UNIVERSITY OF WOLLONGONG
AUSTRALIA

The Role of Education in Intergenerational Economic Mobility in Australia

Final Report

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Executive Summary

The NSW Government Department of Education and Communities has commissioned the University of Wollongong to conduct research on the role of education in intergenerational mobility in Australia. This is the revised Final Report on the project.

The economic literature on this question is not large, especially for Australia. One strand of the empirical literature has sought to estimate causal effects of education, mainly exploiting compulsory schooling reforms as natural experiments. A second strand examines the extent to which geographical variations in intergenerational mobility can be explained by differences in the characteristics of education systems. A third strand of the literature has explored the role of education as a mediator – that is, the role of education as a pathway through which family background affects economic outcomes in the next generation. Our study is in this third strand. The main objective of our research is to study the extent to which education is a mechanism which explains intergenerational transmission of economic (dis)advantage in Australia.

To this end, we have developed an approach which seems to be a methodological innovation. Our approach is related to a mediation model (Baron and Kenny, 1986), but is better able to directly account for the range of family background characteristics which may affect child earnings through the pathway of education or through other mechanisms. The approach estimates the extent to which education mediates the combined effects of all such background variables on child earnings. This methodological innovation has been scrutinised at several academic seminars and conferences, leading to several refinements. But it has not yet been subjected to a formal academic peer review process and so the findings in this report should be treated with caution.

The analysis suggests that family background is a much stronger determinant of economic wellbeing than implied by previous studies:

- Using conventional techniques with the latest available data, we estimate that the 'intergenerational elasticity' of wages is 0.35, which is 34% higher than implied by influential previous studies.

- When all available family background data are incorporated (not just parental earnings), the importance of background is more apparent. For example, males at the 90th percentile of the 'family background index' have expected earnings that are 65% higher than those at the 10th percentile. For females, the corresponding difference is also large (53%). Similarly, children from low socioeconomic backgrounds are unlikely to have high earnings themselves. Amongst people from the lowest quartile of family background, around 40% themselves have earnings in the lowest quartile, while only about 12% have earnings in the top quartile.

There is a positive relationship between socioeconomic background and education, and a positive relationship between education and earnings. It follows that education is one of the mechanisms through which economic advantage is transferred from one generation to the next. As a guiding principle to aid interpretation of the main results, it is noted that if education explains a 'small' component of intergenerational transmission, this implies that access to education is relatively equitable – i.e. family background is not a strong determinant of educational attainment.

The main analysis was conducted using the 2012 wave of HILDA, Australia's main household panel survey. The results suggest that:

- Own-education accounts for around 25%-40% of intergenerational transmission of economic advantage in Australia.
- The role of education appears to be larger for females than for males. There are several potential explanations for this, but it may be explained by a larger 'direct' effect (i.e. through mechanisms other than child's education) of family background for males.
- The mediating role of education is largest for the parental education component of family background.

We have used another, complementary, approach to consider the role of the education system in intergenerational transmission. In a parallel analysis, we estimated the effect of family background on educational attainment, and found it to be considerably (30%) smaller than the effect of family background on earnings. This result provides a different

perspective on the extent to which the education system is 'part of the solution' rather than 'part of the cause' of intergenerational transmission of wellbeing.

We also conducted a complementary analysis of the British Cohort Survey data:

- The analysis suggests that the role of education in transmitting economic advantage is similar in the UK to that of Australia.
- The quality of data items measuring skills in HILDA is relatively poor, and these are not measured in childhood. The British Cohort Study includes high quality items on child's cognitive and non-cognitive skills. Nevertheless, in a 'comparable' analysis of BCS, the estimated role of skills is similar to that found in HILDA. Therefore the lower quality skills measures in HILDA do not seem to bias the Australian results.

This report presents a 'big picture' view on the role of education in intergenerational economic mobility in Australia. The project has not addressed causal questions on the extent to which educational programs or interventions can lift people out of economic disadvantage. The most credible research on such questions has used quasi-experimental techniques that exploit policy changes such as compulsory schooling laws. Rigorous impact evaluations of smaller programs may also be a fruitful avenue for further research. Finally, incorporating elements of random assignment into trials of new initiatives is likely to yield the highest quality evidence on their causal effects on student outcomes, including for students from disadvantaged backgrounds.

1. Background

The NSW Government Department of Education and Communities (The Department) has commissioned the University of Wollongong (UOW) to conduct research on the role of education in intergenerational mobility in Australia. The agreement was executed on 25th March, 2014.

Under the terms of the agreement, the Department is primarily interested in addressing the following research questions:

1. What role does education play in the upward mobility of disadvantaged people?

2. What role does (the lack of) education play in the downward mobility of advantaged people? What role does education play in the entrenchment of advantage?

3. What role does education (or the lack of it) play in upward or downward mobility in the middle of the income spectrum?

4. What is the net effect of education on income mobility (i.e. increasing or decreasing mobility)?

The Department is also interested in these supplementary research questions:

5. Does education have a greater/lesser impact on [upward] mobility for the children of migrants?

6. Does education have a greater/lesser impact on [upward] mobility for people living in rural and remote locations?

7. What is the specific impact of preschool on mobility?

8. How does the inclusion of women's earnings change income mobility (and the above relationships)?

The Department understands that this is a substantial research agenda. Given constraints in existing data, time and funding, the Department has expressed that this research project is intended to 'scratch the surface' of this field. Such research will inform government about

the extent to which education facilitates intergenerational mobility in Australia. It may also lead to further research which builds on this work.

This is the Revised Final Report on the project. The Final Report was revised after receiving feedback from peers at several academic seminars and workshops, as well as from an anonymous peer reviewer engaged by the Department of Education and Communities.

2. Introduction[1]

The study of intergenerational economic mobility, defined as the relationship between the socio-economic background of parents and various economic outcomes of their children when they are adults, is a key issue in the analysis of the transmission of inequality. A number of different factors may affect mobility, such as the country's educational system, the structure of the labour market, and family investments.

Economic mobility can be measured using family income, individual earnings, social class and occupation. Generally, a strong correlation between parents' and children's socio-economic status indicates low mobility and a stronger influence of family background on individual adult lives and may therefore indicate that children born in poorer households may have limited chances to exploit their economic potential (Blanden et al., 2007).

Intergenerational income mobility is an important and recurrent topic in public and political debates. Governments in various Western countries have been concerned with raising their level of socio-economic mobility, as one way to promote equal opportunity for individuals. However, as noted in Blanden (2013), it is difficult to imagine a scenario without any link in socio-economic outcomes between generation, partly because genetic factors are likely to play an important role in the transmissions of education and career prospects from parents to children (Blanden and Macmillan, 2014).

The main objective of this report is to study the extent to which education is a mechanism which explains intergenerational transmission of economic (dis)advantage in Australia. Previous literature has identified Australia as a country with a high degree of mobility, especially when compared to the United Kingdom or the United States. Andrew Leigh's (2007) work was influential in establishing this result, being cited by numerous other

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[1] This report uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) (formerly FaHCSIA), and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either DSS or the Melbourne Institute.

studies. Our own analysis of HILDA data (applying the same techniques as Leigh on other HILDA waves) questions whether Australia is indeed a high mobility country (see Section 4).

In any case, the mechanisms of transmission of economic advantage from parents to children, and in particular the role of education, have received less attention in the literature, and in particular in the Australian context. If the role of education in explaining intergenerational transmission is 'small', this implies that access to education is relatively equitable – i.e. family background is not a strong determinant of educational attainment.

For this report, we have developed what we believe to be a methodological innovation. Our approach is related to a mediation model (Baron and Kenny, 1986), but is better able to directly account for the range of family background characteristics (such as parental occupation, parental education, parental country of birth, mother's age and marital status at child's birth) which may affect both child earnings and education. In our original proposal, we suggested 'imputing' (i.e. approximating) parental income on the basis of parental occupation and education, and using this measure to study the mediating role of education in intergenerational income mobility. We show some estimates using such an approach. But it has numerous limitations which are avoided by instead including all family background characteristics directly in child earnings regressions.[2] Our innovation, which we outline in detail in Section 5, is to interpret predicted values from those child earnings regressions in two ways: holding child characteristics constant (where appropriate), these predicted values are the expected earnings for people with a given family background. These same predicted values are also interpreted as an index of family background (as it relates to child earnings). This eliminates the need to impute income in a separate regression.

We compare results obtained from Australian data with results obtained estimating the same model on data from the British Cohort Study, which includes information on child's cognitive and non-cognitive skills in early childhood (not available in HILDA). The comparison

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[2] This approach assumes that the relative associations between each background variable and parent's income are the same as their relative effects on child income. These relative contributions are also assumed to be constant even after controlling for child's education (this is particularly problematic in the case of parental education). Since the approach typically uses data from the child's generation to conduct the imputation, it assumes that the earnings structure (as it related to occupation and education) has not changed for a generation). All of these limitations are avoided using our approach.

is useful for assessing whether our main results are subject to a major bias because of the lack of information collected early in life on individual cognitive and non-cognitive skills.

3. Literature Review

There is a broad literature analysing intergenerational economic mobility and measuring the degree of persistence of income in various Western countries, but relatively little is known about the transmission mechanisms that may explain different degrees of socio-economic mobility, and in particular about the role of education in explaining these changes.

Research by sociologists on the role of education in promoting socio-economic mobility dates back to the early 1960s (Duncan and Hodge, 1963) and more recent work in this discipline has shown that education (E) is strongly related with social origin (O) and social destination (D) (through the so-called OED triangle, see Goldthrope, 2013 for a review and discussion of the relevant literature). Recent studies have questioned the stability of these relationships and in particular the weakening of the relationship between E and D (see for example Goldthorpe, 1996; Whelan and Layte, 2002).

Economic literature started to engage with this debate in the early 1980s (see for example Atkinson, 1980 and Atkinson and Jenkins, 1984) and in more recent years, economists have analysed cross-country variations in intergenerational income mobility and trends in mobility across time, linking these variations with changes in the educational context (see Black and Devereux, 2011 for a comprehensive review and Pekkarinen, 2009).

There are several economic theories that can help to understand why education should affect income mobility. Traditional economic models of education (see for example Ben-Porath, 1967) assume that investments in education depend on individual preferences and risk attitudes. However, in modern society, these choices are made partly when the child is too young to make decisions by her/himself and therefore are likely to be affected by parental preferences. Further, the theoretical literature on intergenerational mobility of income has emphasised the role of human capital (or education) as an investment made by parents to improve their children's future (see for example Blau and Duncan, 1967; and Becker and Tomes, 1986).

