Occupational Mediation of Intergenerational Income Mobility*

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Abstract

Using novel administrative data from Australia, we examine the role of the parent's and child's occupational choices in shaping intergenerational income mobility. Applying a multilevel mediation analysis, we show that 38.2% of the intergenerational rank–rank slope is explained by a combination of the child's occupation, college education, and the parent's neighbourhood and occupational choices. Among these channels, both the parent's and the child's cognitive occupations play significant roles, each accounting for roughly one-quarter of the observed persistence. The contribution of the child's college education declines substantially once the parent's cognitive occupation is considered. The parent's cognitive occupation plays a more prominent role in locations with a significant presence of the knowledge economy.

Keywords: intergenerational income mobility; occupation mobility; cognitive occupation; multilevel mediation
JEL codes: E24.

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1 Introduction

Intergenerational income mobility (IGM)—or more accurately, the lack of it—is a common feature across many developed countries (Berman, 2018).[1] In this regard, previous studies have documented substantial intergenerational persistence in occupational choices (Beller and Hout, 2006; Constant and Zimmermann, 2004; Escriche, 2007; Eberharter, 2008; Dustmann, 2004).[2] While recent work in labour economics highlights occupation as a key determinant of earnings (e.g., Autor et al., 2003; Acemoglu and Autor, 2011; Kambourov and Manovskii, 2009), the extent to which occupational choices contribute to the lack of income mobility across generations remains underexplored.

In this paper, we examine the role of occupations in shaping intergenerational income mobility using a multi-level mediation analysis.[3] We use administrative data linking parent–child tax records from the Australian Taxation Office (ATO), which uniquely contains detailed occupation and income information. Our analysis considers four key mediators in the intergenerational transmission of income: parental occupation, neighbourhood quality, college education, and the child's occupation. By exploiting the timing of intervention of each mediator, we construct a layered mediation framework to analyse how each stage contributes to the transmission of economic advantage from parents to children.

Our findings show that 38.2% of the intergenerational rank–rank slope is explained by the combination of the child's cognitive occupation, college education, and the parent's neighbourhood and cognitive occupational choices. Among these, both the parent's and child's cognitive occupations play prominent roles, accounting for 10.9% and 9.9% of the rank–rank slope, respectively. Comparing results across different layers of mediation reveals that, without accounting for parental occupation, college education alone explains nearly half of the observed persistence.

Our analysis clearly illustrates that once parental cognitive occupation is included—particularly as a determinant of children's educational attainment—the contribution of the child's college education diminishes, making its role comparable to that of parental cognitive occupation. This suggests that parental occupation may capture unobserved factors such as the transmission of occupation-specific human capital, network, or innate/inherited ability, highlighting the limitations of child's education alone in explaining intergenerational mobility of income.

Finally, we find that the parent's cognitive occupation plays an even larger role in explaining

[1] Chetty, Hendren, Kline, Saez and Turner (2014) and Chetty, Grusky, Hell, Hendren, Manduca and Narang (2017) document a sharp decline in upward intergenerational income mobility in the United States since 1940. Building on Chetty, Grusky, Hell, Hendren, Manduca and Narang (2017), Berman (2018) shows a significant downward trend in absolute mobility across several developed countries during the latter half of the 20th century.

[2] See Black and Devereux (2010) and Ermisch, Jäntti and Smeeding (2012) for comprehensive reviews.

[3] Bolt, French, Maccuish and O'Dea (2021) recently applied a similar multi-level mediation approach to assess how family background and early childhood investments influence intergenerational mobility.

intergenerational income mobility in locations that have either higher level or growth of cognitive occupations, such as in larger urban areas. These results caution against policy approaches that place disproportionate weight on expanding college education as a lever for improving intergenerational mobility. Instead, they highlight the importance of complementary measures, such as occupation-specific counseling and career resources, to support children who lack parental occupational knowledge and networks in navigating their career paths.

Related literature

There is a large international literature on intergenerational income mobility. In Australia, Leigh (2007) finds that there is higher mobility than the United States, with an estimated elasticity of sons' earnings with respect to fathers' earnings around 0.2 during 2001–2004. However, using more recent data, Mendolia and Siminski (2016) estimate a much higher intergenerational earnings elasticity of 0.35, indicating a greater degree of income persistence. This estimate places Australia in a significantly less mobile position than previously suggested. Following the approach of Chetty, Hendren, Kline, Saez and Turner (2014), Deutscher and Mazumder (2020) provide the first estimates of intergenerational mobility in Australia using administrative tax data for over one million individuals born between 1978 and 1982. They find that overall intergenerational persistence is relatively low in Australia, but mobility varies considerably across regions, with the mining boom contributing to strong upward mobility in resource-rich areas. Further, Deutscher (2020) shows that place-based effects on mobility are more pronounced during adolescence than in early childhood. Turning to intergenerational occupational mobility, earlier studies such as Beller and Hout (2006); Constant and Zimmermann (2004); Escriche (2007); Eberharter (2008); Dustmann (2004) document significant occupational persistence using data from the U.S., Germany, and the U.K. We contribute to this literature by providing new evidence on intergenerational income mobility and its relationship to intergenerational occupational choices using unique Australian data.

Our main result is that parental cognitive occupation explains a large part of intergenerational earnings persistence once its role in shaping children's education and occupational choice is accounted for, leaving education with limited marginal impact. Prior work highlights several mechanisms. Doepke and Zilibotti (2008), Doepke and Zilibotti (2017) show that parents transmit preferences and parenting styles that shape occupational choices, with cross-country evidence indicating variation in these styles. Other studies emphasize networks. Lo Bello and Morchio (2022) attribute nearly 80% of UK occupational persistence to parental networks, while Ventura (2023) shows that Dutch "dynastic" doctors are both more likely to enter medicine and earn higher returns. Finally, employer-employee data reveal strong workplace links. Forsberg et al. (2024) find that family background accounts for 70% of firm pay premia in Sweden, and Kramarz and Skans

(2014) show parental ties help children secure their first stable jobs. Together, these findings point to preferences, networks, and workplace links as key drivers of occupational persistence, consistent with our evidence for Australia.

Taken together, these studies suggest that cognitive occupational persistence reflects multiple reinforcing mechanisms—preference transmission, parenting styles, and network effects—that jointly reduce the marginal role of child's education in explaining intergenerational income persistence. Our findings for Australia add to this literature by showing that the parent's cognitive occupation is an important mediator, especially in regions with high growth in cognitive occupations, low mining share and in bigger cities where prominent Go8 universities are located, shaping both children's educational attainment and occupational sorting, and thereby contributing to persistence of inequality across generations.[4]

The remainder of the paper is organized as follows. Section 2 describes the ALife dataset and presents stylized facts. Section 3 decomposes intergenerational income mobility into its key drivers using multi-level mediation analysis. Section 4 presents evidence of spatial heterogeneity in the mediation analysis. Section 5 concludes.

2 Data and stylized facts

2.1 Linked administrative data

This paper uses the ALife dataset from the ATO that covers the 10% sample of the Australian population. In the ALife data, parent-child links are established using a range of data sources, most significantly using flags derived from Medicare enrollment data (see, Deutscher, 2020; Deutscher and Mazumder, 2020; Deutscher and Mazumder, 2021). Our data is an intergenerationally-linked panel data from 1991 to 2018 with information on income, 2-digit occupation, geographical location, and demographic characteristics such as age and gender of parents and children. We restrict our sample to children born between 1979 and 1982. We restrict our sample to couples.[5]

Our measure of income is individual total pre-tax income.[6] We define the lifetime income of parent as the average income of the primary parent between 1991 to 2001, and that of the child as the average income between 2011 and 2018. All income variables are in 2012 Australian dollars. In

[4]The Go8 (Group of Eight) universities in Australia are a group of the country's most research-intensive universities. The eight member institutions are the Australian National University, Monash University, the University of Adelaide, the University of Melbourne, the University of Queensland, the University of Sydney, the University of New South Wales, and the University of Western Australia.

[5]Among the matched parent-child links, 99.55% of parents in our sample are opposite-sex couples.

[6]Unlike Deutscher (2020), we consider the primary parent for our parental income and occupation measure, since defining occupation at the household level is not straightforward. Primary parent is as defined by the Australian Taxation Office. Our results in Section 2 are robust to using other definitions of primary parent such as when the parent is male, female or has the higher lifetime income.

our analysis, we also use lifetime occupation, which is defined as the occupation that an individual holds for the maximum number of years in the corresponding period (i.e. between 1994 to 2001 for the primary parent, since occupation data is not available before 1994, and between 2011 to 2018 for the child).[7] Following Chetty et al. (2014), we rank children based on their incomes relative to other children in the same birth cohort and rank parents based on their incomes relative to other parents.

