HCA includes a flat-rate basic allowance, a sibling allowance, and a means-tested care supplement. Many municipalities add their own supplement. This dual system emerged from a 1985 political compromise: left-wing parties pushed for universal daycare, while the Centre Party (formerly Agrarians) and Conservatives demanded a cash-for-care option to preserve "freedom to choose" and support rural family structures (Kangas & Niemelä, 2026). The result is lower ECEC enrolment in Finland than in other Nordic countries, particularly for children aged one to three (Kangas & Niemelä, 2026; Laaninen, 2025).

Despite running more familisation than its neighbours, Finland outperforms them on aggregate welfare metrics: it achieves the highest redistribution (41% Gini reduction, versus Sweden's 26%), the lowest child poverty (9.5%, versus Sweden's 17.2%), and the smallest child poverty gap (12.3%, versus Sweden's 21.4%). However, this success comes with a trade-off for equality of opportunity. Laaninen (2025) finds that longer home care is associated with lower literacy scores at age 16. This negative effect is modest for children of less-educated mothers but substantially larger for children of immigrants — precisely those who would benefit most from early exposure to the host country's language through ECEC. Finland thus achieves superior aggregate welfare outcomes while accepting a narrow but real cost to equalising life chances for disadvantaged children. Decoupling works at the population level, but not for everyone equally.

Finland thus navigates a fundamental trade-off between welfare and opportunity. On the welfare side, the HCA preserves family autonomy, supports rural family structures, and achieves superior aggregate outcomes: lowest child poverty, highest redistribution, and smallest poverty gap. On the opportunity side, the same policy permits differential skill formation by family background, producing unequal educational trajectories that challenge strict equality of opportunity. Finland prioritises welfare — the maximisation of aggregate well-being and respect for family privacy — over the radical egalitarian demand that no child's life chances should depend on their parents' choices. The apple does not fall far from the tree not because Finland fails to equalise resources, but because it chooses to preserve the family bonds that make the apple theirs. This trade-off is not a policy failure to be corrected. It is the empirically observable price of a political choice: welfare for the many, purchased at the cost of perfect opportunity for the few. The case of Finland, together with our theory of family relationship goods, raises a fundamental question about (de)familisation in the welfare state.

## 6.4 Limitations and Future Research

### 6.4.1 Candid Limitations

A careful evaluation of this dissertation requires acknowledging its necessary limits. The framework developed here is a powerful model for understanding educational persistence, but its generalizability is limited in three important ways — limitations that define the next steps for this research.

*First, domain specificity.* The Fair Progress benchmark and the main 0.15 transmission estimate were built and tested for educational attainment only. The dissertation treats education as a cumulative outcome of a defined developmental process, but it accepts that the relative importance of different transmission channels changes across areas of life. Important outcomes such as health (Halliday et al., 2021) or well-being (Molina et al., 2011) likely involve different intergenerational transfer mechanisms, where the balance of genetic, financial, and relational influences may shift. While the method could, in theory, extend to other social and economic outcomes, applying a model designed for a continuous variable like years of schooling to more discrete or complex outcomes risks measurement problems. An important question for future research is whether the measured "price" of 0.24–0.27 standard deviations in reduced mobility holds in these other areas, or whether the cost of family intimacy differs elsewhere.

*Second, cultural and institutional contingency.* The analysis is rooted in the Swedish and Nordic context. A potential critique is that the transmission effect of the non-shared environment varies across regimes due to differences in family bond intensity. However, this concern does not undermine our approach. Family dynamics are endogenous to the gene-environment system, and traditional twin estimates are context-bound because they scale with a population's specific genetic variance. Our bias-correction framework addresses this directly: the non-shared environment isolates idiosyncratic randomness with no macro-institutional footprint, so the corrected transmission parameter should theoretically remain invariant across contexts. Nevertheless, this theoretical invariance remains an empirical question, and future replication in other institutional settings — such as liberal systems like the United States or United Kingdom (Esping-Andersen, 1990) — is encouraged.

*Third, measurement frontiers.* Despite methodological corrections, separating the different transmission channels remains difficult. The complexities of gene-environment correlation (rGE) and assortative mating create bundles of advantage that are very hard to disentangle. In this framework, rGE is not separately identified but is absorbed into the broader contribution of "natural attributes" — a necessary simplification. While corrections were attempted — such as using the average education of both parents to account for assortative mating — these issues show the need for richer, cross-cultural longitudinal data. Current estimates, especially from twin and adoption samples, are limited by sample size and the resulting statistical uncertainty. Future progress depends on larger, more detailed datasets that can further break down the environmental spectrum and improve our understanding of how the transmission of relational goods interacts with the genetic and social fabric of advantage.

### 6.4.2 Avenues for Future Research

The research framework established in this dissertation provides a base for a future research programme focused on the link between family dynamics, social structures, and intergenerational mobility. The limits identified above are not dead ends, but rather starting points for three connected agendas for future work.

The expansion agenda. The dissertation calls for applying the Fair Progress benchmark and its adjusted mobility measures to areas of life beyond education, thereby creating a fuller picture of intergenerational mobility. While education is a formative and cumulative outcome strongly shaped by family life, a complete picture of intergenerational influence requires examining expected lifetime resources. These

resources better predict key child outcomes such as educational attainment, cognitive skills, criminal involvement, and teenage parenthood (Eshaghnia et al., 2022). This expansion must be careful about methods, accepting that the relative importance of genetic, financial, and relational channels likely varies across these outcomes. Researchers must adapt the framework to avoid measurement problems when treating discrete outcomes — such as specific health conditions or criminal convictions — as continuous variables. The central empirical question is whether the 0.24–0.27 standard deviation "price" of family intimacy remains constant, or whether the cost of decoupling (the unavoidable reduction in mobility) differs in the areas of wealth or well-being.

The decoupling agenda (helping disadvantaged children). Decoupling also means actively helping disadvantaged children obtain some of the benefits of relational goods. Can the state provide mentoring, community programmes, and enrichment activities that give children alternative sources of guidance and support? The goal is not to replace the family but to supplement it. This agenda proposes careful long-term studies of such programmes. The key limit is *autonomy*: interventions must be evaluated not only for effectiveness but also for their effect on the spontaneous, private character of family life (Kalil & Ryan, 2024). The aim is to find policy models that provide support for child development without standardising or intruding into intimate family practices. This is decoupling by building alternatives, not by tearing anything down.

The institutional agenda. Finally, the dissertation requires a deep comparative study of how different welfare state models put the decoupling strategy into practice. It is a known fact that Nordic societies have a lower ICE (Fleury & Gilles, 2018). Future research must separate the mechanisms of this outcome. Is lower persistence achieved mainly by closing the capacity gap through strong, universal public investment in childcare and education — thereby offsetting private resource differences? Or is it more a result of weakening the incentive effect through wage compression and lower returns to elite credentials — thereby reducing the stakes of status competition? Large-N comparative analyses, using the Adjusted Mobility measure, can test how specific policy packages — progressive taxation, wage structures, education spending — work together to manage the estimated 0.24–0.27 SD trade-off. This institutional agenda turns the framework from a normative model into a diagnostic tool for comparing political and economic systems, identifying which state configurations most effectively flatten the slope of the Great Gatsby Curve while respecting the terrain of family life.

# Bibliography


Adermon, A., Lindahl, M., & Palme, M. (2021). Dynastic Human Capital, Inequality, and Intergenerational Mobility. *American Economic Review*, *111*(5), 1523–1548. https://doi.org/10.1257/aer.20190553

Allegrini, A. G., Karhunen, V., Coleman, J. R. I., Selzam, S., Rimfeld, K., von Stumm, S., Pingault, J.-B., & Plomin, R. (2020). Multivariable G–E interplay in the prediction of educational achievement. *PLoS genetics*, *16*(11), e1009153. https://doi.org/10.1371/journal.pgen.1009153

Amin, V., Lundborg, P., & Rooth, D.-O. (2015). The intergenerational transmission of schooling: Are mothers really less important than fathers? *Economics of Education Review*, *47*, 100–117. https://doi.org/10.1016/j.econedurev.2015.01.008

Apouey, B., Nissanov, Z., & Silber, J. (2023). Ordinal Variables and the Measurement of Upward and Downward Intergenerational Educational Mobility in European Countries. *Review of Income and Wealth*, *69*(3), 776–800. https://doi.org/10.1111/roiw.12584

Arneson, R. (2018). Four Conceptions of Equal Opportunity. *The Economic Journal*, *128*(612), F152–F173. https://doi.org/10.1111/ecoj.12531

Arpawong, T. E., Gatz, M., Zavala, C., Gruenewald, T. L., Walters, E. E., & Prescott, C. A. (2023). Nature, Nurture, and the Meaning of Educational Attainment: Differences by Sex and Socioeconomic Status. *Twin Research and Human Genetics*, *26*(1), 1–9. https://doi.org/10.1017/thg.2023.6

Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the "other 99 percent". *Science*, *344*(6186), 843–851. https://doi.org/10.1126/science.1251868

Baderin, A. (2023). 'The Talk': Risk, Racism and Family Relationships. *Political Studies*, *71*(4), 1347–1364. https://doi.org/10.1177/00323217221074894

Baier, T., Eilertsen, E. M., Ystrøm, E., Zambrana, I. M., & Lyngstad, T. H. (2022). An anatomy of the intergenerational correlation of educational attainment – learning from the educational attainments of norwegian twins and their children. *Research in Social Stratification and Mobility*, *79*, 100691. https://doi.org/10.1016/j.rssm.2022.100691

Bailey, M., & Dynarski, S. (2011). *Gains and Gaps: Changing Inequality in U.S. College Entry and Completion* (tech. rep. No. 17633). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w17633

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Becker, B. (2011). Social disparities in children's vocabulary in early childhood. Does pre–school education help to close the gap? *The British Journal of Sociology*, *62*(1), 69–88. https://doi.org/10.1111/j.1468-4446.2010.01345.x

Becker, G. S., & Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of labor economics*, *4*(3 Pt. 2), 1–47. https://doi.org/10.1086/298118

Becker, G. S. (2009). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education* (3rd ed.) [First published 1964]. University of Chicago Press. https://press.uchicago.edu/ucp/books/book/chicago/H/bo3684031

Beckfield, J. (2020). Rising inequality is not balanced by intergenerational mobility. *Proceedings of the National Academy of Sciences*, *117*(1), 23–25. https://doi.org/10.1073/pnas.1919694117

Behrman, J. (2015). Twins Studies in Economics. In *The oxford handbook of economics and human biology* (pp. 385–404). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199389292.013.47

Behrman, J. R., & Rosenzweig, M. R. (2002). Does Increasing Women's Schooling Raise the Schooling of the Next Generation? *American Economic Review*, *92*(1), 323–334. https://doi.org/10.1257/000282802760015757

Behrman, J. R., & Rosenzweig, M. R. (2004). Returns to Birthweight. *Review of Economics and Statistics*, *86*(2), 586–601. https://doi.org/10.1162/003465304323031139

Bingley, P., Cappellari, L., & Tatsiramos, K. (2022). Parental assortative mating and the intergenerational transmission of human capital. *Labour Economics*, *77*, 102047. https://doi.org/10.1016/j.labeco.2021.102047

Bingley, P., Cappellari, L., & Tatsiramos, K. (2023). *On the Origins of Socio–Economic Inequalities: Evidence from Twin Families* (tech. rep. No. 16520). IZA–Institute of Labor Economics. https://www.jstor.org/stable/resrep57422

Biroli, P., Galama, T., von Hinke, S., van Kippersluis, H., Rietveld, C. A., & Thom, K. (2026). The Economics and Econometrics of Gene–Environment Interplay. *Review of Economic Studies*, *93*(1), 144–180. https://doi.org/10.1093/restud/rdaf034

Björklund, A., Lindahl, M., & Plug, E. (2006). The Origins of Intergenerational Associations: Lessons from Swedish Adoption Data. *Quarterly Journal of Economics*, *121*(3), 999–1028. https://doi.org/10.1162/qjec.121.3.999

Black, S. E., Devereux, P. J., & Salvanes, K. G. (2007). From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes. *The Quarterly Journal of Economics*, *122*(1), 409–439. https://doi.org/10.1162/qjec.122.1.409

Black, S. E., Devereux, P. J., Lundborg, P., & Majlesi, K. (2020). Poor Little Rich Kids? The Role of Nature versus Nurture in Wealth and Other Economic Outcomes and Behaviours. *The Review of Economic Studies*, *87*(4), 1683–1725. https://doi.org/10.1093/restud/rdz038

Black, S. E., Devereux, P. J., & Salvanes, K. G. (2005). Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital. *American Economic Review*, *95*(1), 437–449. https://doi.org/10.1257/0002828053828635

Blanden, J. (2013). Cross–country Rankings In Intergenerational Mobility: A Comparison Of Approaches From Economics And Sociology. *Journal of Economic Surveys*, *27*(1), 38–73. https://doi.org/10.1111/j.1467-6419.2011.00690.x

Blanden, J., Erola, J., Kilpi-Jakonen, E., & Macmillan, L. (2024). Introduction: The economic and sociological approaches to studying the intergenerational transmission of inequality: Similarities, differences and convergence. In *Research handbook on intergenerational inequality* (pp. 1–11). Edward Elgar Publishing. https://doi.org/10.4337/9781800888265.00007