In this context, greater income allows parents to invest greater resources on the education of their children. At the same time, children born from more affluent families may have

some characteristics that make it easier for them to learn and progress through their education. These characteristics may be transmitted genetically or through parental example and environmental influences (see also Corak, 2006). Higher levels of education lead to higher income and therefore if access to education and returns to education are the same across various socio-economic statuses, education can be seen as an important instrument to help poor children to attain higher earnings. These concepts have been explored by Solon and Corak (2004) who discussed the possibility for governments to invest in education by directing resources to families from low socio-economic status to reduce the impact of family background.

Screening and signalling theory is one of the most influential responses to human capital theory developed by labour economists. According to this theory, employers face a major difficulty when hiring new employees, as they have very limited information on new entrants' characteristics and abilities (see for example Arrow, 1973; and Stiglitz, 1975). Therefore, employers screen applicants on the basis of their educational qualifications, as such qualifications should certify that potential employees have relevant knowledge and skills. Hence, education can be regarded not just as an investment *per se* but as a way to signal to employers that new entrants have a desirable productive potential. Economists have engaged in several empirical tests to show whether education actually raises productivity or simply signal it (see for example Chevalier et al., 2004).

Incentive enhancing preference theory analyses the mechanisms through which education can increase earnings (see for example Bowles et al., 2001). According to this theory, education does not only increase individuals' knowledge and skills, but also plays a major role in developing values, social norms and preferences, that also determine employee's attractiveness for employers. Further, more educated individuals are more likely to develop traits such as high marginal utility of income, low disutility of effort and low rate of time preferences (future orientation) and these characteristics make individuals more likely to respond to incentives and sanctions in the workplace.

In recent research, there are three strands of literature that analyse the mechanisms relating education to intergenerational income mobility. The first one is focused on analysing the role of the education system (particularly educational reforms) in the mobility

process. Meghir and Palme (2005) study the Swedish comprehensive school reform implemented in the 1950s and 1960s and show that the reform increased the education and lifetime income of high ability students with unskilled parents. However, they do not measure the direct effect of the reform on intergenerational income mobility. Holmlund (2008) analyses the same reform and explicitly tries to disentangle the mechanisms through which the reform may have affected intergenerational income mobility. Her work shows that the reform reduced economic persistence between parents and their children (especially for men) mainly through effects on the individual's own income and not through changes in peer groups and assortative mating. Pekkarinen et al. (2009) analyse the Finnish comprehensive school reform adopted in the 1970s and show that the reform reduced the intergenerational income elasticity by 23% from the pre-reform elasticity of 0.30 to post-reform elasticity of 0.23. Lastly, Dustmann (2004) analyses the impact of parental background on children's educational choices and shows that the relatively low level of intergenerational mobility in Germany is due to the educational system in which students are tracked into academic and vocational schools by age 10. He also shows a convergence for individual from different parental backgrounds over the last decades.

Secondly, a number of studies estimate the role of education in accounting for geographical differences (either within a country or between countries) in economic mobility. Chetty et al. (2014) find that highly mobile areas within the United States tend to have better primary schools (amongst other characteristics). Gregg et al. (2013) decompose intergenerational mobility in three parts: the association between parental income and educational attainment; the association between educational qualifications and income; and the partial association between family income during childhood and own income. Their work shows that differences in income mobility between UK, US and Sweden cannot be explained by educational inequality, while a crucial role seems to be played by the impact of family resources on children's earnings, as in Sweden the expected income at a given qualification level is almost independent of the family of origin. Blanden (2013) summarises the literature on intergenerational mobility across 46 different countries and discusses different theoretical perspectives that can help to understand differences in income mobility across countries, and the role of education in particular. This work shows that mobility is negatively

correlated with inequality and the return to education but positively correlated with a nation's education spending.

The third strand of literature explores the role of education as one of the mediating factors of intergenerational persistence and looks at the variation in income mobility over time. Blanden et al. (2007) analyse the intergenerational socio-economic mobility in Britain using the 1958 National Child Development Study (NCDS) and the 1970 British Cohort Study. They show that skills and educational variables account for a large part of the intergenerational persistence (nearly 46%). The various cognitive and non-cognitive skills measured in childhood account for 32% of this persistence. The importance of skills declines after the inclusion of educational variables in the models, suggesting that the skills mechanism for intergenerational persistence partly operates *through* the pathway of educational attainment. Their analysis of the change of the role of education over time also reveals an increase in the impact of test scores at age 16 and of degree holding, but a sharp fall in the return to staying in education beyond age 16. These changes contribute to explain the overall decrease in intergenerational mobility in the UK over the observed period.

As noted in Blanden and Machin (2004); Blanden and Machin (2008); and Lindley and Machin (2012), the imbalance in access to higher education by family socio-economic status has increased in the UK over the last decades and at the same time wage differentials for more educated individuals have risen steadily. These two trends can help to understand the overall decrease in income mobility, despite the expansion of post-compulsory education. However, work by Blanden and MacMillan (2014) on more recent data has shown that absolute improvements in educational attainment have closed some of the gaps by family background at several important education milestones, even if there is little evidence that these improvements have reduced inequality at the top of the education distribution.

Recent studies have also focused on the role of other (non-education) mediators of intergenerational income persistence. As discussed above, Blanden et al., (2007) consider the role of cognitive and non-cognitive skills in this process, as does Osborn Groves (2005). Using Brazilian data, Bourguignon and Ferriera (2007) estimate the extent to which the effect of 'circumstances' (family background) are mediated by a range of factors including educational attainment.

Investments in early education have received greater attention in the literature, as this kind of early interventions are more likely to enhance economic mobility (see for example Carneiro and Heckman, 2003; Restuccia and Urrutia, 2004).

The evidence on intergenerational socio-economic mobility in Australia is very limited and, to the best of our knowledge, ours is the first study which explicitly addresses the role of education in explaining income mobility. Cobb-Clark (2010) presents evidence from the Youth in Focus project, a large project on the intergenerational transmission of disadvantage, and looks in particular at the transmission of income support across generations. Cobb-Clark and Nguyen (2012) show that children of migrant families enjoy an educational advantage which counters their greater socioeconomic disadvantage. Research based on Youth in Focus has also shown that young people who grew up in families that receive intense income support are more likely to engage in risky behaviours (Cobb-Clark et al., 2012), have lower education and various health problems (e.g. asthma or depression), and these factors are likely to have a negative effect on people's income.

Leigh (2007) calculates intergenerational earnings elasticities, combining four surveys conducted in 1965, 1973, 1987 and 2001-2004. He uses parental occupation to impute earnings, and compares the level of intergenerational income mobility in the 2000s with the degree observed in the 1960s, and with socio-economic mobility observed in the United States. His work shows that intergenerational earnings elasticity in Australia has been relatively constant over time and is likely to be in the range of 0.2- 0.3, which means that if an Australian father's earnings increased by 10 percent, his son's earnings would rise by 2-3 percent. This value is similar to the findings for other OECD countries such as Finland, Canada, Sweden and Germany which have substantially higher intergenerational earnings mobility than other countries such as Italy, the US and the UK (d'Addio, 2007).

4. Is Australia Really Highly Mobile?

As further background to the main analysis, this section briefly re-considers conventional wisdom that Australia is characterised by high intergenerational mobility. We argue that the intergenerational elasticity is considerably higher than previous estimates suggest, and hence that intergenerational mobility is lower.

The 'Great Gatsby' curve (shown below) has received considerable interest in recent years. It shows that income inequality is strongly related (negatively) to intergenerational mobility when comparisons are made between countries.

Figure 1 The 'Great Gatsby' Curve (as published)
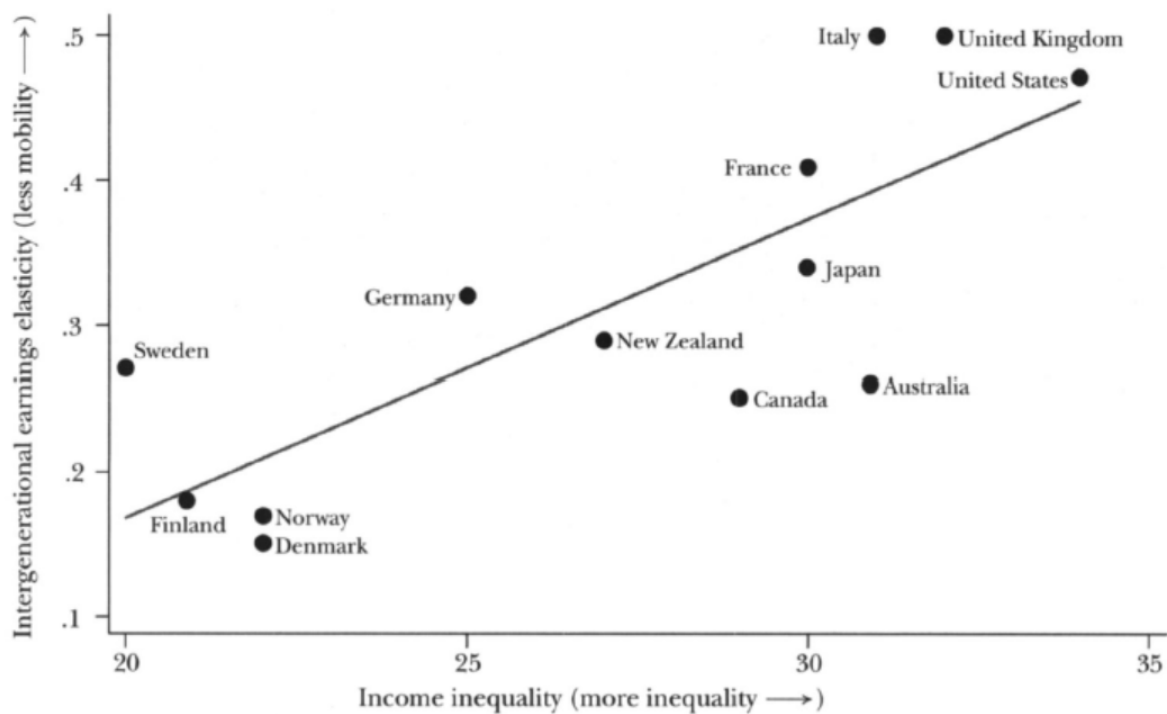
Source: Corak (2013: Figure 1)

Whilst several versions of this figure exist in the literature, each shows Australia as having relatively high mobility (low intergenerational elasticity), given its level of income inequality. The source of the Australian data is Leigh (2007), with adjustments made by Corak (2013). In personal correspondence, Corak stated that the precise adjustment to Leigh's headline

estimate is to multiply by 0.47/0.325. This is to account for methodological differences between Leigh's study and the benchmark US analysis: 0.325 is the estimate for the US when using Leigh's methodology (Leigh 2007: Table 5); 0.47 is the benchmark US measure which Corak uses as the basis of all comparisons in the 'Great Gatsby' curve.