We classify parent's and child's lifetime occupation into three broad categories: Cognitive, Routine, and Manual, following Borland and Coelli (2017). Acemoglu (2002), David (2015) and David, Katz and Kearney (2006) document the impact of technological change in the form of structural change, skill-biased technological innovations, and automation on income distribution and occupational structures. Based on this literature, Borland and Coelli (2017) classify occupations into the economically meaningful categories as Cognitive, Manual, and Routine. Each two-digit (ANZSCO) occupation in the ATO dataset (a unique feature of the Australian dataset wherein the occupation of the tax filer is also reported) is categorized into one of three groups. Details of the occupation classification are reported in Appendix Table A.2.

In our initial sample, the total number of observations are 128,978. To construct a linked sample, we (i) drop observations that are not linked to their parents data; (ii) drop observations if the lifetime income of the child or parent is either missing or negative; (iii) drop observations in the life-time occupation of the child or parent is missing and (iv) drop observation with missing information on characteristics used for spatial mediation analysis such as parent's location or change in cognitive share. Our final sample contains 32,658 child-parent observations. Table A.1 in Appendix provide further details on the sample selection procedure. Table 1 reports the summary statistics of our sample. In our data, the mean age of the parent in 2018 in 67 while that of the child is 39. For the period for which we calculate lifetime income, the age of the parent is between 41-51 and for the child is between 32-39.

To account for the possibility that the missing life-time occupation data is not random and might be associated with individual's life-time income and gender, we address the selection bias. To do that, we construct the inverse probability weight for each observations in our sample by estimating a probit model for observing life-time occupation as a function of individual's life-time income and gender. The inverse of the predicted probabilities are used as the weights in our analysis. Intuitively, this procedure assigns more weight to individuals who have similar characteristics to others but are less likely to appear in the sample. We use these weights for our benchmark analysis, while our main findings hold even if we don't use them.

[7] We prefer to use income and occupation measures over a longer time period to get a measure of life-time income and occupation. Mazumder and Acosta (2015) argue that using either income or occupation at a point in time, that is the single-year approach, for either parent/children can lead to misleading results.

Table 1: Summary Statistics

	Primary Parent	
	Mean	Median
Gender (1=Female)	0.424	0
Age	67	67
Pre-tax income (age 40)	43,514	39,365
Wages and salary (age 40)	37,153	35,260
Lifetime income	78,505	67,984
Lifetime wages	65,595	58,242
	Child	
	Mean	Median
Gender (1=Female)	0.49	0
Age	39	39
Pre-tax income (age 40)	65,692	54,483
Wages and salary (age 40)	55,489	48,759
Lifetime income	114,507	97,723
Lifetime wages	99,600	87,385

Note: The table reports the summary statistics of our linked sample. All income and wages are in 2012 dollars.

2.2 Stylized facts

The left panel in Figure 1 shows a positive relationship between the income rank of parents and children, confirming intergenerational persistence of income in Australia. However, the degree of persistence is relatively low compared to the U.S. and more similar to countries such as Denmark and Norway. The rank–rank slope of parent's income on child's income is 0.115. This finding is similar to Deutscher (2020) and Deutscher and Mazumder (2020).

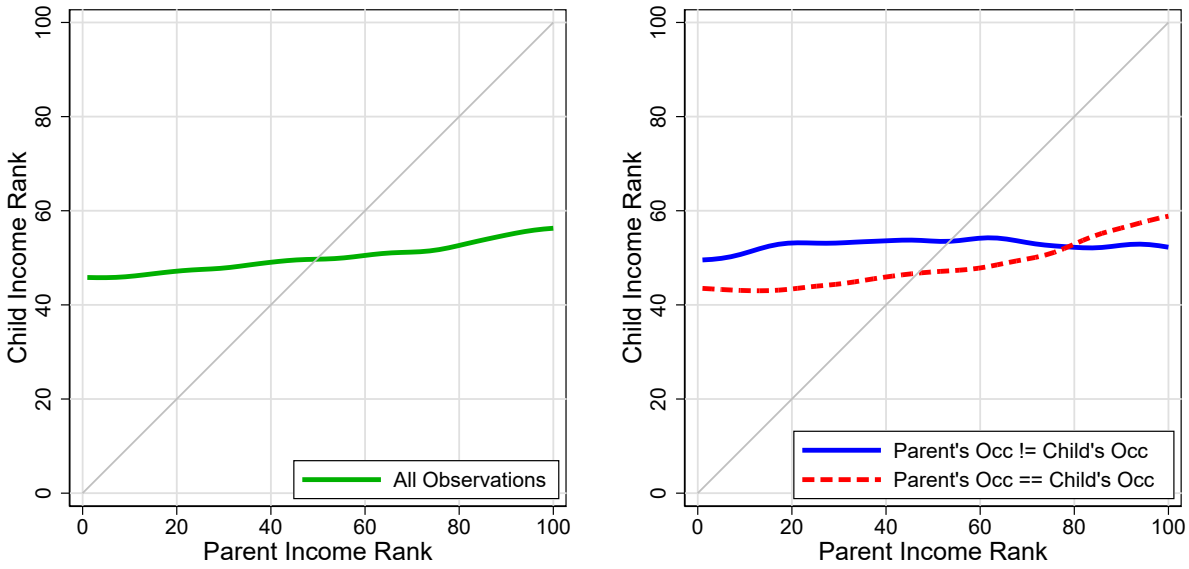

Figure 1: Intergenerational mobility in Australia

The right panel of Figure 1 shows how intergenerational mobility varies with occupational choices. We distinguish between two broad occupational groups—cognitive and non-cognitive—as defined by Acemoglu and Autor (2011).[8] Children are classified as *occupation-switchers* (solid blue line) if they depart from their parent's lifetime occupation, and as *occupation-followers* (dotted red line) if they remain in it. The figure indicates that switchers into or out of cognitive occupations experience markedly lower income persistence, suggesting that occupational choice is an important mediator of intergenerational income transmission, which we analyze in the next section.

3 Mediation analysis

A standard measure of intergenerational mobility of income is obtained by estimating the following equation:

$$y_i^c = \beta_0 + \beta_y y_i^p + \beta_x X_i^c + \epsilon_{y,i}, \tag{1}$$

where child's income rank y_i^c is the dependent variable and the independent variable y_i^p is parent's income rank. X_i^c include control variables such as child's gender and age. The coefficient β_y is the rank-rank slope that measures intergenerational persistence of income, and $(1 - \beta_y)$ captures intergenerational income mobility (IGM). What are the key factors that impact the child's income rank, both directly and indirectly? We examine this in our analysis.

[8] See Appendix Table A.2.

3.1 Decomposition and multilevel mediation analysis

How do the child's occupation (e.g., cognitive, routine, and manual) and education, neighbourhood effects, and the parent's cognitive occupation impact the persistence of income across generations? We allow each of the above factors to affect the child's lifetime earnings directly and also indirectly where the independent variable impacts the mediating factor which then impacts the dependent variable. The structure of our mediation analysis follows logically from the life-cycle timing of human capital development as illustrated in Figure 2 . We allow factors that are determined early

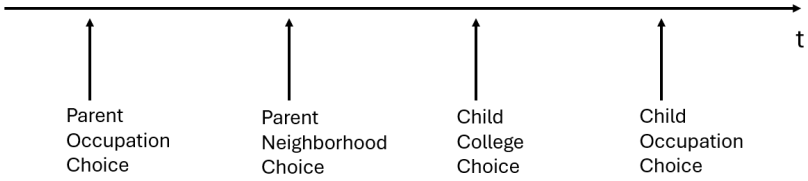

Figure 2: Life-cycle timing

in life (such as neighbourhood and occupation choice of the parent) to impact choices made later in life (such as education and occupation choice of the child). We define neighbourhood effects as the average lifetime income of parents' neighbourhood (Statistical Area 4 in Australia) when the children are, on average, 15.5 years old, as a proxy for neighbourhood quality while growing up. [9] The Statistical Areas Level 4 (SA4) are geographical areas are the largest sub-State regions and are designed to represent labour markets within each State and Territory.[10].

Our analysis thereby allows us to decompose the intergenerational persistence of income into its drivers. The mediation approach is summarized in Figure 3 and it closely follows Bolt et al. (2021) and Gelbach (2016).

Baseline In the baseline analysis, we first estimate the direct effects of each of the four mediating factors along with the key independent variable, parental income rank (y_i^p) on child's income rank (y_i^c). The regression specification is given below:

$$y_i^c = \alpha_y y_i^p + \underbrace{\alpha_{cog}^c O_{cog,i}^c + \alpha_S S_i^c + \alpha_N N_i^p + \alpha_{cog}^p O_{cog,i}^p}_{\text{Four mediators}} + \alpha_X X_i^c + \epsilon_{y,i}, \tag{2}$$

[9] This is based on the fact that in our sample, we compute the parent's lifetime income between 1991-2001 and children in our sample are born between 1979-1982.

[10] In constructing SA4, the objective was to construct areas that reflect the highest degree of interconnectivity between the labour supply (where people live) and labour demand (where people work). The minimum population in an SA4 is 100,000 persons with some exceptions.