Blanden, J., Gregg, P., & Macmillan, L. (2013). Intergenerational Persistence in Income and Social Class: The Effect of Within-Group Inequality. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *176*(2), 541–563. https://doi.org/10.1111/j.1467-985X.2012.01053.x

Blau, P. M., Duncan, O. D., & Tyree, A. (1978). *American Occupational Structure*. Free Press. https://inequality.stanford.edu/publications/media/details/american-occupational-structure

Bohrnstedt, G. W., & Goldberger, A. S. (1969). On the Exact Covariance of Products of Random Variables. *Journal of the American Statistical Association*, *64*(328), 1439–1442. https://doi.org/10.1080/01621459.1969.10501069

Boliver, V. (2013). How fair is access to more prestigious UK universities? *The British journal of sociology*, *64*(2), 344–64. https://doi.org/10.1111/1468-4446.12021

Boliver, V., & Capsada-Munsech, Q. (2024). Intergenerational inequality in education. In *Research handbook on intergenerational inequality* (pp. 13–26). Edward Elgar Publishing. https://doi.org/10.4337/9781800888265.00009

Bonjour, D., Cherkas, L. F., Haskel, J. E., Hawkes, D. D., & Spector, T. D. (2003). Returns to Education: Evidence from U.K. Twins. *American Economic Review*, *93*(5), 1799–1812. https://doi.org/10.1257/000282803322655554

Bourdieu, P. (2018). The Forms of Capital [Original work published 1986]. In J. G. Richardson (Ed.), *The sociology of economic life* (3rd ed., pp. 78–92). Routledge. https://doi.org/10.4324/9780429494338-6

Brandén, G. (2018). *Understanding intergenerational mobility: Inequality, student aid and nature–nurture interactions* (Publication No. 177) [Doctoral dissertation, Uppsala University]. https://www.ifau.se/en/Research/Publications/Dissertation-series/2019/understanding-intergenerational-mobility/

Branigan, A. R., McCallum, K. J., & Freese, J. (2013). Variation in the Heritability of Educational Attainment: An International Meta–Analysis. *Social Forces*, *92*(1), 109–140. https://doi.org/10.1093/sf/sot076

Breen, R., & Jonsson, J. O. (2005). Inequality of Opportunity in Comparative Perspective: Recent Research on Educational Attainment and Social Mobility. *Annual Review of Sociology*, *31*(1), 223–243. https://doi.org/10.1146/annurev.soc.31.041304.122232

Breen, R., & Luijkx, R. (2004). Social Mobility in Europe between 1970 and 2000. In R. Breen (Ed.), *Social mobility in europe* (pp. 37–76). Oxford University PressOxford. https://doi.org/10.1093/0199258457.003.0003

Brighouse, H., & Swift, A. (2014). *Family Values: The Ethics of Parent–Child Relationships*. Princeton University Press. https://doi.org/10.2307/j.ctt7ztpk2

Brighouse, H., & Swift, A. (2022). Who Should Make Decisions About Children's Education? In *Handbook of philosophy of education* (pp. 103–113). Routledge. https://doi.org/10.4324/9781003172246-10

Briley, D. A., & Tucker-Drob, E. M. (2013). Explaining the increasing heritability of cognitive ability across development: a meta–analysis of longitudinal twin and adoption studies. *Psychological science*, *24*(9), 1704–13. https://doi.org/10.1177/0956797613478618

Buchmann, C., & Park, H. (2009). Stratification and the formation of expectations in highly differentiated educational systems. *Research in Social Stratification and Mobility*, *27*(4), 245–267. https://doi.org/10.1016/j.rssm.2009.10.003

Bukodi, E., & Goldthorpe, J. H. (2013). Decomposing 'Social Origins': The Effects of Parents' Class, Status, and Education on the Educational Attainment of Their Children. *European Sociological Review*, *29*(5), 1024–1039. https://doi.org/10.1093/esr/jcs079

Bukodi, E., & Goldthorpe, J. H. (2021). 'Primary' Factors in Intergenerational Class Mobility in Europe: Results from the Application of a Topological Model. *European Sociological Review*, *37*(1), 1–17. https://doi.org/10.1093/esr/jcaa028

Bukodi, E., & Goldthorpe, J. H. (2022). Intergenerational class mobility in industrial and post-industrial societies: Towards a general theory. *Rationality and Society*, *34*(3), 271–301. https://doi.org/10.1177/10434631221093791

Bukodi, E., Paskov, M., & Nolan, B. (2019). Intergenerational Class Mobility in Europe: A New Account. *Social Forces*, *98*(3), 941–972. https://doi.org/10.1093/sf/soz026

Busso, M., Bassi, M., Urzúa, S., & Vargas, J. (2012). *Disconnected: Skills, Education, and Employment in Latin America*. Inter-American Development Bank. https://doi.org/10.18235/0012582

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, *21*(1), C1–C68. https://doi.org/10.1111/ectj.12097

Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States. *The Quarterly Journal of Economics*, *129*(4), 1553–1623. https://doi.org/10.1093/qje/qju022

Clemente-Casinhas, L., Ferreira-Lopes, A., & Martins, L. F. (2025). Using machine learning to unveil the predictors of intergenerational mobility. *Review of Income and Wealth*, *71*(1), e12710. https://doi.org/10.1111/roiw.12710

Cohen, G. A. (2008). *Rescuing justice and equality*. Harvard University Press. https://www.jstor.org/stable/j.ctv1pncqth

Coleman, J. S. (1990). *Foundations of social theory*. Harvard university press. https://www.hup.harvard.edu/books/9780674312265

Collins, R. (1979). *The credential society: An historical sociology of education and stratification*. Columbia University Press. https://www.jstor.org/stable/10.7312/coll19234

Corak, M. (2013). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives*, *27*(3), 79–102. https://doi.org/10.1257/jep.27.3.79

Cowell, F. A., & Flachaire, E. (2018). Measuring mobility. *Quantitative Economics*, *9*(2), 865–901. https://doi.org/10.3982/qe512

Cunha, F., Heckman, J. J., Lochner, L., & Masterov, D. V. (2006). Chapter 12 Interpreting the Evidence on Life Cycle Skill Formation. In *Handbook of the economics of education* (pp. 697–812, Vol. 1). Elsevier. https://doi.org/10.1016/s1574-0692(06)01012-9

De Haan, M., & Schreiner, R. C. (2025). The Intergenerational Transmission of Welfare Dependency. *The Economic Journal*, *135*(669), 1609–1640. https://doi.org/10.1093/ej/ueaf004

Deutscher, N., & Mazumder, B. (2023). Measuring Intergenerational Income Mobility: A Synthesis of Approaches. *Journal of Economic Literature*, *61*(3), 988–1036. https://doi.org/10.1257/jel.20211413

Doepke, M., & Zilibotti, F. (2019). *Love, Money, and Parenting*. Princeton University Press. https://doi.org/10.1515/9780691184210

D'Onofrio, B. M., Turkheimer, E., Emery, R. E., Slutske, W. S., Heath, A. C., Madden, P. A., & Martin, N. G. (2005). A genetically informed study of marital instability and its association with offspring psychopathology. *Journal of abnormal psychology*, *114*(4), 570–86. https://doi.org/10.1037/0021-843x.114.4.570

Duncan, G. J., & Murnane, R. J. (2011). *Whither Opportunity? Rising Inequality and the Uncertain Life Chances of Low–Income Children*. Russell Sage Foundation.

Duong, K. (2024). What really matters for global intergenerational mobility? (R. Amir-ud-Din, Ed.). *Plos One*, *19*(6), e0302173. https://doi.org/10.1371/journal.pone.0302173

Durlauf, S. N., Kourtellos, A., & Tan, C. M. (2022). The Great Gatsby Curve. *Annual Review of Economics*, *14*(1), 571–605. https://doi.org/10.1146/annurev-economics-082321-122703

Dworkin, R. (2000). *Sovereign Virtue: The Theory and Practice of Equality*. Harvard University Press. https://doi.org/10.2307/j.ctv1c3pd0r

Elliot Major, L. (2024). Commentary: How can policy reduce intergenerational inequality? In *Research handbook on intergenerational inequality* (pp. 415–422). Edward Elgar Publishing. https://doi.org/10.4337/9781800888265.00040

Engzell, P., & Tropf, F. C. (2019). Heritability of education rises with intergenerational mobility. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(51), 25386–25388. https://doi.org/10.1073/pnas.1912998116

Eshaghnia, S., Heckman, J., Landersø, R., & Qureshi, R. (2022). *Intergenerational Transmission of Family Influence* (tech. rep. No. 30412). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w30412

Esping-Andersen, G. (1990). *The three worlds of welfare capitalism*. Polity Press. https://www.goodreads.com/book/show/1820711.The_three_worlds_of_welfare_capitalism

Ferreira, F. H. G. (2022). Not all inequalities are alike. *Nature*, *606*(7915), 646–649. https://doi.org/10.1038/d41586-022-01682-3

Fishkin, J. (1984). *Justice, Equal Opportunity and the Family*. Yale University Press. https://doi.org/10.12987/9780300156690

Fleury, N., & Gilles, F. (2018). The intergenerational transmission of education. A meta–regression analysis. *Education Economics*, *26*(6), 557–573. https://doi.org/10.1080/09645292.2018.1517863

Friend, A., DeFries, J. C., Olson, R. K., Pennington, B., Harlaar, N., Byrne, B., Samuelsson, S., Willcutt, E. G., Wadsworth, S. J., Corley, R., & Keenan, J. M. (2009). Heritability of High Reading Ability and its Interaction with Parental Education. *Behavior Genetics*, *39*(4), 427–436. https://doi.org/10.1007/s10519-009-9263-2

Fruehwirth, J. C. (2014). Can Achievement Peer Effect Estimates Inform Policy? A View from Inside the Black Box. *Review of Economics and Statistics*, *96*(3), 514–523. https://doi.org/10.1162/REST_a_00385

Galton, F. (1889). *Natural Inheritance*. Macmillan.

Gheaus, A. (2018). What abolishing the family would not do. *Critical Review of International Social and Political Philosophy*, *21*(3), 284–300. https://doi.org/10.1080/13698230.2017.1398449

Gold, A., Olin, N., & Wang, A. (2017). modmarg: Calculating Marginal Effects and Levels with Errors. https://doi.org/10.32614/CRAN.package.modmarg

Goldthorpe, J. H. (2013). Understanding — and Misunderstanding — Social Mobility in Britain: The Entry of the Economists, the Confusion of Politicians and the Limits of Educational Policy. *Journal of Social Policy*, *42*(3), 431–450. https://doi.org/10.1017/s004727941300024x

Goldthorpe, J. H. (2014). The role of education in intergenerational social mobility: Problems from empirical research in sociology and some theoretical pointers from economics. *Rationality and Society*, *26*(3), 265–289. https://doi.org/10.1177/1043463113519068

Gould, S. J. (1981). *Mismeasure of Man*. Norton. https://wwnorton.com/books/The-Mismeasure-of-Man

Grätz, M. (2024). Empirical Approaches to Measuring Equality of Opportunity. In *Handbook of equality of opportunity* (pp. 817–825). Springer International Publishing. https://doi.org/10.1007/978-3-031-55897-9_83

Grätz, M., & Petrini, S. (2025). The role of polygenic indices in inequality of opportunity (V. Capraro, Ed.). *PNAS Nexus*, *4*(5), pgaf140. https://doi.org/10.1093/pnasnexus/pgaf140

Gregg, P., Jonsson, J. O., Macmillan, L., & Mood, C. (2017). The Role of Education for Intergenerational Income Mobility: A comparison of the United States, Great Britain, and Sweden. *Social Forces*, *96*(1), 121–152. https://doi.org/10.1093/sf/sox051

Grönqvist, E., Öckert, B., & Vlachos, J. (2017). The Intergenerational Transmission of Cognitive and Noncognitive Abilities. *Journal of Human Resources*, *52*(4), 887–918. https://doi.org/10.3368/jhr.52.4.0115-6882R1

Groot, W., & Oosterbeek, H. (1994). Earnings Effects of Different Components of Schooling; Human Capital Versus Screening. *The Review of Economics and Statistics*, *76*(2), 317. https://doi.org/10.2307/2109885

Grusky, D. B., & Cumberworth, E. (2010). A national protocol for measuring intergenerational mobility? *Stanford Center for Study of Poverty and Inequality*, *2*(8). https://inequality.stanford.edu/sites/default/files/grusky_cumberworth_national_protocol_measuring_mobility.pdf

Gundersen, E. C. (2024). Should Foster Care Replace the Family? Child Welfare and the Value of Family Privacy. In *Child welfare and the significance of family* (pp. 225–246). Cappelen Damm Akademisk/NOASP. https://doi.org/10.23865/noasp.209.ch10

Halliday, T., Mazumder, B., & Wong, A. (2021). Intergenerational mobility in self-reported health status in the US. *Journal of Public Economics*, *193*, 104307. https://doi.org/10.1016/j.jpubeco.2020.104307