We take several steps to update and improve these estimates for Australia. The first issue is that the Wave 4 (2004) data produces an elasticity estimate that is lower than for any other wave apart from Wave 1. We replicate Leigh's analysis and repeat it for each wave in HILDA (and with all waves pooled) using the same methods.[3] The results are shown in Figure 2. The upper panel shows unadjusted results which correspond with Leigh's headline estimate.[4] The far-right data point is the preferred estimate, derived from the pooled sample, shown with a robust 95% Confidence Interval that accounts for within-individual error correlation. This estimate is 30% higher than the Wave 4 estimate.

Our second update is to also replicate the PSID component of Leigh's analysis for each available PSID wave. This comparable analysis forms the basis of comparisons between the two countries, and indeed with the other countries shown in Corak's (2013) analysis. We replicated the PSID estimates for 2001, 2003, 2005 and 2007 individually, and with the four waves pooled.[5] We were unable to reproduce Leigh's 2001 PSID estimates, and our sample size (1404) is around four times larger than his, and is similarly large in the other waves. In personal correspondence, Leigh indicated that he may have inadvertently restricted the sample to the cohort born between 1951 and 1959. The estimates vary little between years. The preferred estimate is 0.0306, from the pooled analysis.

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[3] The estimates derived from the pooled sample use a within-wave imputation of fathers' earnings (i.e. for each observation, the imputed father's wage was the same in the pooled analysis as it was in the analysis of each wave individually.) The main regression is augmented with wave fixed effects to account for any systematic changes between waves in sons' earnings.

[4] There is a slight discrepancy in the results we show for 2004 (0.174) and Leigh's published estimate (0.181). This is mostly explained by a change in the occupational classification within HILDA. Leigh's analysis uses the 4-digit ASCO 1997 classification. This classification is not available subsequent to the 2006 wave of data. Instead we use 4-digit ANZSCO 2006, which is available for all waves. However, when use ASCO 1997, the estimate for 2004 increases to 0.178. The remaining discrepancy (0.003) is likely due to revisions to the data that are applied between HILDA releases.

[5] Later PSID waves are not yet available in CNEF.

The higher estimates for the pooled HILDA analysis, combined with the lower estimates for the pooled PSID analysis suggest that intergenerational elasticity in Australia is more similar to the USA then implied by Leigh's estimates. However, the new estimate for the USA remains 35% larger than for Australia, and the difference is statistically significant (p = 0.049).

The lower panel of Figure 2 shows the HILDA estimates for each wave after applying a 'revised' Corak adjustment, which draws on our pooled PSID elasticity estimate of 0.306 instead of Leigh's 0.325. The 95% Confidence Intervals shown are based on a standard error calculation which accounts for the variance of both the HILDA and PSID estimates.[6]

These results suggest that Australia's intergenerational elasticity is considerably higher than implied in the 'Great Gatsby' curve. The pooled estimate for Australia (0.35) is close to the fitted line in Figure 1, and is 34% larger than Corak's published estimate drawing on Leigh.

The results in subsequent sections of this report give further weight to the suggestion that family background is a major determinant of individual earnings.

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[6] They are derived using a 'delta-method' approach, which draws on a first-order Taylor series expansion to estimate the variance of the ratio of two independent random variables: $Var\left(\frac{\hat{\beta}_1}{\hat{\beta}_2}\right) = \frac{Var(\hat{\beta}_1)}{\hat{\beta}_2^2} + \frac{\hat{\beta}_1^2 Var(\hat{\beta}_2)}{\hat{\beta}_2^4}$

Figure 2 Intergenerational Elasticity in Australia and the USA

Panel A: HILDA using Leigh's method for each wave

Panel B: PSID - Using comparable approach

Panel C: HILDA – with Revised Corak Adjustment
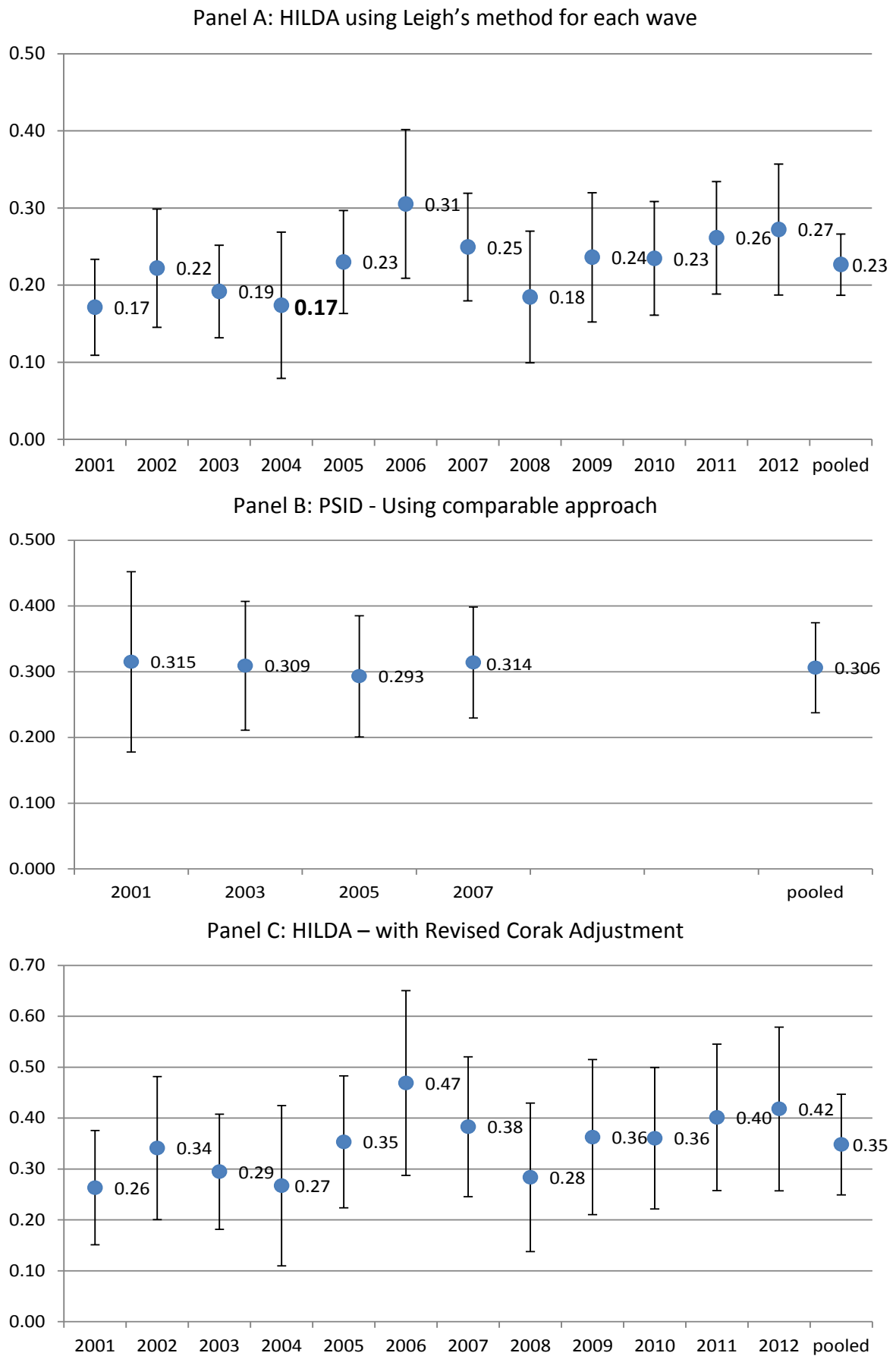
5. Methods

Our main aim is to estimate the role of education in intergenerational economic mobility. We do so using a number of models, which we discuss below. Each model is sequentially motivated by the limitations of the preceding models, which we note. Our preferred approach is Model 3 – which we believe to be a methodological innovation for studying mediation effects. Each model is described below in turn. The section concludes with a discussion of dimensionality reduction.

Model 1a

Following the majority of the previous literature, we begin by considering a simple mediation model which consists of two equations, as shown below:

$$\ln Y_i^{child} = \alpha + \beta^{total} \ln Y_i^{parents} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \tag{1}$$

$$\ln Y_i^{child} = \alpha + \beta^{direct} \ln Y_i^{parents} + \boldsymbol{\gamma' Educ_i^{child}} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \tag{2}$$

where Y_i^{child} is the child's income when s/he is Age_i years old, and $Y_i^{parents}$ is a measure of parental income when the child was of school age. β^{total} is the intergenerational income elasticity, i.e. an aggregate measure of the association between parental income and child income. In equation, (2), a vector of additional variables is also included in the equation, which measures the educational attainment of the child. β^{direct} is the component of β^{total} which is not explained by educational attainment of children.[7] From this model, an estimate of the importance of education as a mechanism for intergenerational income persistence is $1 - \frac{\beta^{direct}}{\beta^{total}}$.

A value of 1 suggests that education is the sole mechanism for intergenerational income persistence. A value of 0 suggests that education is not a mechanism for intergenerational

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[7] Note that π_1 actually represents different parameters in equations (1) and (2), and similarly for π_2. This is also the case in numerous other equations that follow. We ignore this for notational simplicity.

income persistence. Theoretically, this term is unbounded. In practice, the term will lie somewhere between 0 and 1.[8]

Whilst numerous versions of $Y_i^{parents}$ are possible, we prefer a measure which combines the earnings of both parents. We also think that annual earnings are more appropriate than hourly earnings, since annual earnings are a better measure of the actual resources available to the family.

In contrast, we choose hourly earnings of the child as the dependent variable ($\ln Y_i^{child}$). This is the price of a person's time in the labour market, and hence a measure of economic advantage. This measure avoids considerations around part-year or part-time work, which is particularly useful when estimating models which include women in the sample.