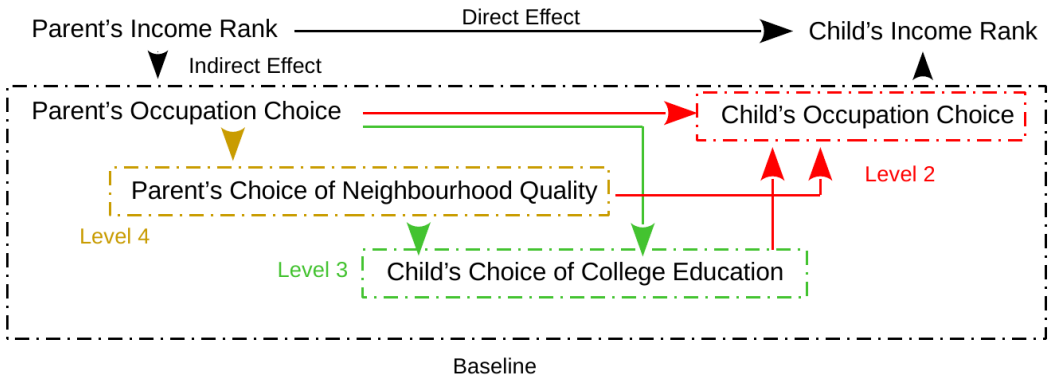

Figure 3: Overview of Mediation Approach

where $O^c_{cog,i}$ is a dummy variable indicating whether the lifetime occupation for child i is cognitive; S^c_i is a dummy variable indicating whether the child has obtained at least a bachelor's degree; N^p_i is the measure of the Neighbourhood quality across parents' locations (i.e. mean log lifetime income in parent's location); $O^p_{cog,i}$ is a dummy variable indicating whether the lifetime occupation for the primary parent of child i is cognitive; X^c_i is a set of controls that include child's gender and age.

Since our goal is to understand how intergenerational income persistence is related to parental income rank both directly and indirectly via mediating factors, we first totally differentiate Equation (2) with respect to y^p_i, which yields:

$$\frac{\mathrm{d}y^c_i}{\mathrm{d}y^p_i} = \alpha_y + \alpha^c_{cog}\frac{\mathrm{d}O^c_{cog,i}}{\mathrm{d}y^p_i} + \alpha_S\frac{\mathrm{d}S^c_i}{\mathrm{d}y^p_i} + \alpha_N\frac{\mathrm{d}N^p_i}{\mathrm{d}y^p_i} + \alpha^p_{cog}\frac{\mathrm{d}O^p_{cog,i}}{\mathrm{d}y^p_i} + \alpha_X\frac{\mathrm{d}X^c_i}{\mathrm{d}y^p_i} \tag{3}$$

where α_y represents the parent-child income rank relationship, adjusted for the different effects of the mediators thereby capturing the partial effect of parent's income rank on child's income rank. If the mediation effects are strong, one would expect that the difference between β_y and α_y would be larger, where β_y is the rank-rank slope in Equation (1).

To estimate other terms in equation (3), we postulate a linear relationship between each of the factors and parental income, y^p_i. For example, to estimate $\dfrac{\mathrm{d}O^c_{cog,i}}{\mathrm{d}y^p_i}$, we assume the following relationship

$$O^c_{cog,i} = \kappa^c_{cog}y^p_i + \kappa^{c,X}_{cog}X^c_i + u_{cog,i}. \tag{4}$$

Thus the total impact of parental income on child's income via child's cognitive occupation is given by $\dfrac{\mathrm{d}y^c_i}{\mathrm{d}O^c_{cog,i}}\dfrac{\mathrm{d}O^c_{cog,i}}{\mathrm{d}y^p_i} = \alpha^c_{cog}\kappa^c_{cog}$. However, note that according to Equation (1), the intergenerational rank-rank slope equals to β_y. Thus, at baseline level, the fraction of intergenerational income

persistence explained by child's choice of cognitive occupation is:

$$\frac{\alpha^c_{cog}\kappa^c_{cog}}{\beta_y}. \tag{5}$$

All other terms of equation (3) are computed in a similar manner. The baseline analysis therefore only considers the direct effects of the mediating factors.

Level 2 - Mediation via child's cognitive occupation choice Child's choice of cognitive occupation $O^c_{cog,i}$ can be affected by their college choice S^c_i, neighbourhood income level during the time when they were growing up N^p_i and parental choice of occupation $O^p_{cog,i}$. To estimate how these mediators affect the IGM both directly and indirectly via child's occupation choice, we first estimate the parameters of an equation which relates child's occupation choice to parental income rank and other mediators:

$$O^c_{cog,i} = \delta_y y^p_i + \delta_S S^c_i + \delta_N N^p_i + \delta^p_{cog} O^p_{cog,i} + \delta_X X^c_i + \epsilon^c_{cog,i} \tag{6}$$

Now allowing $O^c_{cog,i}$ to depend on the other covariates, total differentiation of equation (6) with respect to y^p_i yields:

$$\begin{aligned}\frac{\mathrm{d}y^c_i}{\mathrm{d}y^p_i} =& \alpha_y + \alpha^c_{cog}(\delta_y + \frac{\partial O^c_{cog,i}}{\partial S^c_i}\frac{\mathrm{d}S^c_i}{\mathrm{d}y^p_i} + \frac{\partial O^c_{cog,i}}{\partial N^p_i}\frac{\mathrm{d}N^p_i}{\mathrm{d}y^p_i} + \frac{\partial O^c_{cog,i}}{\partial O^p_{cog,i}}\frac{\mathrm{d}O^p_{cog,i}}{\mathrm{d}y^p_i} + \frac{\partial O^c_{cog,i}}{\partial X^c_i}\frac{\mathrm{d}X^c_i}{\mathrm{d}y^p_i}) + \\ & \alpha_S\frac{\mathrm{d}S^c_i}{\mathrm{d}y^p_i} + \alpha_N\frac{\mathrm{d}N^p_i}{\mathrm{d}y^p_i} + \alpha^p_{cog}\frac{\mathrm{d}O^p_{cog,i}}{\mathrm{d}y^p_i} + \alpha_X\frac{\mathrm{d}X^c_i}{\mathrm{d}y^p_i}\end{aligned} \tag{7}$$

Equation (6) therefore will imply additional indirect effects for the mediating factors. To see this, consider the choice of college education as an example. At level 2, the fraction of IGM explained by college choice is:

$$(\underbrace{\alpha_S\kappa_S}_{\text{direct effect}} + \underbrace{\alpha^c_{cog}\delta_S\kappa_S}_{\text{indirect effect via cognitive occupation}})/\beta_y \tag{8}$$

The direct effect of child's college choice on income rank is the same as in the baseline analysis. However, the indirect effect comes equation (6) which now postulates that child's college choice impacts their occupation choice, $\frac{\partial O^c_{cog,i}}{\partial S^c_i}$. We can obtain the fraction of intergenerational persistence of income explained by neighbourhood quality and parental occupation choice with similar calculations. We can then decompose the fraction of IGM explained by child's occupation choice into two components: a part that can be mediated by other factors, $\frac{\kappa^c_{cog}-\delta_y}{\kappa^c_{cog}}\frac{\alpha^c_{cog}\kappa^c_{cog}}{\beta_y}$, and the remaining part $\frac{\delta_y}{\kappa^c_{cog}}\frac{\alpha^c_{cog}\kappa^c_{cog}}{\beta_y}$.

Level 3 - Mediation via child's cognitive occupation choice and child's college education choice Here we allow child's education choice S_i^c to be impacted by neighbourhood income level N_i^p and parental occupation choice $O_{cog,i}^p$ via the following relationship

$$S_i^c = \gamma_y y_i^p + \gamma_N N_i^p + \gamma_{cog}^p O_{cog,i}^p + \gamma_X X_i^c + \epsilon_{S,i} \tag{9}$$

The total differentiation of Equation (9) with respect to y_i^p yields:

$$\frac{\mathrm{d}S_i^c}{\mathrm{d}y_i^p} = \gamma_y + \gamma_N \frac{\mathrm{d}N_i^p}{\mathrm{d}y_i^p} + \gamma_{cog}^p \frac{\mathrm{d}O_{cog,i}^p}{\mathrm{d}y_i^p} + \gamma_X \frac{\mathrm{d}X_i^c}{\mathrm{d}y_i^p} \tag{10}$$

This level of mediation considers the indirect effect of earlier life decisions on the child's occupation and college education choices. For example, at level 3, the fraction of intergenerational rank-rank slope explained by the Neighbourhood income level :

$$[\ \underbrace{\alpha_N \kappa_N}_{\substack{\text{direct effect of neighbourhood} \\ \text{quality on child's income}}} + \underbrace{\alpha_{cog}^c \delta_N \kappa_N}_{\substack{\text{indirect effect of neighbourhood} \\ \text{quality via child's occupation choice}}} + \underbrace{\gamma_N(\alpha_S + \alpha_{cog}^c \delta_S)\kappa_N}_{\substack{\text{indirect effect of neighbourhood quality} \\ \text{via child's college education choice}}}\ ]/\beta_y \tag{11}$$

where κ_N is a regression coefficient of parental income rank y_i^p on parental neighbourhood choice N_i^p, similar to the form in Equation (4).