Harlaar, N., Dale, P. S., & Plomin, R. (2005). Telephone Testing and Teacher Assessment of Reading Skills in 7-year-olds: II. Strong Genetic Overlap. *Reading and Writing*, *18*(5), 401–423. https://doi.org/10.1007/s11145-005-0271-1

Hartley, R. P., Lamarche, C., & Ziliak, J. P. (2022). Welfare Reform and the Intergenerational Transmission of Dependence. *Journal of Political Economy*, *130*(3), 523–565. https://doi.org/10.1086/717893

Hebb, D., & Donderi, D. (1987). *Textbook of Psychology (Psychology Revivals)* (1st Edition). Psychology Press. https://doi.org/10.4324/9781315819396

Heckman, J., Tian, H., Zhang, Z., & Zhou, J. (2026). *Dynamic Complementarity* (tech. rep. No. 34833). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w34833

Heckman, J. J. (2006). Skill Formation and the Economics of Investing in Disadvantaged Children. *Science*, *312*(5782), 1900–1902. https://doi.org/10.1126/science.1128898

Hjalmarsson, R., & Lindquist, M. J. (2013). The origins of intergenerational associations in crime: Lessons from Swedish adoption data. *Labour Economics*, *20*, 68–81. https://doi.org/10.1016/j.labeco.2012.11.001

Holmlund, H., Lindahl, M., & Plug, E. (2011). The Causal Effect of Parents' Schooling on Children's Schooling: A Comparison of Estimation Methods. *Journal of Economic Literature*, *49*(3), 615–651. https://doi.org/10.1257/jel.49.3.615

Horwitz, B. N., & Neiderhiser, J. M. (2011). Gene–Environment Interplay, Family Relationships, and Child Adjustment. *Journal of marriage and the family*, *73*(4), 804–816. https://doi.org/10.1111/j.1741-3737.2011.00846.x

Hout, M. (2012). Social and Economic Returns to College Education in the United States. *Annual Review of Sociology*, *38*(1), 379–400. https://doi.org/10.1146/annurev.soc.012809.102503

Hu, Y., Behrman, J. R., & Zhang, J. (2021). The causal effects of parents' schooling on children's schooling in urban China. *Journal of Comparative Economics*, *49*(1), 258–276. https://doi.org/10.1016/j.jce.2020.08.001

Hübler, P. M. (2018). Heritability of Time Preference: Evidence from German Twin Data. *Kyklos*, *71*(3), 433–455. https://doi.org/10.1111/kykl.12176

Jenkins, D. G., & Quintana-Ascencio, P. F. (2020). A solution to minimum sample size for regressions (G. Han, Ed.). *Plos One*, *15*(2), e0229345. https://doi.org/10.1371/journal.pone.0229345

Jennings, J. L., Deming, D., Jencks, C., Lopuch, M., & Schueler, B. E. (2015). Do Differences in School Quality Matter More Than We Thought? New Evidence on Educational Opportunity in the Twenty–first Century. *Sociology of Education*, *88*(1), 56–82. https://doi.org/10.1177/0038040714562006

Jerrim, J., & Macmillan, L. (2015). Income Inequality, Intergenerational Mobility, and the Great Gatsby Curve: Is Education the Key? *Social Forces*, *94*(2), 505–533. https://doi.org/10.1093/sf/sov075

Jonathan, S. (2018). Parental partiality. In *The routledge handbook of the philosophy of childhood and children* (pp. 180–190). Routledge. https://doi.org/10.4324/9781351055987-17

Kalil, A., & Ryan, R. (2024). How parenting contributes to intergenerational inequality. In *Research handbook on intergenerational inequality* (pp. 328–341). Edward Elgar Publishing. https://doi.org/10.4337/9781800888265.00034

Kangas, O., & Niemelä, M. (2026). Walks the walk, but doesn't talk the talk: Finnish exceptionalism from the Nordic perspective. In *Beyond the nordic welfare state* (pp. 98–120). Edward Elgar Publishing. https://doi.org/10.4337/9781035375448.00014

Keller, M. C., Medland, S. E., & Duncan, L. E. (2010). Are Extended Twin Family Designs Worth the Trouble? A Comparison of the Bias, Precision, and Accuracy of Parameters Estimated in Four Twin Family Models. *Behavior Genetics*, *40*(3), 377–393. https://doi.org/10.1007/s10519-009-9320-x

Khan, Z. A., & Patra, B. (2024). Intergenerational Mobility in South Asia. *South Asia Economic Journal*, *25*(1), 7–25. https://doi.org/10.1177/13915614241226538

Knigge, A., Maas, I., Stienstra, K., de Zeeuw, E. L., & Boomsma, D. I. (2022). Delayed tracking and inequality of opportunity: Gene–Environment interactions in educational attainment. *npj Science of Learning*, *7*(1), 6. https://doi.org/10.1038/s41539-022-00122-1

Kong, A., Thorleifsson, G., Frigge, M. L., Vilhjalmsson, B. J., Young, A. I., Thorgeirsson, T. E., Benonisdottir, S., Oddsson, A., Halldorsson, B. V., Masson, G., Gudbjartsson, D. F., Helgason, A., Bjornsdottir, G., Thorsteinsdottir, U., & Stefansson, K. (2018). The nature of

nurture: Effects of parental genotypes. *Science*, *359*(6374), 424–428. https://doi.org/10.1126/science.aan6877

Kotera, T., & Seshadri, A. (2017). Educational policy and intergenerational mobility. *Review of Economic Dynamics*, *25*, 187–207. https://doi.org/10.1016/j.red.2017.02.005

Kovas, Y., Haworth, C. M. A., Dale, P. S., & Plomin, R. (2007). The genetic and environmental origins of learning abilities and disabilities in the early school years. *Monographs of the Society for Research in Child Development*, *72*(3), 1–144. https://doi.org/10.1111/j.1540-5834.2007.00439.x

Kraaykamp, G., & van Eijck, K. (2010). The Intergenerational Reproduction of Cultural Capital: A Threefold Perspective. *Social Forces*, *89*(1), 209–231. https://doi.org/10.1353/sof.2010.0087

Krylova, P., Harmacek, J., & Htitich, M. (2026). Social Progress Index 1990–2020: measuring societal wellbeing over 31 years. *International Journal of Social Research Methodology*, *29*(1), 107–122. https://doi.org/10.1080/13645579.2025.2486264

Laaninen, M. (2025). Duration of child home care allowance period and school success: Differences by parental education level and ethnic origins. *Research in Social Stratification and Mobility*, *98*, 101063. https://doi.org/10.1016/j.rssm.2025.101063

Lareau, A. (2003). *Unequal childhoods: Class, race, and family life*. University of California Press. https://www.jstor.org/stable/10.1525/j.ctt1ppgj4

Leone, T. (2019). *Intergenerational mobility in education: Estimates of the worldwide variation*. UNRISD Occasional Paper. https://hdl.handle.net/10419/244371

Lewontin, R. C. (1974). Annotation: the analysis of variance and the analysis of causes. *American journal of human genetics*, *26*(3), 400–11. https://pubmed.ncbi.nlm.nih.gov/4827368/

Lewontin, R. C. (2006). The analysis of variance and the analysis of causes. *International Journal of Epidemiology*, *35*(3), 520–525. https://doi.org/10.1093/ije/dyl062

Lin, N. (1999). Social Networks And Status Attainment. *Annual Review of Sociology*, *25*(1), 467–487. https://doi.org/10.1146/annurev.soc.25.1.467

Liu, G. (2006). Interstate inequality in educational opportunity. *New York University Law Review*, *81*, 2044. https://nyulawreview.org/issues/volume-81-number-6/interstate-inequality-in-educational-opportunity/

Lundborg, P., Nordin, M., & Rooth, D. O. (2018). The intergenerational transmission of human capital: the role of skills and health. *Journal of Population Economics*, *31*(4), 1035–1065. https://doi.org/10.1007/s00148-018-0702-3

Lynch, K. E. (2017). Heritability and causal reasoning. *Biology & Philosophy*, *32*(1), 25–49. https://doi.org/10.1007/s10539-016-9535-1

Malloy, L. C. (2015). Loss aversion, education, and intergenerational mobility. *Education Economics*, *23*(3), 318–337. https://doi.org/10.1080/09645292.2013.823909

Manuck, S. B., & McCaffery, J. M. (2014). Gene–Environment Interaction. *Annual Review of Psychology*, *65*(1), 41–70. https://doi.org/10.1146/annurev-psych-010213-115100

Mastekaasa, A., & Birkelund, G. E. (2023). The intergenerational transmission of social advantage and disadvantage: comprehensive evidence on the association of parents' and children's educational attainments, class, earnings, and status. *European Societies*, *25*(1), 66–86. https://doi.org/10.1080/14616696.2022.2059542

Maurin, E., & McNally, S. (2008). Vive la Révolution! Long-Term Educational Returns of 1968 to the Angry Students. *Journal of Labor Economics*, *26*(1), 1–33. https://doi.org/10.1086/522071

Mayer, S. E. (2002). How Economic Segregation Affects Children's Educational Attainment. *Social Forces*, *81*(1), 153–176. https://doi.org/10.1353/sof.2002.0053

Mitnik, P. A., Cumberworth, E., & Grusky, D. B. (2016). Social Mobility in a High–Inequality Regime. *The ANNALS of the American Academy of Political and Social Science*, *663*(1), 140–184. https://doi.org/10.1177/0002716215596971

Molina, J. A., Navarro, M., & Walker, I. (2011). Intergenerational Well-Being Mobility in Europe. *Kyklos*, *64*(2), 253–270. https://doi.org/10.1111/j.1467-6435.2011.00505.x

Morris, P. (1996). Asia's Four Little Tigers: A comparison of the role of education in their development. *Comparative Education*, *32*(1), 95–110. https://doi.org/10.1080/03050069628948

Mueller, G. P. (2021). *Entropy measures of social mobility: The example of the intergenerational transmission of education* (Working Paper No. 2021-3). FORS (Swiss Foundation for Research in Social Sciences). Lausanne, Switzerland. https://doi.org/10.24440/fwp-2021-00003

Narayan, A., Van der Weide, R., Cojocaru, A., Lakner, C., Redaelli, S., Mahler, D. G., Ramasubbaiah, R. G. N., & Thewissen, S. (2018). *Fair Progress?: Economic Mobility across Generations around the World*. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1210-1

Narusyte, J., Neiderhiser, J. M., D'Onofrio, B. M., Reiss, D., Spotts, E. L., Ganiban, J., & Lichtenstein, P. (2008). Testing different types of genotype–environment correlation: an extended children–of–twins model. *Developmental psychology*, *44*(6), 1591–603. https://doi.org/10.1037/a0013911

Neale, M. C. (2009). Biometrical Models in Behavioral Genetics. In *Handbook of behavior genetics* (pp. 15–33). Springer New York. https://doi.org/10.1007/978-0-387-76727-7_2

Nybom, M. (2018). Intergenerational mobility: A dream deferred. *International Labour Organization Research Paper Series*. https://www.ilo.org/publications/intergenerational-mobility-dream-deferred

Oreopoulos, P., Page, M. E., & Stevens, A. H. (2006). The Intergenerational Effects of Compulsory Schooling. *Journal of Labor Economics*, *24*(4), 729–760. https://doi.org/10.1086/506484

Patacchini, E., & Zenou, Y. (2011). Neighborhood Effects And Parental Involvement In The Intergenerational Transmission Of Education. *Journal of Regional Science*, *51*(5), 987–1013. https://doi.org/10.1111/j.1467-9787.2011.00722.x

Pedersen, J., & Bøyum, S. (2020). Inheritance and the Family. *Journal of Applied Philosophy*, *37*(2), 299–313. https://doi.org/10.1111/japp.12389

Piketty, T. (2000). Chapter 8 Theories of persistent inequality and intergenerational mobility. In *Handbook of income distribution* (pp. 429–476, Vol. 1). Elsevier. https://doi.org/10.1016/s1574-0056(00)80011-1

Plomin, R. (2018). *Blueprint: How DNA Makes Us Who We Are*. MIT Press. https://mitpress.mit.edu/9780262039161/blueprint/

Plomin, R. (2024). Nonshared environment: Real but random. *JCPP Advances*, *4*(3), e12229. https://doi.org/10.1002/jcv2.12229

Plomin, R., & Daniels, D. (2011). Why are children in the same family so different from one another? *International journal of epidemiology*, *40*(3), 563–82. https://doi.org/10.1093/ije/dyq148

Plomin, R., & DeFries, J. (1985). A parent–offspring adoption study of cognitive abilities in early childhood. *Intelligence*, *9*(4), 341–356. https://doi.org/10.1016/0160-2896(85)90019-4

Plomin, R., Fulker, D. W., Corley, R., & DeFries, J. C. (1997). Nature, Nurture, and Cognitive Development from 1 to 16 Years: A Parent–Offspring Adoption Study. *Psychological Science*, *8*(6), 442–447. https://doi.org/10.1111/j.1467-9280.1997.tb00458.x

Plomin, R., & Kovas, Y. (2005). Generalist genes and learning disabilities. *Psychological bulletin*, *131*(4), 592–617. https://doi.org/10.1037/0033-2909.131.4.592