There are a number of limitations of this model, which we will discuss progressively. An initial practical limitation is that there are no available Australian data which include all of the required variables to estimate equations (1) and (2). HILDA does, however, include parental occupation, reported by the child, retrospectively for when the child was aged 14. We thus use an approach similar to Leigh (2007) and much related literature, estimating the earnings of each parent as a function of the parent's own occupation, and the occupational earnings structure from HILDA.[9] In order to impute parental income, the occupation-earnings relationship (**β**) is modelled separately for each sex (using the data on adult children) as:

$$\ln Y_i = \alpha + \boldsymbol{\beta}'\mathbf{Occ}_i + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \tag{3}$$

The estimated coefficients from this model are used to predict the earnings of each parent, with age set to 40 so as to remove any mechanical relationship between age and earnings. A parent's earnings are set to zero if they had no stated occupation. The total estimated earnings of the parents is used in place of actual earnings in equation (1) and (2).

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[8] This will be the case if there is positive association between child's education and child's income and a positive association between parental income and child educational attainment.

[9] Such an approach assumes that the occupational earnings structure amongst the sample of children to be the same as occupational earnings structure a generation earlier. A slight improvement would be to use the occupational earnings structure in Wave 1 of HILDA – at least it's closer to the time at which the parents' occupation was measured. As we will discuss, Model 1 is not our preferred model in any case.

This approach is likely to over-state the true role of education to inter-generational income persistence, because of the omission of numerous other determinants of child's earnings which are likely to be correlated with both child education and with parental earnings (or parental occupation). In other words, the education variables will 'pick-up' the contributions of these other correlated factors. This issue motivates the departures from Model 1A which we discuss below.

Model 1b

As discussed in the literature review, one of the main determinants of earnings which is likely to be correlated with education and parental background is a child's ability. Due to a number of factors, including home environment, parental example, genetics, *etc.* a child from a high income background may have attributes which are rewarded in the labour market, and which also may lead to higher levels of educational attainment. Such skills, broadly defined, may include cognitive skills and non-cognitive attributes. In order to estimate the true role of education, such skills should be taken into account. However, there are a number of challenges involved in accounting for such skills. The first of these is the sequential nature of the complex causal relationship between skills, education and earnings. Consider an extension of Model 1a, which incorporates the role of skills:

$$\ln Y_i^{child} = \alpha + \beta_1 \ln Y_i^{parents} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \tag{4}$$

$$\ln Y_i^{child} = \alpha + \beta_2 \ln Y_i^{parents} + \boldsymbol{\gamma' Educ}_i^{child} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \tag{5}$$

$$\ln Y_i^{child} = \alpha + \beta_3 \ln Y_i^{parents} + \boldsymbol{\theta' Skills}_i^{child} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \tag{6}$$

$$\ln Y_i^{child} = \alpha + \beta_4 \ln Y_i^{parents} + \boldsymbol{\gamma' Educ}_i^{child} + \boldsymbol{\theta' Skills}_i^{child} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \tag{7}$$

The first two equations are the same as in Model 1a. Equation (6) includes child's skills in the model (and not education), whereas equation (7) includes child's education and skills. The combined role of education and skills is $1 - \frac{\beta_4}{\beta_1}$. But isolating the role of education is

more difficult. We have argued above that $1 - \frac{\beta_2}{\beta_1}$ likely overstates the role of education, partly because γ may be picking up the effect of skills. Thus it is tempting to consider only the additional role of education, after skills are already accounted for. This is given by $\frac{\beta_3 - \beta_4}{\beta_1}$. Consider however $1 - \frac{\beta_3}{\beta_1}$. This is an estimate of the (full) contribution of skills to explaining intergenerational income persistence. It has been argued that education is actually the mechanism which at least partially translates skills into earnings, so that $1 - \frac{\beta_3}{\beta_1}$ is at least partially attributable to education (see for example Blanden et al., 2007). Therefore, $\frac{\beta_3 - \beta_4}{\beta_1}$ ignores an important component of the education mechanism. In the absence of any further limitations, one could argue that the role of education has a lower bound of $\frac{\beta_3 - \beta_4}{\beta_1}$ and an upper bound of $1 - \frac{\beta_2}{\beta_1}$.

Furthermore, education can affect (presumably enhance) skills. To the extent that higher skills are a consequence of education, $\frac{\beta_3 - \beta_4}{\beta_1}$ is biased downwards further. To avoid this form of bias, it is desirable to have measures of skill that are collected at an early stage of life. Ideally these would be measured at an age prior to exposure to the education system. In practice, however, most cognitive and non-cognitive skills tests can only be conducted on participants with a given level of maturity, since they involve aspects of literacy and numeracy. The cognitive and cognitive tests included in BCS (at age 6 and 10) would seem to be an excellent compromise for these purposes. In contrast, HILDA only collects data on skills contemporaneously with the adult child's earnings data. This means that observed skills may be partly a function of the respondent's entire educational experience, as well as any downstream effects in adulthood, such as through stimulation associated with occupation or other socio-economic factors. Therefore, $\frac{\beta_3 - \beta_4}{\beta_1}$ is likely more biased downwards in HILDA than in BCS. All of this, however, is contingent on the quality of the variables that measure cognitive and non-cognitive skills, an issue that will be returned to in the next section. If these variables are only partial measures, then the role of skills, as a mechanism explaining persistence, will be underestimated.

Model 2

Quite apart from skills, a child's education may be correlated with a range of other family background characteristics, which influence child earnings, but are also correlated with parental income. This is particularly the case in our model, which by necessity imputes parental income on the basis of parental occupation, as discussed above in relation to Model 1A. Consider for example parental education. A highly educated parent is more likely to have a highly educated child. If, however, the parent's education also improves child earnings directly, i.e. independently of child education, this will lead to the role of education being biased upwards in both of the models considered thus far. This will occur if having an educated parent is a direct resource for the child (independent of child's education and child's skills).

How do we navigate this potential source of bias? One approach is to construct a more comprehensive index of socio-economic background, and use it instead of $Y_i^{parents}$ (or the predicted value of $Y_i^{parents}$ based on occupation alone). For example, we could use information on education and country of birth or other characteristics to enrich the prediction for each parent, replacing equation (3) with:

$$\ln Y_i = \alpha + \boldsymbol{\beta}'\mathbf{Occ}_i + \boldsymbol{\gamma}'\mathbf{Educ}_i + \boldsymbol{\theta}'\mathbf{COB}_i + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i, \tag{8}$$

and to interpret the predicted values (applied out-of-sample - to parents, similarly to model 1a) as a broader measure of socio-economic status of each parent. Whilst we show results using this approach, it is subject to restrictions which seem to be major. Firstly, parameter estimates from equation (8) can be thought of as 'weights', assigned to each component of socio-economic status. These weights are proportional to each variable's relationship with 'own' income. Implicitly, the approach assumes that the *relative* associations between each background variable and parent's income is the same as their relative contributions to child's income.[10] More importantly, these relative contributions are also assumed to be constant even after controlling for child's education. Take the example of parental education. One would expect the importance of parental education (in the child's earnings

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[10] This assumption is also implicit in the Model 1a - equation (3) – approach, with respect to occupation alone.

equation) to be substantially reduced after controlling for child's education, more so than corresponding reductions in the coefficients of other parental variables. But this index approach does not facilitate that sort of flexibility.

Another limitation of this approach is that it requires a common support in all parental characteristics and child characteristics (e.g. in relation to country of birth) – which can lead to some loss of detail in the background variables due to the collapsing of variables that is necessary.[11,12]

Similarly to Model 1b, measures of cognitive and non-cognitive skills can be incorporated in Model 2 in order to estimate bounds on the role of income.

Model 3

Model 3 is motivated by the limitations of the preceding approaches. We propose this approach as a methodological innovation for studying the role of education in intergenerational transmission of economic wellbeing. This approach draws on regression models which each include vectors of all available family background variables directly in the child earnings equations:

$$\ln Y_i^{child} = \alpha + \boldsymbol{\beta_1 Background_i} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \qquad (9)$$

$$\ln Y_i^{child} = \alpha + \boldsymbol{\beta_2 Background_i} + \boldsymbol{\gamma' Educ_i^{child}} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i$$
$$(10)$$

$$\ln Y_i^{child} = \alpha + \boldsymbol{\beta_3 Background_i} + \boldsymbol{\theta' Skills_i^{child}} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i$$
$$(11)$$

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[11] 'Common support' refers to the overlap (between two sub-sets of a sample) in the distributions of a variable. As a hypothetical example, if some members of the 'parent' sample were born in Armenia, whilst none of the 'child' sample were born in Armenia, then Armenia is outside the common support of the country of birth variable.

[12] Again, a weaker version of this limitation is also implicit in the equation (3) approach – with respect to the occupations of parents and children.

$$\ln Y_i^{child} = \alpha + \boldsymbol{\beta_4 Background_i} + \boldsymbol{\gamma' Educ_i^{child}} + \boldsymbol{\theta' Skills_i^{child}} + \pi_1 Age_i + \pi_2 Age_i^2 + \varepsilon_i \qquad (12)$$

$\boldsymbol{Background_i}$ is a vector of many variables, including the occupation, education and country of birth of both parents, as well as the age of the mother at the time of birth and an indicator of whether the child was in a sole parent family. These equations are similar to that of Models 1b and 2, but with the exception that family background is measured by a vector of variables rather than a single indicator. This is a more comprehensive treatment of family background. It is more flexible than in the previous models, as it allows the data to dictate the relative importance of each component of family background to child's income, and allowing these to be flexible as child's education and skills variables are introduced. It does not depend on common support of the child and parental occupation distribution, or on the assumption that the occupational earnings structure is the same for both generations.

The approach does, however, pose a challenge for interpretation, since $\boldsymbol{\beta}$ in each of these four equations is a vector. Summarising the changes in this vector of parameters is not trivial. We propose that this challenge can be navigated, by recognising a dual meaning of predicted values from the regressions. Consider predicted values from equation (9), *holding age constant* at 40. These represent expected child earnings (at age 40) given their individual family background. But these predicted values can also be interpreted as an ordinal *index* of family background as it relates to child income. We can examine the importance of family background by studying the distribution of these predicted values. One useful way to summarise its dispersion is with reference to quantiles of its distribution. Let D denote the difference between the 25th and 75th percentiles of the distribution of predicted values[13]:

$$D = Q_{.75}\left(\ln \widehat{Y^{child}}\right) - Q_{.25}\left(\ln \widehat{Y^{child}}\right)$$

D is the average effect on log earnings of moving from the 25th percentile to the 75th percentile of family background. We can also calculate D for the first equation in models 1

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[13] We also show results using an alternative measure, which compares the 90th and 10th percentiles.

and 2, respectively. A priori, we expect the importance of family background to be greater than implied by the more restrictive measures of family background used in Models (1) and (2). Therefore we expect D to be greater using predicted values from equation (9) than from the corresponding regressions from Models (1) and (2).