The fraction of IGM that is explained by child's college education choice is split into a part mediated by neighbourhood quality and parental occupation choice, $\frac{\kappa_S - \gamma_y}{\kappa_S} \frac{\alpha_S \kappa_S}{\beta_y}$, and the remaining part $\frac{\gamma_y}{\kappa_S} \frac{\alpha_S \kappa_S}{\beta_y}$.

Level 4 - Mediation via child's cognitive occupation choice, child's college education choice and neighbourhood quality Finally, we also allow for neighbourhood income N_i^p to be affected by parental occupation choice $O_{cog,i}^p$:

$$N_i^p = \lambda_y y_i^p + \lambda_{cog}^p O_{cog,i}^p + \lambda_X X_i^c + \epsilon_{N,i} \tag{12}$$

Similarly, the total differentiation of Equation (12) with respect to y_i^p yields:

$$\frac{\mathrm{d}N_i^p}{\mathrm{d}y_i^p} = \lambda_y + \lambda_{cog}^p \frac{\mathrm{d}O_{cog,i}^p}{\mathrm{d}y_i^p} + \lambda_X \frac{\mathrm{d}X_i^c}{\mathrm{d}y_i^p} \tag{13}$$

Substituting Equation (13) into (3), we can obtain the share of IGM explained by parental occupation choice:

$$\{\underbrace{\alpha^p_{cog}\kappa^p_{cog}}_{\substack{\text{direct effect of parent's}\\ \text{cognitive occupation on child's income}}} + \underbrace{\alpha^c_{cog}\delta^p_{cog}\kappa^p_{cog}}_{\substack{\text{indirect effect of parent's cognitive occupation}\\ \text{via child's occupation choice}}} + \underbrace{\gamma^p_{cog}(\alpha_S+\alpha^c_{cog}\delta_S)\kappa^p_{cog}}_{\substack{\text{indirect effect of parent's cognitive occupation}\\ \text{via child's college education choice}}}$$
$$+[\underbrace{\underbrace{\alpha_N}_{\substack{\text{direct effect of neighbourhood}\\ \text{quality on child's income}}} + \underbrace{\alpha^c_{cog}\delta_N}_{\substack{\text{indirect effect of neighbourhood}\\ \text{quality via child's occupation}}} + \underbrace{(\alpha_S+\alpha^c_{cog}\delta_S)\gamma_N}_{\substack{\text{indirect effect of neighbourhood}\\ \text{quality via child's college education}}}}_{\substack{\text{indirect effect of parent's cognitive occupation}\\ \text{via neighbourhood quality}}}]\lambda^p_{cog}\kappa^p_{cog}\}/\beta_y \tag{14}$$

where κ^p_{cog} is a regression coefficient of parental income rank y^p_i on parental occupation choice $O^p_{cog,i}$, similar to the form in Equation (4). Equation (14) captures how parental occupation choice affects child's lifetime income directly and indirectly through child's occupation and college education choice and neighbourhood quality. The fraction of IGM explained by parental neighbourhood quality choice is partially mediated by parental occupation choice, $\frac{\kappa^p_{cog}-\lambda_y}{\kappa^p_{cog}}\frac{\alpha^p_{cog}\kappa^p_{cog}}{\beta_y}$.

3.2 Full-sample results

The results of our multilevel mediation analysis are reported in Table 2. Overall, the factors we consider - child's occupation choice, college choice, parent's neighbourhood and occupation choice - can explain 38.2 % of the slope in parent-child income rank. The baseline column decomposes the intergenerational rank-rank slope by only considering the direct effects of each factor following equation (2). Our findings reveal that the child's cognitive occupation explains the largest fraction of rank-rank slope, accounting for 25.9%.[11] Furthermore, we find that parental cognitive occupation choice has a negative impact on child's lifetime income once we control for parental income, child's choice of cognitive occupation and college and parent's choice of neighbourhood quality. Consequently, considering the direct effects alone, we do not find any evidence that parental choice of cognitive occupations transmits an advantage to the child's income rank beyond what is attributed to other mediators outlined in Table 2.

The second column of Table 2 illustrates the extent to which the fraction of the rank-rank slope attributed to the child's occupation choice is influenced by other mediators, including col-

[11]For example, the role of child's cognitive occupation under the baseline is derived by applying equation 5, which uses the relevant information from Table 3, column (1) and Table A.3, columns (1) and (2) in the appendix. Note the estimates have been rounded to 3 decimal places but the mediation analysis results are calculated using estimates without any rounding.

lege choice, neighbourhood quality and parent's cognitive occupation. After accounting for this mediation, the proportion of the intergenerational rank-rank slope explained by the child's occupation reduces to 9.9%, revealing the indirect effects of other mediators, given by $\frac{\delta_y}{\kappa^c_{cog}}\frac{\alpha^c_{cog}\kappa^c_{cog}}{\beta_y}$. At this level, without allowing for how parental background impact schooling choice, choice of going to college emerges to be the most significant factor explaining child's cognitive occupation.

At Level 3, we consider how the impact of college choice is itself influenced by parental decisions regarding neighbourhood and occupation. Our findings suggest that the impact of college choice on intergenerational mobility is largely explained by parental occupation and neighbourhood choice, resulting in a reduction (by almost half compared to Level 2) of college's contribution to 9.6%, while the contribution of neighbourhood quality and parental cognitive occupation increases to 8.8% and 9.9% respectively. Particularly prominent is the jump in the importance of parental cognitive occupation, from nearly zero in Level 2 to comparable to child's own cognitive occupation in Level 3, once parental occupation is allowed to influence child's college decision.

Moving to our final mediation stage (Level 4), we extend our analysis to consider how measures of neighbourhood quality are mediated by parental cognitive occupation choice. Both the child's and parent's choice of cognitive occupation emerge as significant factors affecting the intergenerational rank-rank slope, with their relative contributions amounting to 9.9% and 10.9%, respectively.

Table 3 presents the results for the mediation analysis at various levels of the analysis. Column (1) of Table 3 presents the estimates based on equation (2) where child's income rank is influenced by the parent's income rank and only the direct effects of the four mediators. Consistent with the baseline column of Table 2, in terms of direct effects of the mediators, child's own cognitive occupation has the largest direct impact on child's income rank, while parent's cognitive occupation has a negative effect conditional on parent's income rank.

Column (2) of Table 3 corresponds to the Level 2 results presented in Table 2 where child's cognitive occupation is influenced by child's college decision, neighbourhood quality and parent's cognitive occupation. This clearly shows that child's college decision is a major influence on the child's choice of cognitive occupation, while parent's cognitive occupation and neighbourhood quality also play a sizable role.

Results corresponding to Level 3 of the multi-level mediation analysis of Table 2 are presented in column (3) of Table 3. At this level, parent's cognitive occupation and neighbourhood quality endogenously influence college decision of the child. At this level 3 of mediation analysis, pivotal role of parent's cognitive occupation emerges in Table 2, and is consistent with the positive impact of parental cognitive occupation on child's college decision in Table 2.

Finally, column (4) of Table 3 corresponds to the Level 4 results presented in Table 2 where Neighbourhood quality is influenced by both parent's income and occupation. At all levels of the

Table 2: Multilevel Mediation Analysis

	Baseline	Level 2	Level 3	Level 4
Cognitive occ. (child)	25.9	9.9	9.9	9.9
	[23, 29.3]	[7.3, 12.9]	[7.3, 12.9]	[7.3, 12.9]
College	12.0	20.5	9.6	9.6
	[10.4, 13.6]	[18.2, 23.1]	[7.6, 11.5]	[7.6, 11.5]
Neighborhood quality	4.7	7.3	8.8	7.7
	[2.8, 6.6]	[5.2, 9.4]	[6.6, 11.0]	[5.8, 9.8]
Cognitive occ. (parent)	-4.4	0.5	9.9	10.9
	[-7.9, -0.09]	[-2.8, 4.3]	[6.4, 14.1]	[7.5, 15.2]
Total (Net)	38.2	38.2	38.2	38.2
	[33.4, 44.1]	[33.4, 44.1]	[33.4, 44.1]	[33.4, 44.1]

Notes: We compute standard errors by bootstrapping the same number of observations with replacement. We apply the multi-level mediation procedure to the simulated data in each replication and record the mediation effect for 250 repetitions. The 95% confidence intervals are in parenthesis. All numbers are reported in %.