Plug, E., & Vijverberg, W. (2003). Schooling, Family Background, and Adoption: Is It Nature or Is It Nurture? *Journal of Political Economy*, *111*(3), 611–641. https://doi.org/10.1086/374185

Pronzato, C. (2012). An examination of paternal and maternal intergenerational transmission of schooling. *Journal of Population Economics*, *25*(2), 591–608. https://doi.org/10.1007/s00148-010-0311-2

Purcell, S. (2002). Variance components models for Gene–Environment interaction in twin analysis. *Twin Research and Human Genetics*, *5*(6), 554–71. https://doi.org/10.1375/136905202762342026

Radl, J., Foley, W., Kröger, L. K., Lorente, P., Palacios-Abad, A., Solga, H., Stuhler, J., & Swarr, M. (2026). The Social Origins of Effort: How Incentives Reduce Socioeconomic Disparities among Children. *American Sociological Review*, *91*(1), 89–122. https://doi.org/10.1177/00031224251401933

Raftery, A. E., & Hout, M. (1993). Maximally Maintained Inequality: Expansion, Reform, and Opportunity in Irish Education, 1921-75. *Sociology of Education*, *66*(1), 41. https://doi.org/10.2307/2112784

Rawls, J. (1971). *A Theory of Justice* (Original edition). Harvard University Press. https://doi.org/10.2307/j.ctvjf9z6v

Reardon, S. F., Weathers, E. S., Fahle, E. M., Jang, H., & Kalogrides, D. (2024). Is Separate Still Unequal? New Evidence on School Segregation and Racial Academic Achievement Gaps. *American Sociological Review*, *89*(6), 971–1010. https://doi.org/10.1177/00031224241297263

Reichenberg, A., Cederlöf, M., McMillan, A., Trzaskowski, M., Kapra, O., Fruchter, E., Ginat, K., Davidson, M., Weiser, M., Larsson, H., Plomin, R., & Lichtenstein, P. (2016). Discontinuity in the genetic and environmental causes of the intellectual disability spectrum. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(4), 1098–103. https://doi.org/10.1073/pnas.1508093112

Rietveld, C. A. (2025). Heritability and public policy – a reappraisal. *The Journal of Economic Inequality*, 1–21. https://doi.org/10.1007/s10888-025-09690-9

Roemer, J. E., & Trannoy, A. (2016). Equality of Opportunity: Theory and Measurement. *Journal of Economic Literature*, *54*(4), 1288–1332. https://doi.org/10.1257/jel.20151206

Roksa, J., & Potter, D. (2011). Parenting and Academic Achievement. *Sociology of Education*, *84*(4), 299–321. https://doi.org/10.1177/0038040711417013

Sacerdote, B. (2007). How Large are the Effects from Changes in Family Environment? A Study of Korean American Adoptees. *The Quarterly Journal of Economics*, *122*(1), 119–157. https://doi.org/10.1162/qjec.122.1.119

Sacerdote, B. (2002). The Nature and Nurture of Economic Outcomes. *American Economic Review*, *92*(2), 344–348. https://doi.org/10.1257/000282802320191589

Sahlberg, P. (2011). The Fourth Way of Finland. *Journal of Educational Change*, *12*(2), 173–185. https://doi.org/10.1007/s10833-011-9157-y

Scarr, S., & McCartney, K. (1983). How People Make Their Own Environments: A Theory of Genotype–Environment Effects. *Child Development*, *54*(2), 424. https://doi.org/10.2307/1129703

Schluter, C., & Van de gaer, D. (2011). Upward Structural Mobility, Exchange Mobility, And Subgroup Consistent Mobility Measurement: US–German Mobility Rankings Revisited. *Review of Income and Wealth*, *57*(1), 1–22. https://doi.org/10.1111/j.1475-4991.2009.00372.x

Segall, S. (2011). If you're a luck egalitarian, how come you read bedtime stories to your children? *Critical Review of International Social and Political Philosophy*, *14*(1), 23–40. https://doi.org/10.1080/13698230.2010.518388

Selita, F., & Kovas, Y. (2019). Genes And Gini: What Inequality Means For Heritability. *Journal of biosocial science*, *51*(1), 18–47. https://doi.org/10.1017/s0021932017000645

Sesardic, N. (2005). *Making Sense of Heritability*. Cambridge University Press. https://doi.org/10.1017/cbo9780511487378

Smith, E. N., & Kruglyak, L. (2008). Gene–Environment interaction in yeast gene expression. *PLoS biology*, *6*(4), e83. https://doi.org/10.1371/journal.pbio.0060083

Smith, G. D. (2010). Mendelian Randomization for Strengthening Causal Inference in Observational Studies: Application to Gene–Environment Interactions. *Perspectives on Psychological Science*, *5*(5), 527–45. https://doi.org/10.1177/1745691610383505

Solon, G. (2009). A model of intergenerational mobility variation over time and place. In M. Corak (Ed.), *Generational income mobility in north america and europe* (pp. 38–47). Cambridge University Press. https://doi.org/10.1017/cbo9780511492549.003

Solon, G. (2018). What Do We Know So Far about Multigenerational Mobility? *The Economic Journal*, *128*(612), F340–F352. https://doi.org/10.1111/ecoj.12495

Stiglitz, J. E., Sen, A., & Fitoussi, J.-P. (2010). *Mismeasuring Our Lives: Why GDP Doesn't Add Up*. The New Press. https://doi.org/10.2307/jj.26193269

Sunde, H. F., Eilertsen, E. M., & Torvik, F. A. (2025). Understanding indirect assortative mating and its intergenerational consequences for educational attainment. *Nature Communications*, *16*(1), 5264. https://doi.org/10.1038/s41467-025-60483-0

Swift, A. (2004). Would Perfect Mobility be Perfect? *European Sociological Review*, *20*(1), 1–11. https://doi.org/10.1093/esr/20.1.1

Swift, A. (2005). Justice, Luck, and The Family: The Intergenerational Transmission of Economic Advantage From a Normative Perspective. In S. Bowles, H. Gintis, & M. O. Groves (Eds.), *Unequal chances* (pp. 256–276). Princeton University Press. https://muse.jhu.edu/pub/267/edited_volume/chapter/1231296

Sypnowich, C. (2022). The Demands Of Equality. *Social Philosophy and Policy*, *39*(2), 210–232. https://doi.org/10.1017/s0265052523000286

Tal, O. (2009). From heritability to probability. *Biology & Philosophy*, *24*(1), 81–105. https://doi.org/10.1007/s10539-008-9129-7

Thompson, O. (2014). Genetic mechanisms in the intergenerational transmission of health. *Journal of health economics*, *35*, 132–46. https://doi.org/10.1016/j.jhealeco.2014.02.003

Torche, F. (2015a). Analyses of Intergenerational Mobility. *The ANNALS of the American Academy of Political and Social Science*, *657*(1), 37–62. https://doi.org/10.1177/0002716214547476

Torche, F. (2015b). Intergenerational Mobility and Equality of Opportunity. *European Journal of Sociology*, *56*(3), 343–371. https://doi.org/10.1017/s0003975615000181

Torche, F. (2021). *Intergenerational mobility in latin america in comparative perspective* (tech. rep. No. 02). United Nations Development Programme. New York, NY. https://www.undp.org/latin-america/publications/intergenerational-mobility-latin-america-comparative-perspective

Tsou, M.-W., Liu, J.-T., & Hammitt, J. K. (2012). The intergenerational transmission of education: Evidence from Taiwanese adoptions. *Economics Letters*, *115*(1), 134–136. https://doi.org/10.1016/j.econlet.2011.12.006

Ulvestad, M. E. S., & Markussen, S. (2023). Born or bred? The roles of nature and nurture for intergenerational persistence in labour market outcomes. *Journal of Population Economics*, *36*(2), 1005–1047. https://doi.org/10.1007/s00148-021-00880-z

Van De Gaer, D., Schokkaert, E., & Maartinez, M. (2001). Three Meanings of Intergenerational Mobility. *Economica*, *68*(272), 519–538. https://doi.org/10.1111/1468-0335.d01-15

Van de Werfhorst, H. G., & Andersen, R. (2005). Social Background, Credential Inflation and Educational Strategies. *Acta Sociologica*, *48*(4), 321–340. https://doi.org/10.1177/0001699305059945

van der Weide, R., Lakner, C., Mahler, D. G., Narayan, A., & Gupta, R. (2024). Intergenerational mobility around the world: A new database. *Journal of Development Economics*, *166*, 103167. https://doi.org/10.1016/j.jdeveco.2023.103167

Van Hootegem, A., Rogne, A. F., Cros, C. T., Røgeberg, O., & Lyngstad, T. H. (2025). Social origins and socioeconomic outcomes: a combined twin and adoption study. *European Sociological Review*, *41*(5), 793–807. https://doi.org/10.1093/esr/jcaf029

Van Hulle, C. A., Lahey, B. B., & Rathouz, P. J. (2013). Operating characteristics of alternative statistical methods for detecting gene–by–measured environment interaction in the presence of Gene–Environment correlation in twin and sibling studies. *Behavior genetics*, *43*(1), 71–84. https://doi.org/10.1007/s10519-012-9568-4

Verweij, R. M., & Keizer, R. (2022). The intergenerational transmission of educational attainment: A closer look at the (interrelated) roles of paternal involvement and genetic inheritance. *PloS one*, *17*(12), e0267254. https://doi.org/10.1371/journal.pone.0267254

Wahlsten, D., Metten, P., Phillips, T. J., Boehm, S. L., Burkhart-Kasch, S., Dorow, J., Doerksen, S., Downing, C., Fogarty, J., Rodd-Henricks, K., Hen, R., McKinnon, C. S., Merrill, C. M., Nolte, C., Schalomon, M., Schlumbohm, J. P., Sibert, J. R., Wenger, C. D., Dudek, B. C., & Crabbe, J. C. (2003). Different data from different labs: lessons from studies of Gene–Environment interaction. *Journal of neurobiology*, *54*(1), 283–311. https://doi.org/10.1002/neu.10173

Wainschtein, P., Jain, D., Zheng, Z., Aslibekyan, S., Becker, D., Bi, W., Brody, J., Carlson, J. C., Correa, A., Du, M. M., Fernandez-Rhodes, L., Ferrier, K. R., Graff, M., Guo, X., He, J., Heard-Costa, N. L., Highland, H. M., Hirschhorn, J. N., Howard-Claudio, C. M., … Visscher, P. M. (2022). Assessing the contribution of rare variants to complex trait heritability from whole-genome sequence data. *Nature Genetics*, *54*(3), 263–273. https://doi.org/10.1038/s41588-021-00997-7

Walberg, H. J., & Tsai, S.-L. (1983). 'Matthew' Effects in Education. *American Educational Research Journal*, *20*(3), 359. https://doi.org/10.2307/1162605

Webster, A. K., & Phillips, P. C. (2025). Epigenetics and individuality: from concepts to causality across timescales. *Nature Reviews Genetics*, *26*(6), 406–423. https://doi.org/10.1038/s41576-024-00804-z

Wilson, R. S. (1983). The Louisville Twin Study: developmental synchronies in behavior. *Child development*, *54*(2), 298–316. http://www.ncbi.nlm.nih.gov/pubmed/6683617

World Bank. (2018). *World Development Report 2018: Learning to Realize Education's Promise*. https://doi.org/10.1596/978-1-4648-1096-1

Wu, X. (2019). Inequality and Social Stratification in Postsocialist China. *Annual Review of Sociology*, *45*(1), 363–382. https://doi.org/10.1146/annurev-soc-073018-022516

Yengo, L., Vedantam, S., Marouli, E., Sidorenko, J., Bartell, E., Sakaue, S., Graff, M., Eliasen, A. U., Jiang, Y., Raghavan, S., Miao, J., Arias, J. D., Graham, S. E., Mukamel, R. E., Spracklen, C. N., Yin, X., Chen, S.-H., Ferreira, T., Highland, H. H., … Hirschhorn, J. N. (2022). A saturated map of common

genetic variants associated with human height. *Nature*, *610*(7933), 704–712. https://doi.org/10.1038/s41586-022-05275-y

Young, M. (1994). *The Rise of the Meritocracy* (2nd Edition) [First published 1958]. Routledge. https://doi.org/10.4324/9781315134642

Zyphur, M. J., Zhang, Z., Barsky, A. P., & Li, W.-D. (2013). An ACE in the hole: Twin family models for applied behavioral genetics research. *The Leadership Quarterly*, *24*(4), 572–594. https://doi.org/10.1016/j.leaqua.2013.04.001

# Appendices

## Appendix 1 General Introduction

There is no appendix associated with Chapter 1.

# Appendix 2 When Does The Apple Fall Permissibly?

There is no appendix associated with Chapter 2.