Next, we repeat the analysis of predicted values in equations (10)-(12), as we hold child's education and/or skills constant. We expect D to be largest from equation (9) and smallest from equation (12). The extent to which D is reduced by holding education and/or skills constant reflects the importance of education and/or skills in mediating the effect of family background on child earnings. Following the intuition from Model 1b, we treat the comparison of D between equations (9) and (10) as an upper bound of the role of education. This is given by $1 - \frac{D_2}{D_1}$, where D_1 is from equation (9) and D_2 is from equation (10). And we treat the compression of the distribution between Models (11) and (12) as a lower bound estimate of the role of education. This is given by $\frac{D_3 - D_4}{D_1}$, where D_3 is from equation (11) and D_4 is from equation (12).

Finally, we can compare the estimated role of education ($1 - \frac{D_2}{D_1}$ and $\frac{D_3 - D_4}{D_1}$) from Model (3) to the roles estimated using Models (1) and (2). This allows us to compare the results from our novel approach to that of simpler, less comprehensive approaches. A priori, we expect that the estimated mediating role of education will be smaller in Model 3, because of its ability to directly and flexibly incorporate effects of family background at each step.

We note that our approach of summarising changes to the distribution of predicted values is mechanically *identical* to a simple comparison of β's, when β represents a single parameter rather than a vector. In other words, $1 - \frac{\beta_2}{\beta_1}$ is identical to $1 - \frac{D_2}{D_1}$, and $\frac{\beta_3 - \beta_4}{\beta_1}$ is identical to $\frac{D_3 - D_4}{D_1}$, whenever Background is a single variable, rather than a vector. To see this, consider equations (1) and (2). Since age is held constant in the process described above, the predicted value of interest from equation 1 is:

$$\ln \widehat{Y_i^{child}} = \hat{\beta}^{total} \ln Y_i^{parents} + c_1 \, ,$$

where c_1 is some constant. It follows that:

$$D_1 = Q_{.75}\left(\ln \widehat{Y^{child}}\right) - Q_{.25}\left(\ln \widehat{Y^{child}}\right)$$

$$= Q_{.75}\left(\hat{\beta}^{total} \ln Y_i^{parents} + c_1\right) - Q_{.25}\left(\hat{\beta}^{total} \ln Y_i^{parents} + c_1\right)$$

$$= \hat{\beta}^{total}\left[Q_{.75}\left(\ln Y_i^{parents}\right) - Q_{.25}\left(\ln Y_i^{parents}\right)\right]$$

Similarly,

$$D_2 = \hat{\beta}^{direct}\left[Q_{.75}\left(\ln Y_i^{parents}\right) - Q_{.25}\left(\ln Y_i^{parents}\right)\right],$$

So that

$$1 - \frac{D_2}{D_1} = 1 - \frac{\hat{\beta}^{direct}\left[Q_{.75}\left(\ln Y_i^{parents}\right) - Q_{.25}\left(\ln Y_i^{parents}\right)\right]}{\hat{\beta}^{total}\left[Q_{.75}\left(\ln Y_i^{parents}\right) - Q_{.25}\left(\ln Y_i^{parents}\right)\right]} = 1 - \frac{\hat{\beta}^{direct}}{\hat{\beta}^{total}}$$

And similarly for $\frac{D_3 - D_4}{D_1}$.

Dimensionality Reduction

Without implementing any dimensionality-reduction techniques, the HILDA regression corresponding to the first equation of 'Model 3' has 616 parameters to be estimated, while the estimation sample consists of 4,697 observations.[14] In this context, potential over-parameterisation is an important practical consideration. Over-parameterisation is the inclusion of too many parameters to be estimated in a given regression model, resulting in imprecise estimation of each parameter. This issue is typically discussed with reference to out-of-sample prediction accuracy. While out-of-sample prediction is not relevant here, imprecisely estimated parameters may imply that the role of family background is not well captured in the model, despite the richness of the data. In fact, we found substantial evidence for this concern in preliminary analysis. Specifically, without dimensionality reduction, we found that the key estimates were sensitive to sample size. Smaller sample sizes (i.e. taking random sub-sets of the main estimation sample) resulted in smaller estimates for the mediating role of education.

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[14] Even more parameters are included in the subsequent regressions; and the sample sizes are even smaller when models are estimated separately by sex.

Thus we pursued a process of reducing the number of parameters to be estimated for the large indicator variables: father's occupation; mother's occupation; father's education; mother's education; father's country of birth; and mother's country of birth. There are numerous approaches to dimensionality reduction. The simplest approach here is to use higher levels of aggregation for each classification. For example, to use a 3-digit occupational classification rather than the more detailed 4-digit classification. In general, higher levels of aggregation result in a larger estimated role of education in explaining the family background effect. A concern with such an approach, however, is the loss of detail in measuring family background. The unmeasured component of family background may be correlated with child's education. Thus the role of education may be over-estimated for the same reasons that we raised in relation to the simple mediation model ('Model 1'). Principal component analysis (factor analysis) was also considered, but this is not a useful technique when the dimensionality issue is characterised by mutually exclusive dummy variables, which are by construction uncorrelated with each other.

Our preferred approach is to use Lubotsky-Wittenberg indexes to summarise each of the 6 indicator variables listed above (Lubotsky and Wittenberg, 2006). These six indexes were constructed using the parameter estimates from a single (un-reduced) version of the first Model 3 equation. These indexes were then used in place of the indicator variables for the subsequent Model 3 regressions. Instead of estimating 607 parameters in the domains of parental occupation, education and country of birth, we are left with just six parameters in these domains after dimensionality reduction. This approach implicitly invokes a restriction on the original specification – for a given indicator variable (e.g. occupation), the effect of each category is assumed to change proportionally between equations. In other words, the mediating role of child's education on the effect of fathers' occupation is assumed to be constant across occupational categories, and similarly for the other indicator variables. This restriction comes at a cost – it does not allow for meaningful heterogeneity-analysis between sections of the background distribution. For example, we cannot confidently address the important question of whether education plays a greater role for intergenerational transmission at the top vs the bottom of the family background distribution. However, we believe that this approach yields more credible estimates of the overall mediating effect of education in Australia.

Initially, we conducted this reduction technique 'in-sample'. But this did not change the results greatly, and did not eliminate the sample-size sensitivity.[15] In the preferred analysis, we instead constructed these indexes using the parameter estimates (as weights) from a regression with the largest possible appropriate sample. This sample consists of the eight waves of HILDA that have the required data to estimate the first Model (3) equation.[16] Thus we used eight times more data to construct more precise weights for the index construction. This amounts to having better (less noisy) measures of family background in the analysis. This approach yields results which are not sensitive to the sample size used in the main regressions. This seems to be the most effective way to address the dimensionality issue whilst retaining the richness of the available data on family background.

The Mediating Role of Education for Various Components of Family Background

Our 'Model 3' approach can also be used to examine the extent to which education mediates the effect of each component of family background. For example, the mediating role of own education may be different for the parental occupation effect to that of parental education effect. To do this, one can examine how the individual coefficients change between the equations in 'Model 3'. A priori, it seems sensible to hypothesise that the mediating role of child education is greater for the parental education component of family background than for other dimensions of family background. This is indeed what we find.

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[15] Conducting this reduction 'in-sample' does not change the estimated effect of family background in the first Model 3 equation at all.

[16] Waves 5-12 have the required data to construct the Lubotsky-Wittenberg indexes. Only one of these (Wave 12) has the required data to conduct the subsequent regressions.

6. Data

HILDA

We draw primarily on the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is a representative longitudinal study of the Australian population that started in 2001. A total of 13,969 individuals in 7,682 households were interviewed in wave 1 through a combination of face-to-face interviews and self-completion questionnaires, for all members of households aged 15 years old and over (Wooden and Watson, 2002). HILDA is an indefinite life panel survey with a strong focus on family formation, income and work. All members of the households interviewed in wave 1 form the basis of the sample and they were interviewed in each subsequent wave, along with any new members of any households which they form. A general top-up sample of around 2000 new households was added in 2011 (Wave 11).

The estimation sample for the main analysis consists of 4,697 persons aged 25-54 who responded in the Wave 12 person questionnaire and who 'currently' received wages or a salary in their main job and who did not migrate to Australia after the age of five.[17] All family background variables (parents' occupation, education, country of birth, etc.) were collected as retrospective recall data from the respondent in the first wave in which they were interviewed, which for most respondents was 2001. Cognitive skills data were collected in Wave 12 for the first time. Data on non-cognitive skills was collected earlier - Big-5 personality traits data were collected in Wave 9 and locus of control data were collected in Wave 11. These were merged onto the Wave 12 data. Observations with missing values for any of the control variables were flagged, but retained in the estimation sample.

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[17] Our primary aim is to study the mediating role of schooling in Australia. People who migrated to Australia after the age of five were excluded from the sample because they did not conduct (all of) their schooling in Australia.

The Lubotsky-Wittenberg indexes were constructed using a larger sample of 31,775 observations across eight waves, as described in Section 5 above. Other than the larger number of waves, the same sample restrictions were applied as for the main analysis.

Key variables used in the HILDA analysis:

$\ln Y_i^{child}$ is the natural logarithm of the hourly wage of the child, derived as 'current weekly gross wages & salary in main job', divided by 'hours per week usually worked in main job'.

$\textbf{\textit{Background}}_i$ is a vector of family background variables:

- Occupation of each parent (4 digit ANZSCO 2006 – which includes up to 374 categories), summarised into two Lubotsky-Wittenberg index variables (one for fathers' occupation, and one for mothers' occupation) as described in the Methods section, above.

- How much schooling each parent completed (a 5 group categorisation ranging from 'none' to 'Year 12 or equivalent') and type of post-school institution each parent received highest level qualification from (if any) (6 groups: University; Teachers College/College of Advanced Education; Institute of Technology; Technical college/TAFE; Employer; and Other), summarised into two Lubotsky-Wittenberg index variables (one each for fathers' and mothers' schooling)

- Country of birth of each parent (categories for each individual country), summarised into two Lubotsky-Wittenberg index variables (one each for fathers' and mothers' country of birth)

- Aboriginal or Torres Strait Islander origin

- Age of mother at time of birth

- Whether child was living in a sole parent family at the age of 14.

- Whether father was unemployed for 6 months or more while the respondent was 'growing up'.