Table 3: Determinants of Child's Income and Mediators

	(1)	(2)	(3)	(4)
	Income rank of child	Cognitive occ. (child)	College	Neighborhood quality
Income rank of parent	0.071***	0.001***	0.001***	0.001***
	(0.006)	(0.000)	(0.000)	(0.000)
Neighborhood quality	4.114***	0.163***	0.101***	
	(0.790)	(0.013)	(0.014)	
College	7.835***	0.397***		
	(0.355)	(0.006)		
Cognitive occ. (child)	13.923***			
	(0.335)			
Cognitive occ. (parent)	-0.890***	0.071***	0.142***	0.027***
	(0.332)	(0.006)	(0.006)	(0.002)
Child gender	-20.021***	0.001	0.121***	-0.002
	(0.294)	(0.005)	(0.005)	(0.002)
Child age	0.062**	0.004***	0.008***	0.004***
	(0.031)	(0.001)	(0.001)	(0.000)
Constant	-0.279	-1.725***	-1.183***	11.103***
	(8.824)	(0.148)	(0.155)	(0.006)
N	32,658	32,658	32,658	32,658
Adjusted R^2	0.214	0.184	0.061	0.060

Notes: The table reports the coefficients with standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

mediation analysis, child's gender and parent's age at birth are included as controls.

The mediation analysis establishes the importance of allowing for a rich multi-level structure. Once we allow for parent's cognitive occupation to endogenously influence child's choice of cognitive occupation, and more importantly, child's college decision, the importance of parent's cognitive occupation in explaining intergenerational persistence of income increases substantially– a pattern that is hidden in the baseline case where all the mediators are treated as exogenous factors and only have a direct impact on rank-rank slope. This points towards the role of parent's cognitive occupation in influencing child's labour market outcomes via many possible mechanisms highlighted in the literature.

Possible mechanisms: Our key finding is that parental cognitive occupation plays a pivotal role in explaining intergenerational earnings persistence once it is allowed to endogenously shape children's college decisions and occupational choices. This highlights the importance of mechanisms beyond education alone in driving persistence of inequality. A large body of work points to the intergenerational transmission of preferences, values, and occupational tastes as a key channel. Doepke and Zilibotti (2008) argue that traits such as patience and work ethic—transmitted from parents to children—were instrumental for social mobility during the Industrial Revolution, enabling the middle class to take advantage of new entrepreneurial opportunities. Doepke and Zilibotti (2017) show that parenting styles (authoritarian, authoritative, permissive) emerge from socioeconomic context and parental values, shaping children's educational and labour market trajectories. In their analysis, cross-country evidence from the World Values Survey suggests that Australia exhibits a balanced mix of parenting styles, contrasting with the more permissive approach in Sweden and the authoritative style in the U.S.

Another mechanism emphasized in recent research is access to parental networks and occupation-specific social capital. Such networks lower search costs and entry barriers into occupations pursued by the parents. Lo Bello and Morchio (2022), using a dynamic model of occupational choice and search frictions in the UK, highlight the roles of comparative advantage, parental preferences, and networks, finding that networks alone account for nearly 80% of occupational persistence—expediting job placement but often at the cost of lower wages. Consistent with this, Ventura (2023) shows that Dutch children are twice as likely to enter medical fields if a parent is employed there, with persistence strongest among high-income families. Leveraging medical school lotteries, she demonstrates that dynastic doctors earn substantially higher returns than their non-dynastic counterparts, underscoring the value of inherited networks.

Finally, administrative evidence highlights the role of family background in shaping early career opportunities independent of skill. Forsberg et al. (2024) use Swedish employer–employee matched data to show that family background explains around 70% of the firm pay premium at age 25.

Similarly, Kramarz and Skans (2014) find that parental workplace ties significantly increase the probability that children obtain their first stable job in the same firm.

Moreover, using a structural model and PSID data from the U.S., Gayle, Golan and Soytas (2015) find that most of the observed intergenerational correlation in earnings is explained through household specialization, parental time investments, and labour-market returns. Their results highlight that persistence arises less from education than from the way family background shapes both human-capital accumulation and labour-market opportunities. This is consistent with our finding that once parental cognitive occupation is accounted for, the marginal role of education diminishes.

While we cannot directly determine the mechanism, in the following section we use the rich regional information in our data to establish spatial variation in the importance of parent's cognitive occupation in explaining intergenerational mobility. This analysis can potentially provide some suggestive evidence towards various economic mechanisms.

4 Spatial analysis of the role of parent's occupation

Administrative tax returns data from the ATO contains information about the child's location at the SA4 level. We use this rich spatial information in the data to conduct the mediation analysis across various subsamples differentiated by regional importance of the knowledge economy. In particular, we consider three cases: (a) locations that have experienced larger growth in cognitive occupation share from the parent's to the child's generation; (b) locations that have a lower presence of mining and (c) locations that have a major university.[12] We show that across various subsamples our key insight from Section 3 holds: parent's cognitive occupation plays a substantially larger role in explaining the rank-rank slope once child's college decision is treated as an endogenous mediator. Moreover, this role of parent's cognitive occupation is amplified in locations with a prominent presence of the knowledge economy.

First, we employ multilevel mediation analysis across regions categorized by cognitive occupation share changes (between parent's and child's generation) above 75 percentiles and below the 25 percentiles. The comprehensive results of our mediation analysis are presented in Table 4. Our focus is on Level 3 of the mediation analysis when child's cognitive occupation and college decisions are treated as endogenous. Compared to the baseline and Level 2 mediation analysis, the role played by parent's cognitive occupation substantially increases in Level 3. This is true in

[12]For the mining share, we compute the proportion of individuals aged 30–34 employed in the mining sector (1 digit level) relative to total employment using 2011 Census data from the Australian Bureau of Statistics which aligns with the children's sample. Similarly, we compute Go8 and Non-Go8 by constructing the employment share in the tertiary education sectors (2 digit level) relative to total employment using 2011 Census data from the Australian Bureau of Statistics. The sample is described in Table A.4.

both panels of Table 4. This key insight is stronger in the lower panel, i.e. in regions that have experienced a larger rise in the employment shares in cognitive occupations, potentially pointing towards a more meaningful role parent's cognitive occupational network play in such regions. Note however, in these regions the role of child's choice of cognitive occupation is diminished.

Table 4: Share of Rank-Rank slope explained (Δ Cog share)

	Baseline	Level 2	Level 3	Level 4
	Δ Cog share: Low			
Cognitive occ. (child)	28.2	12.0	12.0	12.0
	[22.1, 33.8]	[7.2, 19.1]	[7.2, 19.1]	[7.2, 19.1]
College	12.0	21.0	9.1	9.1
	[0.084,0.183]	[0.152,0.317]	[0.038,0.160]	[0.038,0.160]
Neighborhood quality	3.8	6.1	7.6	7.0
	[-0.4, 8.1]	[1.4, 11.5]	[2.9, 13.8]	[2.6, 12.7]
Cognitive occ. (parent)	-5.3	-0.5	9.9	10.5
	[-13.0, 2.2]	[-8.3, 7.1]	[3.1, 17.5]	[3.5, 18.3]
Total	38.7	38.7	38.7	38.7
	[27.7, 53.7]	[27.7, 53.7]	[27.7, 53.7]	[27.7, 53.7]
	Δ Cog share: High			
Cognitive occ. (child)	24.1	7.2	7.2	7.2
	[18.4, 32.9]	[2.3, 13.8]	[2.3, 13.8]	[2.3, 13.8]
College	12.6	20.0	7.6	7.6
	[8.9, 17.9]	[14.3, 27.0]	[2.6, 13.0]	[2.6, 13.0]
Neighborhood quality	6.4	9.6	10.1	8.6
	[1.9, 11.0]	[5.1, 15.7]	[5.2, 15.3]	[4.5, 13.0]
Cognitive occ. (parent)	-5.0	1.3	13.1	14.7
	[-12.5, 2.2]	[-6.0, 9.5]	[5.7, 24.0]	[7.3, 25.6]
Total (Net)	38.1	38.1	38.1	38.1
	[26.8, 52.5]	[26.8, 52.5]	[26.8, 52.5]	[26.8, 52.5]

Notes: We compute standard errors by bootstrapping the same number of observations with replacement. We apply the multi-level mediation procedure to the simulated data in each replication and record the mediation effect for 250 repetitions. The 95% confidence intervals are in parenthesis. All numbers are reported in %.

Next, we examine the relationship between regional production specialization and the relative importance of mediators. Regional variations in commodity and education export volume create differences in labour demand. These demand-driven forces impact relative incomes across occupations, thereby influencing the role of occupation choice in shaping intergenerational mobility across regions. Table 5 presents a multilevel mediation analysis across regions categorized by employment share in the mining industry. Regions with high commodity export exposure require a higher employment share in the mining industry. The overall explanatory power of all mediators in mining-specialized regions is 7.5 percentage points lower than in regions with a lower mining share. Focusing again on the Level 3 of the mediation analysis, we notice the familiar pattern of a strikingly larger role played by parent's cognitive occupation once child's college and occupation are treated as endogenous. While this pattern holds in both the subsamples, it's more prominent in the regions with low mining share i.e. in regions where skill-intensive cognitive occupations dominate the labour market.