# Appendix 3 Bias Due to Gene–Environment Interplay

## Appendix 3.1 Solving the equation system

We consider the total variance in the educational outcome as the sum of nature, nurture, and their interaction:

$$\operatorname{Var}(a) + \operatorname{Var}(u) + \lambda^2 \operatorname{Var}(a) \operatorname{Var}(u) = 1.$$

From previous studies, we observe the following estimators:

$$\begin{aligned}
\beta_d &= \omega \operatorname{Var}(u), \\
\beta_b &= 0.5 \operatorname{Var}(a) + \omega \operatorname{Var}(u) + 0.5\lambda^2 \omega \operatorname{Var}(a) \operatorname{Var}(u), \\
\beta_w &= \omega \cdot \frac{1 + 0.5\lambda^2 \operatorname{Var}(a)}{1 + \lambda^2 \operatorname{Var}(a)}.
\end{aligned}$$

Starting with the expression for $\beta_w$:

$$\beta_w = \omega \cdot \frac{1 + 0.5\lambda^2 \operatorname{Var}(a)}{1 + \lambda^2 \operatorname{Var}(a)},$$

$$\Rightarrow \lambda^2 \operatorname{Var}(a) = \frac{\omega}{2\beta_w - \omega} - 1.$$

Substitute $\lambda^2 \operatorname{Var}(a)$ and $\omega \operatorname{Var}(u) = \beta_d$ into $\beta_b$:

$$2\beta_b = \operatorname{Var}(a) + 2\beta_d + \beta_d \left( \frac{\omega}{2\beta_w - \omega} - 1 \right),$$

$$\Rightarrow 2\beta_b = \operatorname{Var}(a) + \frac{\beta_d \cdot \omega}{2\beta_w - \omega} + \beta_d,$$

$$\Rightarrow \operatorname{Var}(a) = 2\beta_b - \beta_d - \frac{\beta_d \cdot \omega}{2\beta_w - \omega}.$$

Now substitute $\lambda^2 \operatorname{Var}(a)$ and $\operatorname{Var}(a)$ into the variance identity:

$$\begin{aligned}
&\operatorname{Var}(a) + \operatorname{Var}(u) + \lambda^2 \operatorname{Var}(a) \operatorname{Var}(u) = 1, \\
&\Rightarrow 2\beta_b - \beta_d - \frac{\beta_d \cdot \omega}{2\beta_w - \omega} + \operatorname{Var}(u) + \left( \frac{\omega}{2\beta_w - \omega} - 1 \right) \operatorname{Var}(u) = 1, \\
&\Rightarrow 2\beta_b - \beta_d - \frac{\beta_d \cdot \omega}{2\beta_w - \omega} + \frac{\omega}{2\beta_w - \omega} \operatorname{Var}(u) = 1.
\end{aligned}$$

Solving for $\operatorname{Var}(u)$:

$$\begin{aligned}
&\operatorname{Var}(u) = \left(1 - 2\beta_b + \beta_d + \frac{\beta_d . \omega}{2\beta_w - \omega}\right) \frac{2\beta_w - \omega}{\omega} \\
&= (1 - 2\beta_b + \beta_d) \frac{2\beta_w - \omega}{\omega} + \beta_d
\end{aligned}$$

We also have:

$$\begin{aligned}
&\beta_d = \omega \operatorname{Var}(u) \\
&= \omega \left( (1 - 2\beta_b + \beta_d) \frac{2\beta_w - \omega}{\omega} + \beta_d \right) = (1 - 2\beta_b + \beta_d)(2\beta_w - \omega) + \beta_d \omega \\
&= 2\beta_w (1 - 2\beta_b + \beta_d) - (1 - 2\beta_b)\omega
\end{aligned}$$

Solving for $\omega$:

$$\omega = \frac{2\beta_w (1 - 2\beta_b + \beta_d) - \beta_d}{1 - 2\beta_b} = 2\beta_w - \beta_d \frac{1 - 2\beta_w}{1 - 2\beta_b}.$$

Now plug this into the expression for $\operatorname{Var}(a)$:

$$\operatorname{Var}(a) = \frac{2(\beta_b - \beta_w)}{1 - 2\beta_w}.$$

Finally, substitute into the expression for $\operatorname{Var}(u)$:

$$\operatorname{Var}(u) = \frac{\beta_d (1 - 2\beta_b)}{2\beta_w (1 - 2\beta_b) - \beta_d (1 - 2\beta_w)}.$$

## Appendix 3.2 Partial derivatives

The partial derivative of

$$\omega = 2\beta_w - \beta_d \frac{1-2\beta_w}{1-2\beta_b}$$

is:

- with respect to $\beta_w$:

$$2 + \frac{2\beta_d}{1-2\beta_b}$$

- with respect to $\beta_b$:

$$-\frac{2\beta_d(1-2\beta_w)}{(1-2\beta_b)^2}$$

- with respect to $\beta_d$:

$$-\frac{1-2\beta_w}{1-2\beta_b}$$

The partial derivative of

$$\mathrm{Var}(a) = \frac{2(\beta_b - \beta_w)}{1-2\beta_w}$$

is:

- with respect to $\beta_w$:

$$\frac{4\beta_b - 2}{(1-2\beta_w)^2}$$

- with respect to $\beta_b$:

$$\frac{2}{1-2\beta_w}$$

The partial derivative of

$$\mathrm{Var}(u) = \frac{\beta_d(1-2\beta_b)}{2\beta_w(1-2\beta_b) - \beta_d(1-2\beta_w)}$$

is:

- with respect to $\beta_w$:

$$-\frac{2\beta_d(1-2\beta_b)((1-2\beta_b)+\beta_d)}{(2\beta_w(1-2\beta_b)-\beta_d(1-2\beta_w))^2}$$

- with respect to $\beta_b$:

$$\frac{2\beta_d^2(1-2\beta_w)}{(2\beta_w(1-2\beta_b)-\beta_d(1-2\beta_w))^2}$$

- with respect to $\beta_d$:

$$\frac{2\beta_w(1-2\beta_b)^2}{(2\beta_w(1-2\beta_b)-\beta_d(1-2\beta_w))^2}$$

## Appendix 3.3 Estimates of Holmlund et al. (2011)

### Descriptive analysis

| **Means (standard deviations)** | **Random sample** | **Twin sample** | | **Adoptee sample** | |
|---|---|---|---|---|---|
| | | **All** | **Twin pairs with different years of education** | **Swedish born** | **Foreign born** |
| Father's schooling | 11.25 (2.80) | 10.99 (2.82) | 11.28 (2.66) | 11.48 (2.93) | 12.41 (2.89) |
| Mother's schooling | 11.29 (2.52) | 10.83 (2.52) | 11.01 (2.55) | 11.62 (2.52) | 12.37 (2.54) |
| Child's schooling | 12.76 (2.04) | 12.82 (2.01) | 12.85 (2.03) | 11.83 (1.87) | 12.66 (1.86) |
| N | 607,214 | 9,947 | 5,109 | 496 | 4,893 |

## Regression coefficients

| | **Controls for assortative mating** | **Intergenerational associations** | | | **Intergenerational effects** | | |
|---|---|---|---|---|---|---|---|
| | | Father (1) | Mother (2) | Father +Mother (3) | Father (4) | Mother (5) | Father +Mother (6) |
| **1. Random sample** | | **OLS estimates** | | | | | |
| 607,214 children; at least one of the parents is born 1943–-55. | (no) | 0.23 (0.00)** | 0.28 (0.00)** | | | | |
| | (yes) | 0.15 (0.00)** | 0.19 (0.00)** | 0.17 (0.00)** p = 0.00 | | | |
| | N | 471,940 | 547,399 | 607,214 | | | |
| **2. Twins** | | **OLS estimates** | | | **Difference estimates** | | |
| 2,110 twin fathers and 2,940 twin mothers (where at least one is) born 1943–-55 with 9,947 children. | (no) | 0.21 (0.01)** | 0.25 (0.01)** | | 0.12 (0.03)** | 0.06 (0.03)* | |
| | (yes) | 0.15 (0.01)** | 0.17 (0.01)** | 0.16 (0.01)** p = 0.31 | 0.11 (0.03)** | 0.04 -0.03 | 0.07 (0.02)** p = 0.10 |
| | N | 4,061 | 5,886 | 9,947 | 4,061 | 5,886 | 9,947 |
| **3. Adoption families** | | **OLS estimates using own-birth children** | | | **OLS estimates using adopted children** | | |
| 160 own-birth children and 496 adopted children **born in Sweden**. At least one of the parents is born 1943–-55. | (no) | 0.21 (0.09)* | 0.28 (0.07)** | | 0.10 (0.03)** | 0.11 (0.03)** | |
| | (yes) | 0.11 (0.09) | 0.25 (0.08)** | 0.13 (0.04)** p = 0.47 | 0.06 (0.04)+ | 0.05 -0.04 | 0.08 (0.02)** p = 0.20 |
| | N | 106 | 155 | 160 | 325 | 470 | 496 |
| 912 own-birth children and 4,893 adopted children born abroad (**foreign-born adoptees**). At least one of the parents is born 1943-–55. | (no) | 0.19 (0.03)** | 0.22 (0.03)** | | 0.04 (0.01)** | 0.04 (0.01)** | |
| | (yes) | 0.13 (0.04)** | 0.15 (0.04)** | 0.14 (0.02)** p = 0.51 | 0.04 (0.01)* | 0.03 (0.01)** | 0.03 (0.01)** p = 0.35 |
| | N | 665 | 861 | 912 | 3,793 | 4,690 | 4,893 |

## Appendix 3.4 Non-shared environment includes $G \times E$, not $rGE$

A cornerstone of modern behavioural genetics is the claim that non-shared environmental effects are "real but random" (Plomin, 2024). As Plomin observes, three decades of research into exogenous predictors — such as differential parenting or peer groups — have identified only "culprits" that explain a negligible $1\%$–$2\%$ of the variance in psychopathology (Plomin, 2024). Faced with this predictive impasse, Plomin attributes the residual variance to endogenous biological noise: "non-shared environment might not be caused by anything we would call an event [...] but reflect endogenous processes such as noisy biological systems [...] or idiosyncratic subjective perceptions" (Plomin, 2024).

However, this "randomness" may be an artefact of the additive ACE framework rather than a biological reality. An alternative interpretation suggests that the non-shared component ($e^2$) does not reflect stochastic events, but rather the unshared portion of gene–environment interaction ($G \times E$). To adjudicate this, one must distinguish between two forms of gene–environment interplay (Horwitz & Neiderhiser, 2011):

- *Genotype–environment correlation ($rGE$):* Occurs when genetic propensities influence environmental exposure through passive, evocative, or active mechanisms (Allegrini et al., 2020; Scarr & McCartney, 1983). Crucially, standard twin models fail to assign $rGE$ to the non-shared component unless the specific environment is explicitly modelled as a genetically influenced trait (Narusyte et al., 2008). If non-shared environment included $rGE$, it would be non-random, as $rGE$ is systematic.
- *Gene–environment interaction ($G \times E$):* Captures the "contingency" of development, where the effect of $G$ on phenotype $Y$ is conditional on $E$ (Baron & Kenny, 1986; Lynch, 2017). In a full variance decomposition, this manifests as $V_{G\times E}$. Non-shared environment can include $G \times E$ because the environment, by definition, varies between twins, and whenever an external environmental factor is introduced into the system, it necessarily interacts with the individual's genetic makeup.

The structural misallocation of $G \times E$ in additive models can be illustrated using the classical rectangle analogy (Lewontin, 1974). If the area of a rectangle is defined as $A = L \times W$, the variance in area decomposes into contributions from length, width, and their interaction (Tal, 2009). Analogously, suppose a phenotype is generated by a multiplicative process:

$$Y = G \times E,$$

where $G \sim \mathcal{N}(\mu_G, \sigma_G^2)$, $E \sim \mathcal{N}(\mu_E, \sigma_E^2)$, and $\mathrm{Cov}(G, E) = \rho\sigma_G\sigma_E$. Following Bohrnstedt and Goldberger (1969), the exact variance of $Y$ is:

$$\mathrm{Var}(Y) = \mu_E^2\sigma_G^2 + \mu_G^2\sigma_E^2 + \sigma_G^2\sigma_E^2 + \rho^2\sigma_G^2\sigma_E^2 + 2\rho\mu_G\mu_E\sigma_G\sigma_E.$$

Generalising this to a twin design with shared environmental correlation $\mathbf{r_E} := \mathrm{Corr}(E_1, E_2)$, we obtain the phenotypic covariance for monozygotic (MZ) and dizygotic (DZ) twins:

$$\mathrm{Cov}_{\mathrm{MZ}} = \mathbf{r_E}\mu_G^2\sigma_E^2 + \mu_E^2\sigma_G^2 + \mathbf{r_E}\sigma_G^2\sigma_E^2 + 2\mu_G\mu_E\rho\sigma_G\sigma_E + \rho^2\sigma_G^2\sigma_E^2,$$

$$\mathrm{Cov}_{\mathrm{DZ}} = \mathbf{r_E}\mu_G^2\sigma_E^2 + \frac{1}{2}\mu_E^2\sigma_G^2 + \frac{1}{2}\mathbf{r_E}\sigma_G^2\sigma_E^2 + \mu_G\mu_E\rho\sigma_G\sigma_E + \frac{1}{4}\rho^2\sigma_G^2\sigma_E^2.$$

Applying the standard twin covariance decomposition to this multiplicative structure yields the following parameter estimates:

$$h^2_{\text{twin}} = 2\frac{\mathrm{Cov}_{MZ} - \mathrm{Cov}_{DZ}}{\mathrm{Var}(Y)} = \frac{\mu_E^2\sigma_G^2 + \mathbf{r_E}\sigma_G^2\sigma_E^2 + 2\mu_G\mu_E\rho\sigma_G\sigma_E + \frac{3}{2}\rho^2\sigma_G^2\sigma_E^2}{\mathrm{Var}(Y)}.$$

The shared and non-shared environmental components are:

$$c^2 = r_{\mathrm{MZ}} - h^2_{\text{twin}} = \mathbf{r_E}\frac{\mu_G^2\sigma_E^2}{\mathrm{Var}(Y)} - \frac{1}{2}\frac{\rho^2\sigma_G^2\sigma_E^2}{\mathrm{Var}(Y)},$$

$$e^2 = 1 - r_{\mathrm{MZ}} = (1 - \mathbf{r_E})\frac{\mu_G^2\sigma_E^2 + \sigma_G^2\sigma_E^2}{\mathrm{Var}(Y)}.$$

These derivations demonstrate a systematic "sorting" effect within the ACE model. First, the $rGE$ parameter ($\rho$) is entirely absent from $e^2$; it is instead partitioned into $h^2_{\text{twin}}$ and $c^2$. Second, the interaction term $\sigma_G^2\sigma_E^2$ is split: a shared fraction ($\mathbf{r_E}$) inflates the genetic estimate $h^2_{\text{twin}}$, while the unshared fraction $(1 - \mathbf{r_E})$ is channelled directly into $e^2$.