- Number of siblings ever had

The obvious omission from the 'background' vector is family income. Retrospective family income data were not collected in HILDA.[18] It is not clear how important this omission is. The detailed vector of other family background characteristics will be correlated with, and hence should pick up much of, the income effect. However, the omission of income suggests that the estimated importance of family background will be underestimated. Following a similar argument as the comparison between models 1 and 3, the omission of family income might also lead the estimated role of education to be biased upwards.[19]

$Educ_i^{child}$ is a vector of (own) educational attainment variables:

- Highest education level achieved (8 categories, ranging from Postgrad – masters of doctorate, to Year 11 and below)

- Highest year of school completed (9 categories, ranging from Year 12 to Attended primary school but did not finish, as well as a category for special needs school)

- Main field of study of highest post school qualification (15 categories, e.g. Information Technology; Law; Nursing; Creative arts)

- Which university obtained highest post school qualification from (44 categories)

- Type of school attended (government, catholic non-government, other non-government)

$Skills_i^{child}$ is a vector of cognitive and non-cognitive skill variables:

- Three Cognitive skills variables (Backwards digits score; Word pronunciation score (short NART); Symbol-digit modalities score), as described by Wooden (2013).

- Seven Locus of Control variables, each measured on a 7-point Likert scale (e.g. 'Can do just about anything')

- Indices for each of the 'Big 5' personality traits (Agreeableness; Conscientiousness; Emotional stability; Extroversion; Openness to experience), derived from a 36 item inventory

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[18] Whilst HILDA is a panel survey, it is still too short (12 years) to use direct observations of family income for people in the study population (aged 25-54 in 2012).

[19] We considered using another data source (like for example PSID, for the USA) to explore the importance of the omission of income, but this was not pursued because the importance of income itself may be quite different in the USA. Thus it would not be clear if conclusions from such an analysis would be transferable to Australia.

British Cohort Study

We compare the results from HILDA with corresponding results derived from the British Cohort Study (BCS). BCS is a survey of more than 17,000 children born in Great Britain between 4th and 11th April 1970. The survey has followed the lives of these individuals and collected information on health, physical, educational and social development and economic circumstances of their families. Since the birth surveys, there have been seven waves of data, with information collected at age 5, 10, 16, 26, 30, 34 and 42. Employees were asked to provide information on their usual pay, pay period, and hours usually worked in a week. We use this information to derive hourly earnings at age 26, 30, 34 and 42.

We also collect data on individual educational qualifications and we construct a vector $Educ_i^{child}$, including the information on the highest qualification attained at every wave (6 groups, ranging from Post-degree qualification to Low High School graduate). Various parental background characteristics were collected at every wave and we use information on parental age and marital status at birth, country of birth and parental occupation and education when the child was 16.

In the analysis performed with BCS, $Background_i$ is a vector of family background variables including:

- Occupation of each parent (which includes around 300 categories)
- How much schooling each parent completed (a 7 group categorisation ranging from 'none' to Degree or equivalent)
- Region of birth for each parent (12 categories representing countries or groups of countries)
- Age of mother at time of birth
- Whether child was living in a sole parent family at birth.

We construct a panel data set, by pooling all the different waves of BCS data and using data on individual earnings at age 26, 30, 34, 38 and 42. The estimation sample consists of 24,244 observations. At each wave, employees are asked to report their usual pay, the pay

period, and the hours usually worked in a week. We use this information to construct hourly earnings. Observations for individuals who are self-employed are dropped from the analysis. Parental education and occupation are derived from information collected when the child was 16. The model also includes information on both parents' region of birth, marital status and age of the mother when the child was born. At each wave, information on the child's highest academic qualification is also collected. Standard errors in all regressions are clustered on the individual to account for multiple observations per individual used in each model.

Following Blanden et al. (2007) we perform factor analysis on several variables collecting behavioural ratings. We then include in the model a vector $Skills_i^{child}$ of cognitive and non-cognitive skill variables including:

- antisocial and neurotic behaviour at age 5
- English Picture Vocabulary test (EPVT) and a copying test administered at age 5
- Indicators of behaviours at age 10:
    - antisocial attitude
    - clumsiness
    - concentration
    - extroversion
    - hyperactivity
    - anxiety
- A reading and a maths test administered at age 10.

HILDA (Comparable-with-BCS version)

We also estimate a second version of the HILDA analysis which is intended to be as comparable as possible to the BCS analysis. This involves limiting the sample to the set of persons aged 26-42 and excluding persons born overseas. These sample restrictions leave 2,550 observations for the main analysis and 17,240 observations for the L-W index creation.

This version also involves collapsing some of the explanatory variables or dropping variables from the Background vectors and especially the Education vector. The modified versions of these are shown below:

Comparable-to-BCS $Background_i$ variables:

- Occupation of each parent (4 digit ANZSCO 2006) summarised into two Lubotsky-Wittenberg index variables (one for fathers' occupation, and one for mothers' occupation) as described in the Methods section, above.

- How much schooling each parent completed (a 3 group categorisation: Year 10 or below; Year 11 or equivalent; Year 12 or equivalent) and type of post-school institution each parent received highest level qualification from (if any) (6 groups: University; Teachers College/College of Advanced Education; Institute of Technology; Technical college/TAFE; Employer; and Other), summarised into two Lubotsky-Wittenberg index variables (one each for fathers' and mothers' schooling)

- Country of birth of each parent (collapsed into 10 categories), summarised into two Lubotsky-Wittenberg index variables (one each for fathers' and mothers' country of birth)

- Age of mother at time of birth

- Whether child was living in a sole parent family at the age of 14.

Comparable-to-BCS $Educ_i^{child}$ variables:

- Highest education level achieved (5 categories, ranging from Postgrad – masters of doctorate, to Year 11 and below)

The Skills vector was unchanged despite major comparability issues, explicitly because we sought to judge whether the inclusion of HILDA's skills measures have similar effects on the results as compared to that of the superior skills measures in the BCS.

7. Results for Australia

The Importance of Family Background for Child Earnings

Table 1 is an attempt to convey the apparent importance of family background for hourly earnings, as implied by each of the three models. The table summarises the distribution of predicted log hourly earnings, at various quantiles of the 'family background' distribution. As described in Section 5, each model has a different process of accounting for family background as a determinant of child earnings. The lowest six rows of the table contain the most important information. They show *differences* in predicted earnings between children at various percentiles of 'parental background'. For example, the Model 1 results suggest that people at the 75th percentile of 'family background' have expected earnings that are around 9 per cent higher than those at the 25th percentile. Moving from the 10th to 90th percentile of family background is associated with earnings that are 19 per cent higher. Model 2, whilst using a broader set of family background characteristics in the imputation model, leads to similar conclusions.

As expected, given the richer and more flexible approach, the effect of family background is estimated to be much larger in Model 3. The model suggests that people at the 75th percentile of 'family background' have expected earnings that are 24% higher than those at the 25th percentile. People at the 90th percentile of 'family background' have expected earnings that are 52% higher than those at the 10th percentile. When each gender is analysed separately, family background matters even more (for both sexes). This is despite the fact that gender is controlled for in the analysis when both sexes are combined. A likely explanation is that various aspects of family background matter differently for males and for females and so the specification in the combined-gender analysis is too restrictive. Males at the 90th percentile have expected earnings that are 65% higher than those at the 10th percentile. For females, the corresponding difference is also large (53%).

Table 1 – Predicted Log Hourly Earnings, by Percentile of 'Family Background'

Percentiles	Model 1	Model 2	Model 3 both genders	males	females
p1	3.158	3.183	3.008	2.953	2.954
p5	3.278	3.284	3.154	3.156	3.065
p10	3.321	3.325	3.214	3.245	3.126
p15	3.342	3.342	3.248	3.307	3.169
p20	3.359	3.367	3.279	3.340	3.198
p25	3.376	3.384	3.307	3.371	3.222
p30	3.389	3.398	3.330	3.398	3.242
p35	3.399	3.409	3.352	3.420	3.267
p40	3.409	3.419	3.370	3.441	3.286
p45	3.415	3.425	3.388	3.463	3.310
p50	3.423	3.435	3.408	3.484	3.328
p55	3.431	3.443	3.427	3.513	3.349
p60	3.439	3.452	3.448	3.536	3.372
p65	3.446	3.458	3.469	3.558	3.395
p70	3.454	3.466	3.494	3.586	3.423
p75	3.464	3.474	3.520	3.617	3.452
p80	3.472	3.484	3.548	3.648	3.484
p85	3.482	3.492	3.583	3.691	3.514
p90	3.492	3.506	3.630	3.747	3.549
p95	3.509	3.525	3.698	3.841	3.627
p99	3.555	3.570	3.891	4.055	3.805
P60 - P40	0.030	0.033	0.078	0.094	0.086
expressed as % difference in expected wage	3.0%	3.3%	8.1%	9.9%	9.0%
P75 - P25	0.087	0.090	0.213	0.246	0.230
expressed as % difference in expected wage	9.1%	9.4%	23.7%	27.9%	25.9%
P90 - P10	0.171	0.181	0.416	0.502	0.423
expressed as % difference in expected wage	18.7%	19.8%	51.6%	65.1%	52.7%

These results are of substantive interest. But their main implication for the present study is to highlight that the family background measures used in Models 1 and 2 greatly understate the actual importance of family background for child earnings. To the extent that child's education is correlated with those unmeasured family background factors, analyses from Models 1 and 2 will likely overestimate the role of education in explaining the intergeneration persistence of economic advantage. These results lend support for Model 3 as the preferred approach.

The Role of Education in Inter-generational Transmission of Economic Well-Being

Table 2 shows the key results, which summarise the importance of education as a mechanism for intergenerational transmission, as estimated using each of the methods described in Section 5. For each model, the table shows an 'upper bound' (estimated using a model which ignores skills) and a 'lower bound' (estimated using a model which ignores the role of education as a pathway for skills to influence earnings). As discussed above, the lower bound is $\frac{D_3-D_4}{D_1}$, which for models 1 and 2 is identical to $\frac{\beta_3-\beta_4}{\beta_1}$. The upper bound is $1-\frac{D_2}{D_1}$, which for models 1 and 2 is identical to $1-\frac{\beta_2}{\beta_1}$.

As expected, the estimated role of education is largest in Model 1, followed by Model 2 and then Model 3. Model 1 implies that education accounts for between 31% and 62% of intergenerational transmission and does not differ greatly by gender. In Model 2, the mediating role of education is slightly smaller (between 29% and 59%) and is considerably larger for females than for males.