Table 5: Share of Rank-Rank slope explained (Mining Industry share)

	Baseline	Level 2	Level 3	Level 4
	Low Mining share			
Cognitive occ. (child)	26.3 [20.4, 35.1]	9.9 [4.5, 16.2]	9.9 [4.5, 16.2]	9.9 [4.5, 16.2]
College	10.0 [7.3, 14.0]	17.7 [13.9, 23.7]	7.4 [3.6, 11.9]	7.4 [3.6, 11.9]
Neighborhood quality	5.3 [1.7, 9.8]	7.2 [3.5, 12.3]	7.0 [3.2, 12.2]	5.6 [2.6, 9.9]
Cognitive occ. (parent)	-3.2 [-10.8, 3.7]	3.4 [-4.3, 11.1]	13.9 [6.2, 23.7]	15.3 [7,3, 25.1]
Total	38.3 [28.6, 52.6]	38.3 [28.6, 52.6]	38.3 [28.6, 52.6]	38.3 [28.6, 52.6]
	High Mining share			
Cognitive occ. (child)	25.5 [18.6, 35.0]	6.6 [0.3, 13.1]	6.6 [0.3, 13.1]	6.6 [0.3, 13.1]
College	15.3 [10.1, 21.9]	25.3 [17. 5, 35.2]	12.6 [5.8, 21.0]	12.6 [5.8, 21.0]
Neighborhood quality	-3.1 [-9.2, 2.2]	0.2 [-5.9, 5.5]	1.7 [-4.5, 7.3]	1.6 [-4.4, 7.0]
Cognitive occ. (parent)	-6.9 [-16.5, 1.5]	-1.3 [-10.0, 7.7]	9.9 [1.6, 20.2]	10.0 [1.6, 20.3]
Total (Net)	30.8 [17.6, 48.2]	30.8 [17.6, 48.2]	30.8 [17.6, 48.2]	30.8 [17.6, 48.2]

Notes: We compute standard errors by bootstrapping the same number of observations with replacement. We apply the multi-level mediation procedure to the simulated data in each replication and record the mediation effect for 250 repetitions. The 95% confidence intervals are in parenthesis. All numbers are reported in %.

Table 6 presents multilevel mediation results across regions categorized by whether they have a university belonging to the Group of Eight (Go8). Regions with a Go8 university are generally high-income areas. In these regions, the proportion of the rank-rank slope explained by all medi-

ators is 49.1%, which is significantly higher than in regions without a Go8 university. When the direct effect of factors is broken down into the indirect effect by other early-life mediators, as shown in Level 4, parental occupation choice significantly contributes to the intergenerational rank-rank slope in Go8 regions, accounting for 55% of the total contribution by mediators. This is understandable, as high-income regions typically have the greatest exposure to technological change, leading to a larger income gap between cognitive and non-cognitive occupations. Consequently, parental choice of cognitive occupation plays a more significant role in explaining the intergenerational rank-rank slope. Interestingly, while parent's cognitive occupation plays a much larger role in explaining IGM in larger urban areas (characterized by the presence of a Go8 university), child's own cognitive occupation plays a similar role compared to non-Go8 areas.

Table 6: Share of Rank-Rank slope explained (Go8)

	Baseline	Level 2	Level 3	Level 4
	Non-Go8			
Cognitive occ. (child)	24.3	10.1	10.1	10.1
	[21.3,27.8]	[7.7, 12.6]	[7.7, 12.6]	[7.7, 12.6]
College	10.7	18.5	9.0	9.0
	[9.1, 12.6]	[15.9, 21.7]	[6.9, 11.5]	[6.9, 11.5]
Neighborhood quality	4.6	6.9	8.2	7.4
	[2.8, 6.6]	[5.0, 9.1]	[6.1, 10.6]	[5.4, 9.6]
Cognitive occ. (parent)	-4.7	-0.6	7.6	8.4
	[-7.6, -1.2]	[-3.4, 3.0]	[4.4, 11.5]	[5.3, 12.3]
Total (Net)	34.9	34.9	34.9	34.9
	[30.1, 40.8]	[30.1, 40.8]	[30.1, 40.8]	[30.1, 40.8]
	Go8			
Cognitive occ. (child)	34.4	8.6	8.6	8.6
	[19.8, 64.4]	[-3.8, 25.4]	[-3.8, 25.4]	[-3.8, 25.4]
College	19.4	30.5	13.8	13.8
	[11.1, 37.7]	[17.5, 59.6]	[1.2, 36.7]	[1.2, 36.7]
Neighborhood quality	-0.8	0.7	-0.7	-0.6
	[-10.1, 10.9]	[-9.3, 13.5]	[-11.7, 11.7]	[-9.5, 9.2]
Cognitive occ. (parent)	-4.0	9.3	27.3	27.2
	[-25.8, 15.2]	[-9.7, 36.7]	[9.4, 65.7]	[9.6, 67.2]
Total (Net)	49.1	49.1	49.1	49.1
	[24.3, 106.9]	[24.3, 106.9]	[24.3, 106.9]	[24.3, 106.9]

Notes: We compute standard errors by bootstrapping the same number of observations with replacement. We apply the multi-level mediation procedure to the simulated data in each replication and record the mediation effect for 250 repetitions. The 95% confidence intervals are in parenthesis. All numbers are reported in %.

Possible mechanisms In our empirical results, we find that the role of parental cognitive occupation in explaining intergenerational income persistence is significantly larger in regions characterized by (a) high growth in cognitive occupations across generations, (b) a low mining share,

and (c) large urban centers that have prominent Go8 universities. In Australia, where population is concentrated in a few urban areas, these classifications often overlap. The implication is that parental occupation matters most in highly educated urban regions with strong growth in cognitive jobs.

Conceptually, the value of parental occupation could differ across regions. In semi-urban or rural areas, occupational networks may help children access scarce cognitive jobs. In contrast, in urban, high-growth, high-education regions, such networks may be especially valuable after entry, by supporting career progression and amplifying returns through thicker labour markets. Our data indicate the latter dominates: parental cognitive occupations have greater impact in urban areas.

This finding aligns with evidence that cities shape occupational choice and labour-market outcomes by improving job matching and expanding opportunities. Papageorgiou (2022) shows that larger cities provide more occupational options and higher wages through better matches. Moretti and Yi (2024) similarly find that thick labour markets improve the quality of worker–firm matches, particularly for college graduates and in industries where human capital is specialized, consistent with matching externalities and labour pooling as mechanisms behind agglomeration economies. Our findings indicate that availability of greater opportunities for cognitive jobs and parental background in cognitive jobs complement each other contributing towards persistence of inequality.

5 Conclusion

In this paper, we use intergenerationally linked tax returns data from Australia with detailed information on income, occupation, location, and other demographic characteristics. Multi-level mediation analysis, modeled following a life cycle pattern of endogenous decisions, allows us to uncover how cognitive occupation of parents play a prominent role in explaining intergenerational mobility of income. This is especially so once child's own cognitive occupation and college choices are modeled as endogenous decisions mediated by parental occupation. We document that there is significant spatial variation in the role parental occupation plays. Cities, or regions with high levels or growth in cognitive occupations, are examples of local labour markets where parent's cognitive occupation plays an even larger role in explaining intergenerational persistence of income.

Our analysis has a number of policy implications. Education is traditionally viewed as the precursor of social mobility, and it undoubtedly plays a very important role in our analysis. But we show that it is important to acknowledge the influence of parental background on the choice of both occupation and education of children if we were to understand the influence of circumstances at birth in shaping adult labour market outcomes. Also, cities with their thicker

labour markets and higher returns for cognitive occupations definitely bring more opportunities, but those opportunities are not necessarily equally shared among children with varied backgrounds. We leave structural analysis of a quantitative spatial model to understand the role cities play in the joint determination of intergenerational income and occupation mobility for future research.

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Online Appendix

A Additional tables

Table A.1 reports how different sample selection criteria affect our sample.