# Appendix 4 What Should Perfect Mobility Look Like?

## Appendix 4.1 Table of countries

| Code | Country | Region | Obs. | Absolute | Relative | Adjusted |
|---|---|---|---|---|---|---|
| SSD | South Sudan | Sub-Saharan Africa | 343 | 0.05 | 0.64 | 0.00 |
| TCD | Chad | Sub-Saharan Africa | 517 | 0.12 | 0.46 | 0.09 |
| BDI | Burundi | Sub-Saharan Africa | 2159 | 0.14 | 0.46 | 0.10 |
| BTN | Bhutan | South Asia | 781 | 0.16 | 0.21 | 0.12 |
| MLI | Mali | Sub-Saharan Africa | 3893 | 0.15 | 0.29 | 0.12 |
| CAF | Central African | Sub-Saharan Africa | 266 | 0.14 | 0.53 | 0.17 |
| BFA | Burkina Faso | Sub-Saharan Africa | 914 | 0.20 | 0.22 | 0.18 |
| SEN | Senegal | Sub-Saharan Africa | 1086 | 0.23 | 0.40 | 0.23 |
| BEN | Benin | Sub-Saharan Africa | 9161 | 0.25 | 0.26 | 0.25 |
| GNB | Guinea-Bissau | Sub-Saharan Africa | 444 | 0.26 | 0.36 | 0.27 |
| ETH | Ethiopia | Sub-Saharan Africa | 3345 | 0.28 | 0.32 | 0.27 |
| ZMB | Zambia | Sub-Saharan Africa | 2596 | 0.24 | 0.58 | 0.30 |
| TON | Tonga | East Asia and Pacific | 239 | 0.29 | 0.73 | 0.31 |
| TZA | Tanzania | Sub-Saharan Africa | 3066 | 0.31 | 0.57 | 0.32 |
| MRT | Mauritania | Sub-Saharan Africa | 1673 | 0.31 | 0.57 | 0.32 |
| NER | Niger | Sub-Saharan Africa | 2772 | 0.34 | 0.48 | 0.34 |
| GIN | Guinea | Sub-Saharan Africa | 874 | 0.30 | 0.38 | 0.35 |
| AFG | Afghanistan | South Asia | 3956 | 0.34 | 0.47 | 0.37 |
| LBR | Liberia | Sub-Saharan Africa | 2169 | 0.29 | 0.63 | 0.37 |
| MOZ | Mozambique | Sub-Saharan Africa | 442 | 0.37 | 0.41 | 0.37 |
| MWI | Malawi | Sub-Saharan Africa | 2327 | 0.37 | 0.63 | 0.37 |
| TGO | Togo | Sub-Saharan Africa | 1363 | 0.36 | 0.42 | 0.38 |
| GMB | Gambia | Sub-Saharan Africa | 12586 | 0.36 | 0.49 | 0.39 |
| RWA | Rwanda | Sub-Saharan Africa | 1154 | 0.38 | 0.49 | 0.39 |
| CZE | Czech Republic | Europe and Central Asia | 1291 | 0.26 | 0.61 | 0.39 |
| CMR | Cameroon | Sub-Saharan Africa | 591 | 0.37 | 0.40 | 0.40 |
| VUT | Vanuatu | East Asia and Pacific | 475 | 0.37 | 0.60 | 0.40 |
| CIV | Ivory Coast | Sub-Saharan Africa | 1085 | 0.39 | 0.41 | 0.40 |
| UZB | Uzbekistan | Europe and Central Asia | 601 | 0.20 | 0.78 | 0.41 |
| SDN | Sudan | Sub-Saharan Africa | 1077 | 0.37 | 0.29 | 0.41 |
| UGA | Uganda | Sub-Saharan Africa | 1020 | 0.38 | 0.56 | 0.42 |
| SLE | Sierra Leone | Sub-Saharan Africa | 616 | 0.39 | 0.39 | 0.43 |
| COM | Comoros | Sub-Saharan Africa | 636 | 0.41 | 0.61 | 0.43 |
| SWZ | Eswatini | Sub-Saharan Africa | 191 | 0.38 | 0.62 | 0.43 |
| SVK | Slovakia | Europe and Central Asia | 461 | 0.32 | 0.61 | 0.43 |
| AZE | Azerbaijan | Europe and Central Asia | 592 | 0.23 | 0.59 | 0.44 |
| HUN | Hungary | Europe and Central Asia | 685 | 0.33 | 0.40 | 0.44 |
| STP | Sao Tome and Principe | Sub-Saharan Africa | 189 | 0.42 | 0.77 | 0.46 |
| COD | Congo-Kinshasa | Sub-Saharan Africa | 13688 | 0.41 | 0.52 | 0.46 |
| PNG | Papua New Guinea | East Asia and Pacific | 622 | 0.42 | 0.63 | 0.46 |
| MDG | Madagascar | Sub-Saharan Africa | 6766 | 0.43 | 0.35 | 0.46 |
| DJI | Djibouti | Middle East and North Africa | 3035 | 0.44 | 0.53 | 0.46 |
| NAM | Namibia | Sub-Saharan Africa | 459 | 0.38 | 0.56 | 0.47 |
| NPL | Nepal | South Asia | 3799 | 0.45 | 0.39 | 0.48 |
| GHA | Ghana | Sub-Saharan Africa | 8583 | 0.43 | 0.47 | 0.48 |
| HND | Honduras | Latin America and Caribbean | 1974 | 0.45 | 0.45 | 0.48 |
| SLV | El Salvador | Latin America and Caribbean | 1669 | 0.44 | 0.55 | 0.48 |
| IRQ | Iraq | Middle East and North Africa | 25502 | 0.41 | 0.51 | 0.48 |
| NIC | Nicaragua | Latin America and Caribbean | 1726 | 0.44 | 0.59 | 0.49 |
| PHL | Philippines | East Asia and Pacific | 8252 | 0.41 | 0.85 | 0.50 |
| COG | Congo-Brazzaville | Sub-Saharan Africa | 580 | 0.35 | 0.40 | 0.50 |

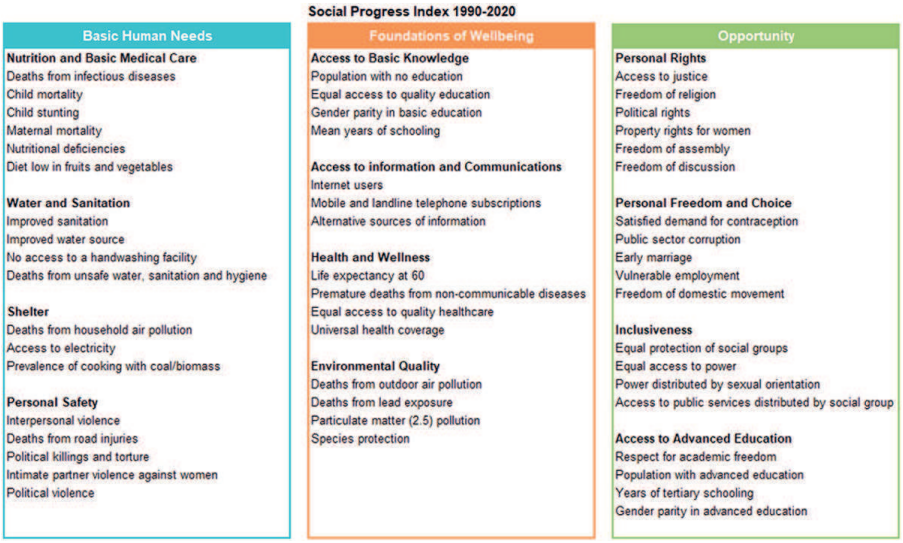
| | | | | | | |
|---|---|---|---|---|---|---|
| PAK | Pakistan | South Asia | 4504 | 0.45 | 0.43 | 0.51 |
| BGR | Bulgaria | Europe and Central Asia | 445 | 0.36 | 0.43 | 0.51 |
| KGZ | Kyrgyzstan | Europe and Central Asia | 561 | 0.40 | 0.64 | 0.52 |
| GAB | Gabon | Sub-Saharan Africa | 2381 | 0.40 | 0.59 | 0.52 |
| ARM | Armenia | Europe and Central Asia | 426 | 0.26 | 0.52 | 0.52 |
| GTM | Guatemala | Latin America and Caribbean | 7053 | 0.49 | 0.29 | 0.52 |
| SRB | Serbia | Europe and Central Asia | 489 | 0.44 | 0.55 | 0.53 |
| KEN | Kenya | Sub-Saharan Africa | 1654 | 0.42 | 0.66 | 0.54 |
| AUT | Austria | Europe and Central Asia | 955 | 0.41 | 0.52 | 0.54 |
| CRI | Costa Rica | Latin America and Caribbean | 1681 | 0.48 | 0.64 | 0.54 |
| LAO | Laos | East Asia and Pacific | 475 | 0.49 | 0.61 | 0.54 |
| LSO | Lesotho | Sub-Saharan Africa | 308 | 0.49 | 0.38 | 0.55 |
| NGA | Nigeria | Sub-Saharan Africa | 3629 | 0.46 | 0.44 | 0.56 |
| MMR | Myanmar | East Asia and Pacific | 456 | 0.52 | 0.25 | 0.57 |
| URY | Uruguay | Latin America and Caribbean | 1595 | 0.52 | 0.56 | 0.58 |
| AGO | Angola | Sub-Saharan Africa | 476 | 0.50 | 0.36 | 0.58 |
| LKA | Sri Lanka | South Asia | 570 | 0.55 | 0.59 | 0.59 |
| MNE | Montenegro | Europe and Central Asia | 562 | 0.48 | 0.46 | 0.59 |
| MDA | Moldova | Europe and Central Asia | 349 | 0.49 | 0.53 | 0.59 |
| SLB | Solomons | East Asia and Pacific | 521 | 0.54 | 0.47 | 0.60 |
| PSE | Palestine | Middle East and North Africa | 1071 | 0.53 | 0.62 | 0.60 |
| BGD | Bangladesh | South Asia | 1604 | 0.55 | 0.41 | 0.60 |
| DEU | Germany | Europe and Central Asia | 1346 | 0.38 | 0.73 | 0.61 |
| DOM | Dominicana | Latin America and Caribbean | 1571 | 0.55 | 0.71 | 0.61 |
| CHN | China | East Asia and Pacific | 5823 | 0.56 | 0.52 | 0.61 |
| EST | Estonia | Europe and Central Asia | 1062 | 0.36 | 0.61 | 0.62 |
| FJI | Fiji | East Asia and Pacific | 584 | 0.58 | 0.61 | 0.63 |
| CHE | Switzerland | Europe and Central Asia | 774 | 0.45 | 0.66 | 0.63 |
| XKX | Kosovo | Europe and Central Asia | 652 | 0.54 | 0.61 | 0.63 |
| TJK | Tajikistan | Europe and Central Asia | 541 | 0.50 | 0.77 | 0.64 |
| IND | India | South Asia | 27662 | 0.56 | 0.42 | 0.64 |
| MKD | Macedonia | Europe and Central Asia | 470 | 0.57 | 0.48 | 0.64 |
| ROU | Romania | Europe and Central Asia | 316 | 0.54 | 0.31 | 0.64 |
| KAZ | Kazakhstan | Europe and Central Asia | 445 | 0.42 | 0.67 | 0.64 |
| HRV | Croatia | Europe and Central Asia | 363 | 0.54 | 0.55 | 0.65 |
| PRY | Paraguay | Latin America and Caribbean | 2108 | 0.59 | 0.59 | 0.65 |
| MUS | Mauritius | Sub-Saharan Africa | 1092 | 0.58 | 0.88 | 0.65 |
| BIH | Bosnia | Europe and Central Asia | 484 | 0.58 | 0.55 | 0.65 |
| ARG | Argentina | Latin America and Caribbean | 1945 | 0.59 | 0.64 | 0.65 |
| MAR | Morocco | Middle East and North Africa | 3804 | 0.61 | 0.51 | 0.67 |
| PAN | Panama | Latin America and Caribbean | 2545 | 0.55 | 0.51 | 0.67 |
| TLS | Timor-Leste | East Asia and Pacific | 2203 | 0.62 | 0.42 | 0.67 |
| BLR | Belarus | Europe and Central Asia | 458 | 0.43 | 0.68 | 0.67 |
| ITA | Italy | Europe and Central Asia | 332 | 0.57 | 0.67 | 0.68 |
| KHM | Cambodia | East Asia and Pacific | 872 | 0.62 | 0.45 | 0.68 |
| SVN | Slovenia | Europe and Central Asia | 689 | 0.54 | 0.64 | 0.68 |
| ECU | Ecuador | Latin America and Caribbean | 13457 | 0.60 | 0.51 | 0.68 |
| GEO | Georgia | Europe and Central Asia | 351 | 0.47 | 0.55 | 0.69 |
| TUV | Tuvalu | East Asia and Pacific | 57 | 0.58 | 0.75 | 0.69 |
| HTI | Haiti | Latin America and Caribbean | 444 | 0.63 | 0.41 | 0.69 |
| KIR | Kiribati | East Asia and Pacific | 197 | 0.62 | 0.74 | 0.69 |
| LTU | Lithuania | Europe and Central Asia | 796 | 0.48 | 0.70 | 0.70 |
| POL | Poland | Europe and Central Asia | 1143 | 0.60 | 0.65 | 0.70 |
| USA | United States | North America | 3660 | 0.43 | 0.67 | 0.71 |
| LVA | Latvia | Europe and Central Asia | 284 | 0.51 | 0.61 | 0.71 |
| TUN | Tunisia | Middle East and North Africa | 1844 | 0.64 | 0.60 | 0.71 |
| PER | Peru | Latin America and Caribbean | 2334 | 0.64 | 0.61 | 0.71 |
| FIN | Finland | Europe and Central Asia | 1025 | 0.51 | 0.76 | 0.72 |
| ISL | Iceland | Europe and Central Asia | 248 | 0.51 | 0.76 | 0.72 |