The preferred model is Model 3. Using the 75th and 25th percentiles of the distribution, these results suggest that education accounts for between 26% and 41% of intergenerational persistence. This range is similar (25% to 40%) when the 90th and 10th percentiles are used instead. This suggests that education has a substantial role in explaining intergenerational transmission. However, the majority of the family background effect is transmitted through other mechanisms. We return to this issue subsequently.

Table 2 – The Role of Education as a Mechanism for Intergenerational Transmission of Economic Well-Being

Estimated role of Education	Model 1	Model 2	Model 3 P75-P25	Model 3 P90-P10
both genders (of child)				
lower bound	31%	29%	26%	25%
upper bound	62%	59%	41%	40%
Males				
lower bound	31%	22%	20%	19%
upper bound	63%	51%	35%	32%
Females				
lower bound	28%	36%	26%	26%
upper bound	58%	67%	38%	37%

Model 3 suggests that education may have a larger role in intergenerational transmission of advantage for females than for males. *A priori*, two hypothesised explanations for this result are a stronger relationship for females between background and education, or between education and earnings. We explored this further. We ran regressions of educational attainment[20] on the family background index created using Model 3. Controlling only for a quadratic in age, the estimated effect of family background was actually slightly (5%) smaller for females.[21] We then ran regressions of the log hourly wage on educational attainment. Again controlling for age, the returns to schooling were estimated to be 15% smaller for females. Each of these estimates are subject to sampling error, but they do not support either hypothesised explanation for the gender difference.

We leave the explanation of this discrepancy for further work, but we make some additional observations. First, the total effect of family background is larger for males than for females (Table 1). Perhaps the 'direct' effect of family background is stronger for males if, for example, their employment opportunities are more strongly affected by their parent's social

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[20] We used a simple summary measure of educational attainment (years of schooling) – in place of the more comprehensive (but less tractable) vector of educational attainment variables that were used in the main analysis. This measure ignores effects of family background on the types of schooling attained (e.g. field of study, institution of study, private versus public schooling, etc.)

[21] We use a different approach to further study the role of family background on educational attainment later in this section. That analysis leads to similar conclusions on gender differences.

capital networks, or if their career aspirations are more strongly aligned with that of their parents. A more subtle explanation relates to the fact that females in our estimation sample are more likely to be highly educated (35% of females have post-school qualifications, compared to 27% of males). This could explain the result if the mediating effect of education is highly nonlinear. Finally, we note the well-known problems associated with non-random selection into employment (i.e. females are more likely to select into employment on skill) which make it difficult to make any conclusions on the sources of the gender difference.

The Mediating Role of Education for Various Components of Family Background

Briefly, we now consider the mediating role of education for each dimension of family background. Still drawing on the same 'Model 3' results presented above, we consider changes between the equations in individual coefficients rather than changes in 'D'. As hypothesised, the mediating role of own education is largest for parental education, especially father's education. In the 'upper bound' results with both sexes combined, own education is estimated to mediate 69% of the effect of father's education, 55% for mother's education, 33% for father's occupation, 32% for mother's occupation, 38% for father's country of birth and 34% for mother's country of birth. Using the 'lower bound' results, the same conclusion is reached- own education is estimated to mediate 38% of the effect of father's education, 32% for mother's education, 22% for father's occupation, 21% for mother's occupation, 28% for father's country of birth and 23% for mother's country of birth.

The Role of Education in Explaining Immobility

This section explores the role of education in explaining immobility of people from disadvantaged backgrounds, as well as the immobility of people from advantaged backgrounds. The analysis draws on the family background indices created within Model 3 above.

Table 3 is a transition probability matrix which shows the probability of being in each quartile of hourly earnings[22], given one's family background quartile. For example, only 12.6% of people from the lowest background quartile have hourly earnings in the top quartile, while 39.3% have earnings in the lowest quartile. Overall, these matrices reaffirm the major role of family background as a determinant of earnings, which was first described in Table 1. This persistence appears slightly stronger when each gender is considered separately. Similarly to Table 1, this is probably because the various aspects of family background matter differently for males and for females.

For both genders, more than two-fifths of people from the lowest background quartile have earnings in the lowest quartile, while about 11% of them reach the top earnings quartile. Similarly and conversely, around 45% of people from the highest background quartile have earnings in the top quartile, with only 12% in the lowest quartile. Amongst those in the middle half of the background distribution, about 55% have earnings in the middle half of the earnings distribution. They are slightly more likely to have earnings in the lowest quartile than in the top quartile.

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[22] Earnings quartiles are assigned after holding age (and sex, for the combined gender analysis) constant.

Table 3 – Transition Probability Matrix

Family Background Index	Hourly wage quartile				
	lowest quartile	2nd	3rd	highest quartile	total
	Both Genders				
lowest quartile	39.3%	31.4%	16.7%	12.6%	100.0%
2nd	27.2%	27.8%	25.1%	20.0%	100.0%
3rd	21.0%	23.0%	29.6%	26.5%	100.0%
highest quartile	12.6%	17.9%	28.5%	40.9%	100.0%
	Males				
lowest quartile	42.0%	28.3%	18.0%	11.7%	100.0%
2nd	27.8%	29.1%	24.0%	19.0%	100.0%
3rd	18.5%	28.1%	30.1%	23.4%	100.0%
highest quartile	11.8%	14.4%	27.8%	45.9%	100.0%
	Females				
lowest quartile	42.6%	31.6%	14.6%	11.2%	100.0%
2nd	27.6%	31.4%	25.8%	15.2%	100.0%
3rd	18.4%	22.6%	30.7%	28.3%	100.0%
highest quartile	11.3%	14.5%	28.9%	45.3%	100.0%

Another way to express those results is from simple binary regressions which model the probability of having earnings in a given section of the distribution as a function of having a certain family background. For example, we can model the effect of being in the lowest family background quartile on the probability of having earnings in the bottom quartile. We specify a linear probability model of the following form, noting that the results are not sensitive to probit or logit specifications:

$$\Pr(Y\_Q1_i^{child} = 1) = \alpha + \beta\, Background\_Q1_i + \varepsilon_i \qquad\qquad (13)$$

Where $Y\_Q1_i^{child}$ is a binary indicator of having hourly earnings in the lowest quartile of the distribution, and $Background\_Q1$ is a binary variable indicating that the person's family background index (as estimated from the first equation of Model 3, as described in Section 5) is in the lowest quartile of the distribution. In this model, α is the probability of everyone else (ie those in the top three quarters of the background distribution) having earnings in the lowest quartile, while β is the additional probability for those in the lowest background quartile.

We then proceed to estimate the component of β that is explained by differences in educational attainment, following the intuition of the main analysis above. That is, we see how β changes, after adding controls for education and/or skills. We continue to use linear probability models.[23]

We then repeat the analysis for the top quartiles of background and earnings. Table 4 shows the results of this exercise, for both genders combined and separately, focussing on immobility in the lowest and highest quartiles. The results suggest that (relatively low) education explains 28% - 48% of immobility of people in the lowest quartile of the background distribution. This effect is smaller for males (16% to 32%) compared to females (28% to 42%).

Education explains a similar proportion of the immobility of those in the top background, with smaller effects again present for males.

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[23] Probit and logit versions of these models do not always converge (i.e. they do not produce any estimates at all due to a breakdown in the optimisation algorithm), probably because of the large number of explanatory variables included in the models. Where they do converge, they lead to very similar results (marginal effects) to that of the linear probability models.

Table 4 – The Role of Education in Immobility

	(1)	(2)	(3)	(4)	Role of education lower bound	upper bound
Panel A: Both Genders Combined						
Binary dependent variable: earnings in lowest quartile						
effect of background quartile 1	0.191	0.100	0.151	0.098	28%	48%
education controls	no	yes	no	yes		
skills controls	no	no	yes	yes		
Binary dependent variable: earnings in highest quartile						
effect of background quartile 4	0.213	0.110	0.173	0.108	31%	48%
education controls	no	yes	no	yes		
skills controls	no	no	yes	yes		
Panel B: Males						
Binary dependent variable: earnings in lowest quartile						
effect of background quartile 1	0.226	0.154	0.181	0.144	16%	32%
education controls	no	yes	no	yes		
skills controls	no	no	yes	yes		
Binary dependent variable: earnings in highest quartile						
effect of background quartile 4	0.279	0.192	0.242	0.192	18%	31%
education controls	no	yes	no	yes		
skills controls	no	no	yes	yes		
Panel C: Females						
Binary dependent variable: earnings in lowest quartile						
effect of background quartile 1	0.235	0.136	0.203	0.137	28%	42%
education controls	no	yes	no	yes		
skills controls	no	no	yes	yes		
Binary dependent variable: earnings in highest quartile						
effect of background quartile 4	0.271	0.146	0.245	0.149	35%	46%
education controls	no	yes	no	yes		
skills controls	no	no	yes	yes		

Does the Education System Promote Intergenerational Persistence or Mobility?

The analysis above suggests that education 'explains' some component of intergenerational transmission of economic advantage. This positions education as 'part of the problem' rather than 'part of the solution' to intergenerational transmission of disadvantage. In a sense, this is a correct interpretation to the extent that people from disadvantaged backgrounds receive less schooling. However, it is informative to consider the *extent* to which family background determines educational outcomes, and compare this to the extent to which family background determines earnings. In other words, we know that family background is a major determinant of earnings, but is family background a *smaller* determinant of educational attainment?[24] If so, then perhaps one can gauge the extent to which the education system is actually facilitating intergenerational mobility rather than contributing to intergenerational transmission.

To this end, we repeated the analysis that underlies Table 1 (Model 3), this time with educational attainment (instead of earnings) as the dependent variable.[25] The first measure we used is ln(years of schooling). This is a simple and transparent summary measure of educational attainment. The limitation of this measure, however, is that it ignores many aspects of educational attainment which may be related to both earnings and to family background. This includes school sector (private; catholic; public), as well as field and institution of tertiary education. Thus we created a second dependent variable, which is an educational attainment index. This variable summarises all available educational attainment

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[24] One could argue that such a comparison should give consideration to the variance of each outcome variable. Indeed the variance of log hourly wages is considerably larger than the variance of either of our educational attainment measures. However, both earnings and educational attainment are cardinal measures, and the relationship between education and earnings is systematic. On this basis, we believe it is appropriate to make such comparisons of the absolute effects of family background in each domain.