Table A.1: Sample Selection Criteria

	Observations	
Selection Criteria	Excluded	Remaining
Total number of obs		128,978
Linked to parents data	77,280	51,698
Nonmissing parent income	1,015	50,683
Nonmissing child income	4,941	45,742
Nonmissing child life-time occupation	2,111	43,631
Nonmissing parent life-time occupation	10,192	33,439
Nonmissing spatial mediation analysis characteristics	781	32,658
Final Sample		32,658

The occupation classification followed in our analysis is given in Table A.2 below

Table A.2: Occupation Classification

		Occupation
Cognitive	Managers	Chief Executives, General Managers and Legislators
		Farmers and Farm Managers
		Specialist Managers
		Hospitality, Retail and Service Managers
	Professionals	Arts and Media Professionals
		Business, Human Resource and Marketing Professionals
		Design, Engineering, Science and Transport Professionals
		Education Professionals
		Health Professionals
		ICT Professionals
		Legal, Social and Welfare Professionals
	Technicians	Engineering, ICT and Science Technicians
Routine	Trades	Automotive and Engineering Trades Workers
		Construction Trades Workers
		Electrotechnology and Telecommunications Trades Workers
		Skilled Animal and Horticultural Workers
		Other Technicians and Trades Workers
	Clerical and Administrative	Office Managers and Program Administrators
		Personal Assistants and Secretaries
		General Clerical Workers
		Inquiry Clerks and Receptionists
		Numerical Clerks
		Clerical and Office Support Workers
		Other Clerical and Administrative Workers
	Sales	Sales Representatives and Agents
		Sales Assistants and Salespersons
		Sales Support Workers
	Machinery Operators	Machine and Stationary Plant Operators
		Mobile Plant Operators
		Road and Rail Drivers
		Storepersons
	Labourers	Construction and Mining Labourers
		Factory Process Workers
		Farm, Forestry and Garden Workers
		Other Labourers
Manual	Service Workers	Health and Welfare Support Workers
		Carers and Aides
		Hospitality Workers
		Protective Service Workers
		Sports and Personal Service Workers
	Non-Routine Labourers	Cleaners and Laundry Workers
		Food Preparation Assistants
		Food Trades Workers

Table A.3 reports the estimate of equations 1 and 4 with standard errors in parenthesis.

Table A.3: Estimate of rank-rank slope and parent's income on various mediators

	(1) Income rank of child	(2) Cognitive occ. (child)	(3) College	(4) Neighborhood quality	(5) Cognitive occ. (parent)
Income rank of parent	0.115***	0.002***	0.002***	0.001***	0.006***
	(0.006)	(0.000)	(.000)	(0.000)	(0.000)
Child gender	-18.404***	0.049***	0.121***	-0.002	-0.001
	(0.310)	(0.005)	(0.005)	(0.002)	(0.005)
Child age	0.278***	0.009***	0.010***	0.005***	0.008***
	(0.032)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	45.333***	0.037	-0.092***	11.098***	-0.180***
	(0.945)	(0.016)	(0.015)	(0.006)	(0.014)
N	32,658	32,658	32,658	32,658	32,658
Adjusted R^2	0.119	0.029	0.041	0.056	0.126

The following table reports the sample size for the analysis in Section 4.

Table A.4: Sample Size

Group	**Sub-Group**	**Sample Size**
Full Sample		32658
Cognitive share changes	high	7886
	low	8249
Mining share	high	8107
	low	8773
Education	With Go8	4906
	Without Go8	27752

The following tables report the estimates underlying the spatial analysis in Section 4.

Table A.5: Determinants of Child Income and Mediators: Low vs. High Cognitive Share

	(1) Income rank of child	(2) Cognitive occ. (child)	(3) College	(4) Neighborhood quality
Panel A: Low Cognitive Share				
Income rank of parent	0.060***	0.001***	0.001***	0.001***
	(0.011)	(0.000)	(0.000)	(0.000)
Neighborhood quality	3.194*	0.140***	0.098***	
	(1.766)	(0.030)	(0.031)	
College	7.304***	0.407***		
	(0.756)	(0.012)		
Cognitive occ. (child)	13.603***			
	(0.688)			
Cognitive occ. (parent)	-0.965	0.065***	0.147***	0.017***
	(0.652)	(0.011)	(0.011)	(0.004)
Child gender	-21.518***	0.015	0.118***	0.001
	(0.569)	(0.010)	(0.010)	(0.004)
Child age	0.033	0.005***	0.007***	0.003***
	(0.063)	(0.001)	(0.001)	(0.000)
Constant	10.575	-1.548***	-1.183***	11.102***
	(19.730)	(0.332)	(0.344)	(0.012)
N	8,249	8,249	8,249	8,249
Adjusted R^2	0.220	0.182	0.063	0.050
Panel B: High Cognitive Share				
Income rank of parents	0.069***	0.001***	0.001***	0.001***
	(0.012)	(0.000)	(0.000)	(0.000)
Neighborhood quality	4.349***	0.149***	0.025	
	(1.401)	(0.023)	(0.025)	
College	8.519***	0.342***		
	(0.692)	(0.011)		
Cognitive occ. (child)	14.526***			
	(0.681)			
Cognitive occ. (carent)	-0.895	0.077***	0.157***	0.041***
	(0.679)	(0.012)	(0.012)	(0.006)
Child gender	-14.361***	-0.008	0.105***	-0.003
	(0.619)	(0.010)	(0.011)	(0.005)
Child age	0.018	0.003**	0.005***	0.005***
	(0.064)	(0.001)	(0.001)	(0.001)
Constant	-3.542	-1.414***	-0.164	11.104***
	(15.667)	(0.261)	(0.275)	(0.015)
N	7,886	7,886	7,886	7,886
Adjusted R^2	0.171	0.148	0.048	0.070

Notes: The table reports the coefficients with standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.6: Determinants of Child Income and Mediators: Low vs. High Mining Share

	(1) Income rank of child	(2) Cognitive occ. (child)	(3) College	(4) Neighborhood quality
Panel A: Low Mining Share				
Income rank of parent	0.066***	0.001***	0.001**	0.001***
	(0.011)	(0.000)	(0.000)	(0.000)
Neighborhood quality	4.713**	0.118***	-0.0133	
	(1.554)	(0.027)	(0.028)	
College	7.121***	0.379***		
	(0.657)	(0.0104)		
Cognitive occ. (child)	14.684***			
	(0.688)			
Cognitive occ. (parent)	-0.588	0.0821***	0.150***	0.0403***
	(0.647)	(0.011)	(0.012)	(0.005)
Child Gender	-17.670***	-0.025**	0.127***	-0.002
	(0.573)	(0.010)	(0.010)	(0.004)
Child Age	0.116*	0.003**	0.006***	0.004***
	(0.059)	(0.001)	(0.001)	(0.000)
Constant	-8.934	-1.139***	0.201	11.167***
	(17.406)	(0.303)	(0.316)	(0.0112)
N	8,773	8,773	8,773	8,773
Adjusted R^2	0.197	0.162	0.050	0.058
Panel B: High Mining Share				
Income rank of parent	0.056***	0.000**	0.001***	0.001***
	(0.012)	(0.000)	(0.000)	(0.000)
Neighborhood quality	-2.168	0.179***	0.079**	
	(1.832)	(0.030)	(0.031)	
College	8.384***	0.429***		
	(0.740)	(0.012)		
Cognitive occ. (child)	12.754***			
	(0.686)			
Cognitive occ. (parent)	-1.136	0.073***	0.133***	0.010**
	(0.675)	(0.011)	(0.011)	(0.004)
Child gender	-25.786***	0.008	0.137***	0.004
	(0.592)	(0.010)	(0.010)	(0.004)
Child age	-0.028	0.005***	0.010***	0.002***
	(0.0640)	(0.001)	(0.001)	(0.000)
Constant	79.319***	-1.938***	-1.017***	11.162***
	(20.560)	(0.338)	(0.346)	(0.012)
N	8,107	8,107	8,107	8,107
Adjusted R^2	0.245	0.197	0.067	0.047

Notes: The table reports the coefficients with standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.7: Determinants of Child Income and Mediators: Non-Go8 vs Go8

	(1) Income rank of child	(2) Cognitive occ. (Child)	(3) College	(4) Neighborhood
Panel A: Non-Go8				
Income rank of parent	0.078***	0.001***	0.001***	0.001***
	(0.006)	(0.000)	(0.000)	(0.000)
Neighborhood quality	4.471***	0.161***	0.091***	
	(0.864)	(0.015)	(0.015)	
College	7.560***	0.402***		
	(0.386)	(0.006)		
Cognitive occ. (child)	13.684***			
	(0.358)			
Cognitive occ. (parent)	-1.014***	0.064***	0.137***	0.021***
	(0.357)	(0.006)	(0.006)	(0.003)
Child gender	-21.247***	0.003	0.125***	-0.002
	(0.314)	(0.005)	(0.005)	(0.002)
Child age	0.067**	0.004***	0.007***	0.004***
	(0.033)	(0.001)	(0.001)	(0.000)
Constant	-4.285	-1.708***	-1.076***	11.108***
	(9.644)	(0.164)	(0.169)	(0.007)
Observations	27,752	27,752	27,752	27,752
Adj. R^2	0.225	0.180	0.059	0.053
Panel B: Go8				
Income rank of parent	0.031**	0.000	0.001***	0.001***
	(0.016)	(0.000)	(0.000)	(0.000)
Neighborhood quality	-0.354	0.048	-0.051	
	(1.992)	(0.032)	(0.035)	
College	8.426***	0.330***		
	(0.906)	(0.014)		
Cognitive occ. (child)	14.524***			
	(0.921)			
Cognitive occ. (parent)	-0.384	0.088***	0.132***	0.034***
	(0.884)	(0.015)	(0.015)	(0.006)
Child gender	-12.837***	-0.010	0.094***	-0.002
	(0.809)	(0.013)	(0.014)	(0.006)
Child age	-0.001	0.005***	0.009***	0.005***
	(0.089)	(0.001)	(0.001)	(0.001)
Constant	52.186**	-0.306	0.667*	11.148***
	(22.382)	(0.363)	(0.392)	(0.017)
Observations	4,906	4,906	4,906	4,906
Adj. R^2	0.145	0.141	0.041	0.061