| | | | | | | |
|---|---|---|---|---|---|---|
| VEN | Venezuela | Latin America and Caribbean | 1922 | 0.66 | 0.67 | 0.74 |
| MNG | Mongolia | East Asia and Pacific | 540 | 0.64 | 0.75 | 0.75 |
| FRA | France | Europe and Central Asia | 804 | 0.62 | 0.73 | 0.75 |
| YEM | Yemen | Middle East and North Africa | 2774 | 0.68 | 0.70 | 0.75 |
| JPN | Japan | East Asia and Pacific | 380 | 0.55 | 0.71 | 0.75 |
| BEL | Belgium | Europe and Central Asia | 870 | 0.59 | 0.69 | 0.75 |
| IDN | Indonesia | East Asia and Pacific | 7078 | 0.68 | 0.59 | 0.76 |
| ALB | Albania | Europe and Central Asia | 513 | 0.67 | 0.60 | 0.77 |
| BOL | Bolivia | Latin America and Caribbean | 1566 | 0.67 | 0.56 | 0.77 |
| ZAF | South Africa | Sub-Saharan Africa | 4113 | 0.70 | 0.80 | 0.78 |
| ISR | Israel | Middle East and North Africa | 1486 | 0.61 | 0.80 | 0.78 |
| TUR | Turkey | Europe and Central Asia | 735 | 0.71 | 0.42 | 0.78 |
| JOR | Jordan | Middle East and North Africa | 4045 | 0.69 | 0.75 | 0.79 |
| GRC | Greece | Europe and Central Asia | 218 | 0.69 | 0.68 | 0.79 |
| CHL | Chile | Latin America and Caribbean | 12708 | 0.69 | 0.62 | 0.79 |
| EGY | Egypt | Middle East and North Africa | 9810 | 0.71 | 0.61 | 0.79 |
| NOR | Norway | Europe and Central Asia | 809 | 0.55 | 0.67 | 0.79 |
| UKR | Ukraine | Europe and Central Asia | 590 | 0.53 | 0.62 | 0.79 |
| GBR | United Kingdom | Europe and Central Asia | 761 | 0.63 | 0.82 | 0.79 |
| VNM | Vietnam | East Asia and Pacific | 617 | 0.70 | 0.53 | 0.80 |
| SWE | Sweden | Europe and Central Asia | 769 | 0.59 | 0.64 | 0.80 |
| MEX | Mexico | Latin America and Caribbean | 7928 | 0.71 | 0.60 | 0.81 |
| CPV | Cabo Verde | Sub-Saharan Africa | 890 | 0.73 | 0.62 | 0.81 |
| COL | Colombia | Latin America and Caribbean | 8478 | 0.72 | 0.53 | 0.82 |
| DNK | Denmark | Europe and Central Asia | 519 | 0.62 | 0.80 | 0.82 |
| RUS | Russia | Europe and Central Asia | 1166 | 0.48 | 0.59 | 0.83 |
| NZL | New Zealand | East Asia and Pacific | 116 | 0.67 | 0.81 | 0.83 |
| IRL | Ireland | Europe and Central Asia | 1459 | 0.72 | 0.65 | 0.83 |
| CYP | Cyprus | Europe and Central Asia | 400 | 0.74 | 0.80 | 0.84 |
| LBN | Lebanon | Middle East and North Africa | 671 | 0.74 | 0.59 | 0.84 |
| BWA | Botswana | Sub-Saharan Africa | 342 | 0.75 | 0.73 | 0.85 |
| NLD | Netherlands | Europe and Central Asia | 727 | 0.73 | 0.75 | 0.86 |
| PRT | Portugal | Europe and Central Asia | 726 | 0.77 | 0.52 | 0.86 |
| ESP | Spain | Europe and Central Asia | 1028 | 0.76 | 0.68 | 0.87 |
| AUS | Australia | East Asia and Pacific | 2843 | 0.66 | 0.77 | 0.87 |
| CAN | Canada | North America | 3305 | 0.69 | 0.74 | 0.88 |
| BRA | Brazil | Latin America and Caribbean | 6081 | 0.79 | 0.64 | 0.88 |
| IRN | Iran | Middle East and North Africa | 8131 | 0.80 | 0.66 | 0.90 |
| MYS | Malaysia | East Asia and Pacific | 7311 | 0.82 | 0.71 | 0.91 |
| THA | Thailand | East Asia and Pacific | 2603 | 0.85 | 0.64 | 0.95 |
| MDV | Maldives | South Asia | 424 | 0.86 | 0.90 | 0.96 |
| KOR | South Korea | East Asia and Pacific | 2042 | 0.89 | 0.81 | 0.98 |
| TWN | Taiwan-China | East Asia and Pacific | 605 | 0.91 | 0.66 | 1.00 |

*Notes.* The data are from the Global Database on International Mobility (GDIM) 2023, filtered for cohort 1980, maximum parent education, and all children. Absolute (mobility) is measured as $CAT$, Relative (mobility) as $1 - BETA$, and the Adjusted (mobility) refers to a newly defined measure introduced in this study. Countries are classified into regions according to the World Bank regional grouping. The table is sorted by the Adjusted (mobility) measure.

## Appendix 4.2 Social Progress Index

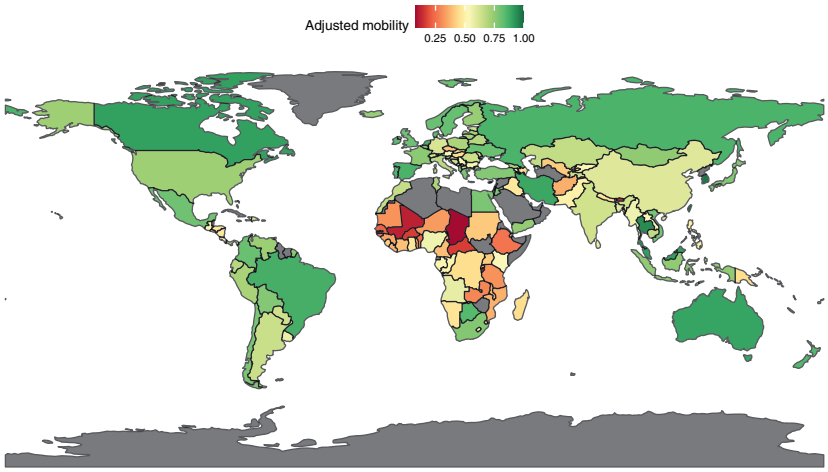
The Social Progress Index (SPI) is a comprehensive measure of societal well-being that excludes economic factors such as GDP and instead focuses entirely on social and environmental outcomes (Krylova et al., 2026). It assesses countries across three broad dimensions. The first, Basic Human Needs, includes indicators such as nutrition, medical care, water and sanitation, shelter, and personal safety. The second, Foundations of Wellbeing, covers access to basic education, access to information and communications, health and wellness, and environmental quality. The third dimension, Opportunity, evaluates the extent to which individuals enjoy personal rights, personal freedom and choice, social inclusion and equity, and access to advanced education.

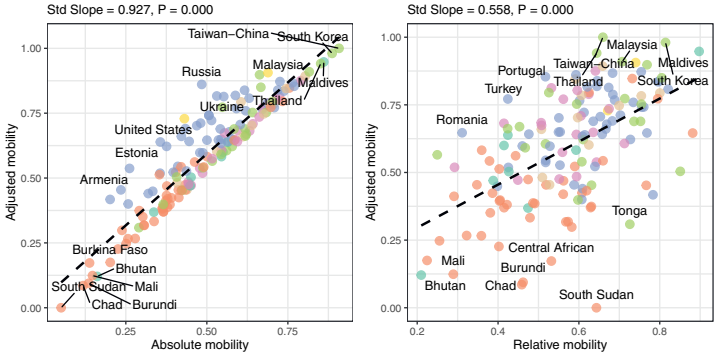



Source: Krylova et al. (2026)

## Appendix 4.3 Sensitivity analysis

These figures below were generated using the same data and methods as Figure 4.2, Figure 4.3, and Figure 4.4, respectively, with the only adjustment being a change in the intergenerational transmission effect to $\omega = 0.1$. The results show no significant difference compared to $\omega = 0.15$.






**Burkina Faso**

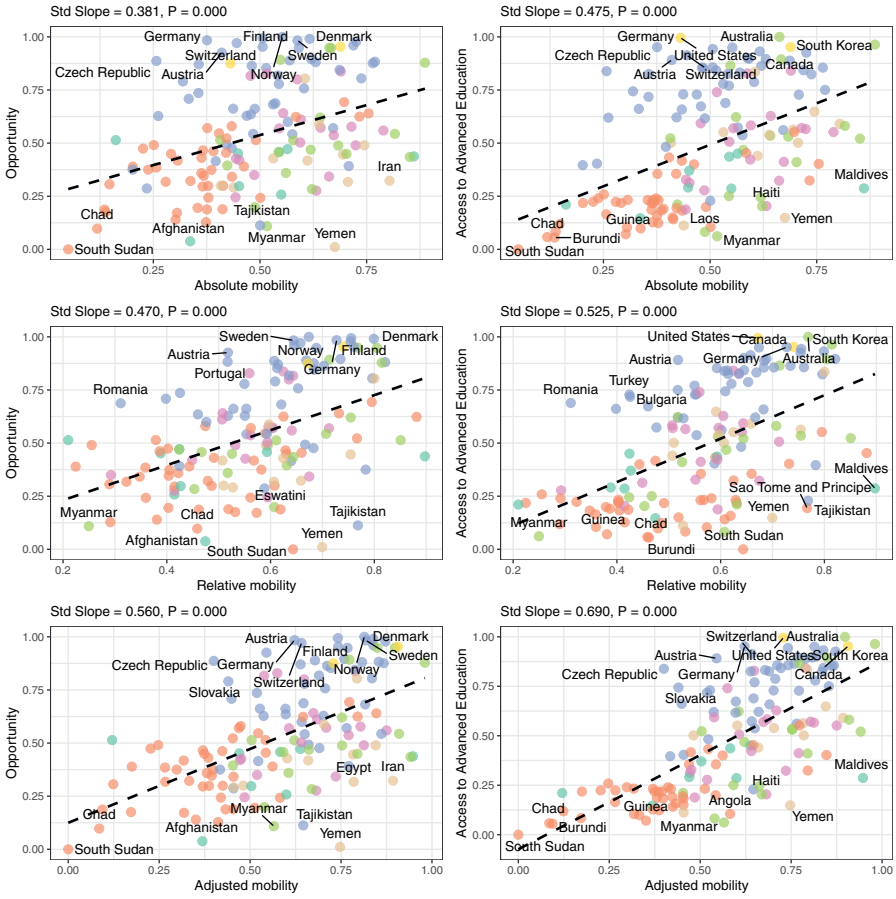
Absolute mobility = 0.20, Adjusted mobility = 0.17