[25] To mirror the main analysis, the Lubotsky-Wittenberg family background indexes were re-created using all 8 waves of data, with ln(years of education) used as the dependent variable.

variables into a single Lubotsky-Wittenberg index, using weights which correspond to the estimated relationship between each educational variable and own earnings.[26]

Table 5 – The importance of Family Background for Educational Attainment

	both genders	males	females
Dependent Variable: ln(years of schooling)			
P60 - P40	0.043	0.043	0.051
expressed as % difference in expected wage	4.4%	4.3%	5.3%
P75 - P25	0.117	0.116	0.136
expressed as % difference in expected wage	12.4%	12.3%	14.6%
P90 - P10	0.239	0.256	0.272
expressed as % difference in expected wage	27.0%	29.2%	31.3%
Dependent Variable: L-W Education Index			
P60 - P40	0.053	0.058	0.057
expressed as % difference in expected wage	5.4%	5.9%	5.9%
P75 - P25	0.151	0.152	0.156
expressed as % difference in expected wage	16.2%	16.4%	16.8%
P90 - P10	0.307	0.334	0.308
expressed as % difference in expected wage	36.0%	39.7%	36.0%

The key results from both versions are shown in Table 5. This table shows differences in predicted educational attainment between various percentiles of the family distribution, similar to the lower panel of Table 1 (Model 3). The upper panel shows results for educational attainment measured in (log) years of schooling. It suggests that people at the higher end of the background distribution are expected to receive considerably more education. For example, those at the 90th family background percentile can expect to receive 27% more years of schooling (approximately 3 more years) compared to those at the 10th percentile. The corresponding discrepancy is slightly larger for females than for

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[26] Specifically, this is the predicted value from a regression of ln(hourly earnings) on all available educational attainment variables (as detailed in the data section which describes key HILDA variables), after controlling for sex and a quadratic in age. Only Wave 12 was used as it has all of the required variables.

males. The more comprehensive education index is used in the lower panel. Here the importance of background is larger still (as expected). Those on the 90th background percentile can expect to receive 36% more schooling. Interestingly, the difference between genders is small here, and if anything the importance of background is larger for men. While family background has a larger effect on the quantity of schooling for women (upper panel), this is offset by the types of education induced. This presumably relates to field and institution of tertiary study, perhaps also in terms of secondary school sector.

These results should be compared to the corresponding (Model 3) results in Table 1. This comparison reveals that family background is a considerably smaller determinant of educational attainment than the corresponding relationship between family background and earnings. Comparing the P90 – P10 results for both genders combined, the family background effect is around 30% smaller for educational attainment than the family background effect for earnings.[27] A comparison of P75 – P25 results leads to a similar conclusion (31%). Comparisons of the other summary measures also give similar results.

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[27] (1 – 36%/51.6%)*100%

8. Comparisons to the UK (British Cohort Study)

We now repeat the preferred 'Model 3' analysis using data from the British Cohort Study (BCS) and compare these to additional results from HILDA. The HILDA analysis here is modified from the main analysis in order to maximise comparability with BCS (as described in Section 6).

We do this for two purposes. Firstly, we seek to determine whether education has a smaller role in explaining the effect of background between the two countries. We also seek to gain insights into whether the (inferior) set of skills variables in HILDA are serving their intended purpose. That is, we are particularly interested in whether the inclusion of skills measured at early childhood (as are included in BCS) impacts the results differently to the inclusion of skills measured contemporaneously with wages (as are included in HILDA).

In the first stage of the 'Model 3' approach, we estimate the impact of parental background on child's hourly earnings, without controlling for the child's education or skills.

Table 6 follows the same structure as Table 1. The results suggest that the importance of family background as a determinant of earnings is smaller in the UK than in Australia. In the BCS, people at the 90th (75th) percentile of 'family background' have expected earnings that are around 38% (15%) higher than those at the 10th (25th) percentile. The corresponding estimate is 54% (26%) in HILDA. These gaps in expected earnings are always slightly larger when the sexes are analysed separately (as they are in the main analysis).

Table 6 – Predicted Log Hourly Earnings, by Percentile of 'Family Background' – BCS and 'comparable' HILDA

Percentiles	BCS			HILDA		
	both genders	males	females	both genders	males	females
p1	1.683	1.710	1.533	2.986	2.862	2.816
p5	1.848	1.904	1.701	3.145	3.146	3.016
p10	1.915	1.976	1.790	3.202	3.247	3.096
p15	1.948	2.028	1.836	3.240	3.301	3.143
p20	1.972	2.059	1.864	3.268	3.341	3.181
p25	1.983	2.073	1.880	3.292	3.357	3.208
p30	1.990	2.080	1.890	3.315	3.377	3.237
p35	1.998	2.084	1.900	3.338	3.401	3.263
p40	2.009	2.099	1.911	3.356	3.416	3.287
p45	2.018	2.114	1.924	3.378	3.443	3.316
p50	2.032	2.128	1.939	3.397	3.461	3.340
p55	2.042	2.155	1.947	3.419	3.479	3.364
p60	2.053	2.178	1.964	3.438	3.500	3.386
p65	2.071	2.189	1.980	3.458	3.527	3.408
p70	2.097	2.209	2.005	3.486	3.563	3.430
p75	2.122	2.240	2.036	3.520	3.597	3.459
p80	2.151	2.276	2.066	3.552	3.629	3.492
p85	2.189	2.324	2.096	3.588	3.675	3.526
p90	2.234	2.373	2.146	3.633	3.726	3.569
p95	2.310	2.459	2.224	3.701	3.841	3.665
p99	2.494	2.709	2.662	3.887	4.064	3.830
P60 - P40	0.044	0.079	0.053	0.081	0.083	0.099
expressed as % difference in expected wage	4.5%	8.2%	5.4%	8.5%	8.7%	10.4%
P75 - P25	0.139	0.167	0.156	0.228	0.239	0.251
expressed as % difference in expected wage	14.9%	18.2%	16.9%	25.6%	27.0%	28.5%
P90 - P10	0.319	0.397	0.356	0.431	0.479	0.472
expressed as % difference in expected wage	37.6%	48.7%	42.8%	53.9%	61.4%	60.3%

Table 7 follows the structure of Table 2. It shows the percentage of the family background effect that is explained by child's education. It suggests that education plays a similar role in explaining the effect of family background on earnings in the UK and in Australia. For example, using the 75th and 25th percentiles, these results suggest that education accounts for between 18% and 30% of intergenerational persistence in the UK, compared to between 16% and 29% in Australia. The results are similar (13% to 26% for the UK; 16% to 28% for Australia) when the 90th and 10th percentiles are used instead. Similarly to Australia, education in the United Kingdom plays a larger role for females.

Table 7 – The Role of Education as a Mechanism for Intergenerational Transmission of Economic Well-Being – BCS and 'comparable' HILDA

Estimated role of Education	BCS		HILDA	
	P75-P25	P90-P10	P75-P25	P90-P10
both genders (of child)				
lower bound	18%	13%	16%	16%
upper bound	30%	26%	29%	28%
males				
lower bound	11%	6%	9%	8%
upper bound	14%	17%	20%	15%
females				
lower bound	16%	14%	21%	17%
upper bound	27%	23%	28%	25%

The estimated role of education for Australia is smaller in Table 7 than in the main results (Table 2). This is to be expected because the main analysis includes a much richer set of own-education variables.

Further, skills do not have a systematically larger role in explaining intergenerational transmission in BCS as compared to HILDA. This can be seen by comparing the difference between the lower bound and upper bound estimates of the role of education in BCS and in HILDA. For example, this difference equals 12 to 13 percentage points in the combined gender analysis in BCS, and it also equals 12 to 13 percentage points in HILDA. This is despite the much higher quality data on skills collected in BCS. There is hence no evidence that the lower quality skills measures in HILDA result in biased lower bounds of the Australian results.

9. Conclusions

This report presents a 'big picture' view on the role of education in intergenerational economic mobility in Australia. In doing so, we have developed a novel methodological approach to study the extent to which education mediates the effect of family background characteristics on earnings in the next generation. This methodological innovation has been scrutinised at several academic seminars and conferences, which has led to several refinements, but it has not yet been subjected to formal academic peer review and so the findings in this report should be treated with caution.

Our results suggest that family background is a major determinant of economic wellbeing in Australia. They suggest that family background has a much larger role than implied by previous studies. Further, there is a positive relationship between family background and education, and a positive relationship between education and earnings. It follows that education is one of the mechanisms through which economic advantage is transferred from one generation to the next.

Our results suggest that education mediates around 25%-40% of intergenerational transmission of economic advantage in Australia. The upper bound (40%) is estimated using models which ignore skills (which are correlated with both education and family background). Conversely, the lower bound (25%) is estimated using models which ignore the role of education as a pathway through which skills influence earnings. The role of education thus appears to be substantial. However, economic advantage is transmitted between generations mainly through other mechanisms.

The estimated role of education in transmitting economic advantage is similar for the UK as for Australia.

The role of education appears to be larger for females than for males. This, in turn, is due to a stronger relationship between family background and educational attainment for females.

This project has not addressed causal questions on the extent to which educational programs or interventions can lift people out of economic disadvantage. The most credible research on such questions has used quasi-experimental techniques that exploit policy

changes such as compulsory schooling laws. Rigorous impact evaluations of smaller programs may be a fruitful avenue for further research. Incorporating elements of random assignment into trials of new initiatives is likely to produce the highest quality evidence on their causal effects on student outcomes, including those from disadvantaged backgrounds.

Appendix A – Robustness Test

This Appendix shows the results of a key sensitivity test. It considers whether the main results are sensitive to the exclusion of persons whose family background index may be poorly estimated due to 'small cells'. Since there is a large number of indicator variables in the family background vector, the role of some of these variables in explaining earnings is likely to be poorly estimated if there are few observations in the same category (of occupation, or country of birth, etc.).

For this robustness test, observations were excluded from the analysis if any of the person's background characteristics (i.e. occupation, country of birth or educational attainment of either parent) was shared by less than 20 observations in the Lubotsky-Wittenberg index construction sample. This led to the exclusion of 8.4% of the sample used for the main analysis. The results are shown in Table 8, which follows the structure of Table 2. It shows that the key results are not greatly sensitive to the exclusion of observations in 'small cells'. However, the estimated role of education is slightly higher overall, and also for females, with the exclusion of those observations.

Table 8 – Small-cell Robustness Test for The Role of Education as a Mechanism for Intergenerational Transmission

	Model 3	
Estimated role of Education	P75-P25	P90-P10
both genders (of child)		
lower bound	28%	28%
upper bound	44%	44%
Males		
lower bound	20%	19%
upper bound	34%	34%
Females		
lower bound	30%	30%
upper bound	42%	42%

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