Notes: The table reports the coefficients with standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.8: Estimate of rank-rank slope: Low vs. High Cognitive Share

	Income rank of child	Cognitive occ. (child)	College	Neighborhood quality	Cognitive occ. (parent)
Panel A: Low cognitive share					
Income rank of parent	0.098***	0.002***	0.002***	0.001***	0.005***
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Child gender	-19.814***	0.062***	0.117***	0.001	-0.006
	(0.596)	(0.010)	(0.010)	(0.004)	(0.010)
Child age	0.231***	0.010***	0.009***	0.003***	0.009***
	(0.065)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	44.629***	-0.053	-0.119***	11.099***	-0.197***
	(1.855)	(0.031)	(0.028)	(0.012)	(0.029)
N	8,249	8,249	8,249	8,249	8,249
Adjusted R^2	0.136	0.031	0.040	0.048	0.115
Panel B: High cognitive share					
Income rank of parent	0.112***	0.002***	0.002***	0.002***	0.006***
	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)
Child gender	-13.091***	0.027**	0.105***	-0.003	-0.003
	(0.657)	(0.011)	(0.011)	(0.005)	(0.010)
Child age	0.175**	0.006***	0.006***	0.005***	0.007***
	(0.068)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	49.424***	0.260***	0.093***	11.098***	-0.143***
	(2.008)	(0.034)	(0.033)	(0.015)	(0.029)
N	7,886	7,886	7,886	7,886	7,886
Adjusted R^2	0.065	0.018	0.026	0.063	0.144

Notes: The table reports the coefficients with standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.9: Estimate of rank-rank slope: Low vs. High Mining Share

	Income rank of child	Cognitive occ. (child)	College	Neighborhood quality	Cognitive occ. (parent)
Panel A: Low Mining Share					
Income rank of parent	0.106***	0.002***	0.001***	0.001***	0.006***
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Child gender	-16.472***	0.021*	0.125***	-0.002	-0.012
	(0.608)	(0.011)	(0.010)	(0.004)	(0.010)
Child age	0.272***	0.007***	0.006***	0.004***	0.006***
	(0.063)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	46.634***	0.181***	0.033	11.162***	-0.127
	(1.855)	(0.032)	(0.030)	(0.011)	(0.027)
N	8,773	8,773	8,773	8,773	8,773
Adjusted R^2	0.096	0.018	0.031	0.049	0.126
Panel B: High Mining Share					
Income rank of parent	0.081***	0.002***	0.001***	0.001***	0.005***
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Child gender	-23.750***	0.070***	0.139***	0.004	0.013
	(0.623)	(0.011)	(0.010)	(0.004)	(0.010)
Child age	0.185***	0.011***	0.011***	0.002***	0.010***
	(0.066)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	53.567***	-0.030	-0.170***	11.159***	-0.216***
	(1.932)	(0.032)	(0.028)	(0.012)	(0.029)
N	8,107	8,107	8,107	8,107	8,107
Adjusted R^2	0.168	0.027	0.049	0.046	0.105

Notes: The table reports the coefficients with standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.10: Estimate of rank-rank slope: Low vs High Mining Share

	Income rank of child	Cognitive ccc. (child)	College	Neighborhood quality	Cognitive occ. (parent)
Panel A: Low Mining Share					
Income rank of parent	0.106***	0.002***	0.001***	0.001***	0.006***
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Child gender	-16.472***	0.021*	0.125***	-0.002	-0.012
	(0.608)	(0.011)	(0.010)	(0.004)	(0.010)
Child age	0.272***	0.007***	0.006***	0.004***	0.006***
	(0.063)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	46.634***	0.181***	0.033	11.162***	-0.127
	(1.855)	(0.032)	(0.030)	(0.011)	(0.027)
N	8,773	8,773	8,773	8,773	8,773
Adjusted R^2	0.096	0.018	0.031	0.049	0.126
Panel B: High Mining Share					
Income rank of parent	0.081***	0.002***	0.001***	0.001***	0.005***
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
Child gender	-23.750***	0.070***	0.139***	0.004	0.013
	(0.623)	(0.011)	(0.010)	(0.004)	(0.010)
Child age	0.185***	0.011***	0.011***	0.002***	0.010***
	(0.066)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	53.567***	-0.030	-0.170***	11.159***	-0.216***
	(1.932)	(0.032)	(0.028)	(0.012)	(0.029)
N	8,107	8,107	8,107	8,107	8,107
Adjusted R^2	0.168	0.027	0.049	0.046	0.105

Notes: The table reports the coefficients with standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B Additional figures

Alternative definitions of primary parent and IGM: In this section we present the results that show that our results are robust to using alternative definitions of parents.

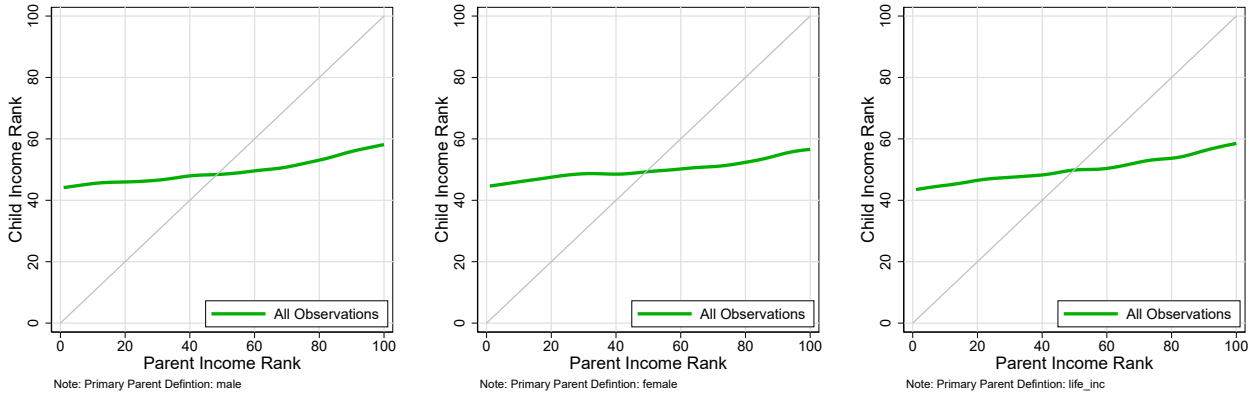

Figure B.1: Intergenerational mobility and primary parent

Notes: This figure shows the relationship between child's life-time income rank and parents' income rank using different primary parent definitions. In the left panel, the primary parent is male, in the middle panel the primary parent is female and the right panel is based on parent that has the highest lifetime income. The rank-rank slope is 0.149, 0.107, and 0.147 respectively. The y-axis is the child's mean life-time income rank at each percentile of parents' income rank plotted on the x-axis.

Child's education, occupation, and their relationship with IGM: Figure B.2 explores hetero-

geneity in mobility by education and occupation. The left panel shows that children with a bachelor's degree rank, on average, 12 percentile points higher in the income distribution than children without a degree. Importantly, this education premium is largest for children from lower-income families, suggesting that education helps mitigate disadvantage at the bottom of the parental income distribution. The right panel highlights the strong role of occupation: children in cognitive occupations rank 14 percentiles higher than those in routine occupations and 26 percentiles higher than those in manual work. Figure B.2 suggests that while the child's education and occupation impacts the average rank but it's influence on intergenerational income persistence is limited.

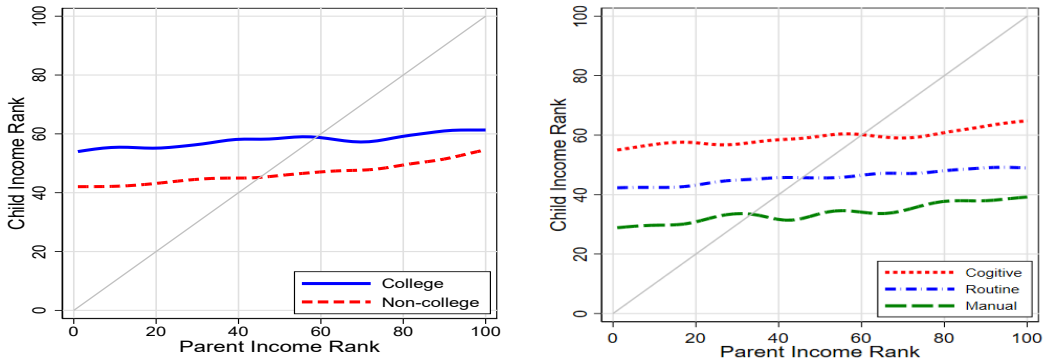

Figure B.2: Intergenerational Mobility by education (left) and occupation (right)