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| P1 | 72.9 | 6.8 | 9.8 | 0.1 | 0.4 |
| P2 | 2 | 0.6 | 0.7 | 0 | 0.5 |
| P3 | 1.5 | 0.8 | 1.2 | 0 | 1 |
| P4 | 0 | 0 | 0 | 0 | 0.6 |
| P5 | 0 | 0 | 0.1 | 0 | 0.7 |

**Uzbekistan**

Absolute mobility = 0.20, Adjusted mobility = 0.42

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| P1 | 0 | 0 | 0 | 0.3 | 0 |
| P2 | 0 | 0 | 0.9 | 0 | 0 |
| P3 | 0 | 0.2 | 2.6 | 6 | 0.7 |
| P4 | 0 | 0 | 8.7 | 44.1 | 6.1 |
| P5 | 0 | 0 | 3.4 | 17.5 | 9.4 |


Std Slope = 0.381, P = 0.000
Germany
Finland
Denmark
Switzerland
Sweden
Czech Republic
Austria
Norway
Iran
Chad
Tajikistan
Afghanistan
Myanmar
Yemen
South Sudan
Opportunity
Absolute mobility
Std Slope = 0.475, P = 0.000
Germany
Australia
South Korea
Czech Republic
United States
Canada
Austria
Switzerland
Maldives
Haiti
Chad
Guinea
Laos
Yemen
Burundi
Myanmar
South Sudan
Access to Advanced Education
Absolute mobility
Std Slope = 0.470, P = 0.000
Sweden
Denmark
Austria
Norway
Finland
Portugal
Germany
Romania
Eswatini
Myanmar
Chad
Tajikistan
Yemen
Afghanistan
South Sudan
Opportunity
Relative mobility
Std Slope = 0.525, P = 0.000
United States
Canada
South Korea
Austria
Germany
Australia
Turkey
Romania
Bulgaria
Maldives
Sao Tome and Principe
Yemen
Tajikistan
Myanmar
Guinea
Chad
South Sudan
Burundi
Access to Advanced Education
Relative mobility
Std Slope = 0.560, P = 0.000
Austria
Denmark
Finland
Czech Republic
Germany
Sweden
Norway
Switzerland
Slovakia
Egypt
Iran
Chad
Myanmar
Tajikistan
Afghanistan
Yemen
South Sudan
Opportunity
Adjusted mobility
Std Slope = 0.690, P = 0.000
Switzerland
Australia
Austria
United States
South Korea
Czech Republic
Germany
Canada
Slovakia
Maldives
Haiti
Angola
Chad
Guinea
Yemen
Burundi
Myanmar
South Sudan
Access to Advanced Education
Adjusted mobility

# Appendix 5 How Much Limitation On Educational Mobility?

There is no appendix associated with Chapter 5.

# Appendix 6 General Discussion

There is no appendix associated with Chapter 6.

# Declaration

The author used artificial intelligence tools in this dissertation solely as support tools and under careful control. The author takes full responsibility for all content, arguments, analyses, and conclusions presented in this work. AI was not used to generate original ideas, research questions, theoretical arguments, or interpretations. Its role was limited to assisting with technical and practical tasks.

The author used the free versions of DeepSeek and NotebookLM primarily to improve language quality. These tools assisted with grammar, sentence flow, and clarity in text written by the author. All suggested changes were reviewed by the author, who made the final decisions on wording. AI was also used to support coding work, mainly to clean code and identify minor bugs. The main methods, coding logic, and structure were developed by the author. AI did not influence the choice of methods or the interpretation of results.

AI tools were also used to support the literature review process in a careful and limited way. DeepSeek helped identify relevant research areas and potential key studies. NotebookLM was used to skim selected papers (downloaded directly from recognised library databases), summarise key points, and quickly locate relevant sections, with clear links to the original sources. This approach saved time by avoiding unrelated content but did not replace careful reading or academic judgement. All analysis, comparison of studies, and critical discussion were carried out by the author. The literature review was written by organising and linking ideas from genuine academic papers indexed on Google Scholar and accessed through library databases, thereby reducing concerns about false or fabricated sources.

# Impact paragraph

This dissertation reframes a long-standing issue in free societies: the tension between family autonomy and equal opportunity. Its impact extends beyond academia, offering new ways to measure mobility, design policy, and understand inequality in public debate.

The theoretical and conceptual contribution is substantial. The dissertation challenges the common view that all intergenerational persistence is undesirable. By introducing the "Fair Progress" framework, it shifts attention away from the unrealistic goal of "perfect mobility" and toward a more practical question: whether social progress is broadly shared. This reframing affects how scholars understand and evaluate mobility. At the same time, the work brings behavioural genetics and political philosophy into closer integration than prior studies typically achieve. It makes the philosophical idea of Familial Relationship Goods empirically tractable. By grounding abstract debates — particularly the equality of opportunity trilemma — in empirical evidence, the dissertation provides a new model for studying opportunity. It also offers a balanced position between views that accept existing inequalities and those that call for radical restructuring.

The methodological and empirical impact is equally significant. The dissertation introduces the "Adjusted Mobility" metric — a diagnostic tool that uses a baseline informed by normative considerations, separates permissible from problematic persistence, and tracks who benefits from social progress. This metric could become a standard in comparative mobility research. The methodological approach — combining twin and adoption studies to account for gene-environment interplay — provides a cleaner estimate of the transmission effect of Familial Relationship Goods — approximately 0.15 in education. Most notably, the work gives a first estimate of the "price" of family closeness: a reduction in educational mobility of 0.24 to 0.27 standard deviations. This finding transforms a previously theoretical trade-off into concrete evidence.

The policy and societal implications follow directly from these contributions. Rather than seeking to eliminate family influence, policy should embrace a decoupling strategy. This strategy preserves family relationships that are considered permissible while limiting their contribution to entrenched inequality. Three policy bundles operationalise this approach. First, closing the capacity gap requires universal, high-quality early childhood education and care. This intervention narrows early skill gaps without prescribing how families interact. Second, lowering

the incentive effect counters high-stakes status competition through progressive taxation and wage compression. When inequality is high, the rewards for elite credentials are large, prompting advantaged parents to invest heavily in maintaining their children's status. Reducing after-tax income differences and narrowing wage gaps lowers these stakes. Third, building alternative supports ensures that children who lack relational goods at home gain access to other sources of guidance. These sources include mentoring programmes, community centres, and public libraries. Such interventions complement family relationships rather than replacing them.

The mechanisms behind decoupling follow the developmental trajectory of family influence. In early childhood, family influence operates through direct practices needed for flourishing — practices that we consider protected. At this stage, the state's role is enabling: universal supports help families cultivate relational goods without dictating their form. As children grow, family influence increasingly works through accumulated advantage, where early relational goods contribute to learning resources and educational paths. At this later stage, the state's role shifts to interrupting: reforms in school tracking, admissions systems, and wage structures reduce the translation of family advantage into rigid inequality.

A clarification is important here: decoupling cannot entirely separate intrinsic goods from extrinsic advantages. The same family practices that provide love and belonging also convey knowledge, cultural habits, and social capital. Decoupling does not sever these connections; instead, it lowers the stakes of unequal transmission. When rewards for advantage are moderated and public alternatives are robust, unequal family resources have less effect on life chances. Empirically, the research shows the stakes clearly: preserving family relationship goods reduces educational mobility by approximately 0.24 to 0.27 standard deviations. This reduction is not a policy failure; it reflects the price of family intimacy. A society seeking balance acknowledges this trade-off openly. Decoupling does not remove the parent-child link but flattens the slope of the Great Gatsby Curve. The apple may not fall far from the tree, yet every child has ground to roll as far as their own effort and talent allow. A balanced society lies not in removing the tree, but in tending the ground around it.

Future research follows three agendas. The expansion agenda applies the Fair Progress framework to health, wealth, and well-being, thereby providing a more complete picture of intergenerational opportunity. The decoupling agenda examines how state and community actions can supplement relational goods, using interventions that respect family autonomy. The institutional agenda encourages comparative studies across welfare state regimes to identify which institutional arrangements most effectively reduce intergenerational persistence while protecting family life.

Overall, the dissertation reframes the mobility debate. It shows that a part of intergenerational persistence is not a problem to be eliminated but the necessary cost of valuable human relationships. By doing so, it replaces a narrative of policy failure with a framework for principled, practical governance. The work equips scholars, policymakers, and citizens with conceptual tools to pursue an achievable form of opportunity — one that aims for fair progress rather than a perfect, and ultimately undesirable, equality that would sacrifice family bonds.

# Publications

- Duong, K. (2026). Measuring norm strength: The specificity of fairness under meritocracy in Europe. *Acta Psychologica*. https://doi.org/10.1016/j.actpsy.2026.106859 [New approach in the field of normology].
- Duong, K. (2025). If inequality is an economic choice, what is the relationship between inequality and growth? *Structural Change and Economic Dynamics*. https://doi.org/10.1016/j.strueco.2025.02.014 [Multiobjective optimization algorithms in operations research].
- Duong, K. (2024). What really matters for global intergenerational mobility? *PLOS ONE*. https://doi.org/10.1371/journal.pone.0302173 [Media coverage by EurekAlert and Mirage News].
- Duong, K. (2024). Is meritocracy just? New evidence from Boolean analysis and machine learning. *Journal of Computational Social Science*. https://doi.org/10.1007/s42001-024-00287-2 [Novel approach combining true–false logic (philosophy) and causal machine learning].
- Duong, K., & Flaherty, E. (2023). Does growth reduce poverty? The mediating role of carbon emissions and income inequality. *Economic Change and Restructuring*. https://doi.org/10.1007/s10644-022-09462-9 [Derived from my research master's thesis using generalized method of moments].

## Working papers

- Duong, K., Groot, W., & De Witte, K. (2026). What makes a family a family? The inevitable inequality in intergenerational educational transmission. *To submit to a journal*. [In *Doctoral dissertation* (Chaps. 2–3)].
- Duong, K., Groot, W., & De Witte, K. (2026). What should perfect mobility look like? Fair progress in the intergenerational mobility in education. *To submit to a journal*. [In *Doctoral dissertation* (Chap. 4)].
- Duong, K., Groot, W., & De Witte, K. (2026). The price of protecting family relationships for educational mobility. *To submit to a journal*. [In *Doctoral dissertation* (Chap. 5)].
- Duong, K., Erola, J., & Lehti, H. (2026). Gender-equality paradox under meritocracy: Measuring gender specialization across societies. *To submit to a journal*. [Normology to explain the relationship between meritocracy and gender norms].

# About the Author

Quoc Khanh Duong is a researcher focusing on social and economic inequalities, applying computational and quantitative methods, including machine learning, to address persistent socioeconomic challenges. His work emphasises promoting equal opportunity in the digital era. He is currently a doctoral researcher in Social Sciences (primarily Sociology, with engagements in Economics, Psychology, and Philosophy) at the INVEST Research Flagship Center, University of Turku, Finland, where his research focuses on meritocracy and social norms (normology). He previously earned an M.Litt (Research) in Economic Sociology from Maynooth University (2021–2023), funded by the Irish Research Council (EUR 55,000). His master's thesis, *The Roles of Poverty and Inequality as Factors in the Impact of Climate Change*, was published in *Economic Change and Restructuring*. He also holds a Bachelor in International Business Economics from Foreign Trade University, HCMC Campus (2016), Vietnam.

Duong has published both single-authored and collaborative work in peer-reviewed journals. His single-authored studies include *Measuring norm strength: The specificity of fairness under meritocracy in Europe* (*Acta Psychologica*, 2025), *If inequality is an economic choice, what is the relationship between inequality and growth?* (*Structural Change and Economic Dynamics*, 2025), *What really matters for global intergenerational mobility?* (*PLOS ONE*, 2024), and *Is meritocracy just? New evidence from Boolean analysis and Machine Learning* (*Journal of Computational Social Science*, 2024). His collaborative work covers growth, poverty, and sustainability, and he has several working papers on global education mobility and the intergenerational transmission of education. He contributes to the academic community as a peer reviewer for *Economic Change and Restructuring*, *Economics of Innovation and New Technology*, *Social Science Quarterly*, *Environment, Development and Sustainability*, *PLOS ONE*, *Humanities and Social Sciences Communications*, *Structural Change and Economic Dynamics*, and *Applied Research in Quality of Life*.

His research makes use of large cross-national datasets including the World Values Survey, ISSP, ESS, EU-SILC, LIS, SWIID, WDI, and GDIM. Methodologically, his work applies clustering, dimensionality reduction, latent variable modelling, causal inference approaches (RCT, DID, RDD), generalised random forests, social network analysis, and simulation. He is proficient in CRAN-R and Stata, with working knowledge of Python, and uses QUARTO, Jupyter Notebook, and LaTeX for research reporting. Beyond academia, he has held professional roles as a Generative AI Annotator at Covalen Ltd in Ireland. He was also a member of the Society for the Advancement of Socioeconomics and is the author of the sci-fi novella *The E-Man*, published on Amazon.

## What makes a family a family?

It isn’t genes, money, or power.

