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Educational pathways and earnings trajectories of second-generation immigrants in Australia: New insights from linked census-administrative data

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This study employs 2011 Census data linked to population-based administrative datasets to explore disparities in educational attainment and earnings trajectories among Australian-born children of diverse parental migration backgrounds from mid-adolescence to early adulthood. Non-English Speaking Background (NESB) second-generation immigrants exhibit superior academic outcomes, primarily driven by children of parents from select Asian countries. These individuals are more likely to complete higher education, particularly bachelor's and master's degrees, and specialise in fields such as management and commerce, health, natural and physical sciences, and engineering. Children of NESB immigrant parents initially earn less than their peers with Australian-born parents at ages 21–22. However, this gap closes by ages 23–24 and reverses by ages 26–27, with children of NESB fathers out-earning their counterparts by ages 28–29. Conversely, children of English-Speaking Background (ESB) immigrant parents, who exhibit weaker academic performance, also experience lower earnings compared to peers with Australian-born parents. This disparity emerges by ages 22–23 and widens throughout the study period, peaking at ages 28–29. The findings underscore the academic and economic advantages of NESB second-generation immigrants, contrasting with the challenges faced by ESB migrant counterparts. Overall, the results highlight the critical role

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This paper uses unit record data from the Person Level Integrated Data Asset (PLIDA). These data are proprietary and researchers wishing to use them must seek approval from the relevant institutions. Information about these data can be accessed through this link: https://www.abs.gov.au/about/data-services/data-integration/integrated-data/person-level-integrated-data-asset-plida. The replication code is available on the corresponding author's website: https://sites.google.com/view/nguyen-ha/publications.

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of education in supporting the economic integration of migrants and their descendants in the host country.

Keywords: Migration; Intergenerational Correlation; Education; Income; Census; Administrative data; Australia

JEL classifications: I24; J24; J15; J62

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1. Introduction

According to the 2021 Census, nearly 30% of individuals living in Australia are foreign-born, and 48% have at least one foreign-born parent (ABS 2024). These figures represent a significant increase from the 2011 Census, which reported that approximately 27% of the population were born overseas, and 43% had at least one foreign-born parent. Given the current and projected increasing significance of children of migrants in Australia's labour market, it is essential to comprehensively understand their post-school outcomes. Moreover, since Australia's migrants originate from diverse linguistic and cultural backgrounds, it is important to account for this heterogeneity, as individuals from different backgrounds may encounter varied experiences in education and the labour market. Understanding these dynamics is critical for informing policies aimed at enhancing the integration and success of all migrant groups in Australian society (Borjas 1999; Abramitzky & Boustan 2017; Alesina & Tabellini 2024).

This paper examines the educational pathways and earnings trajectories of Australian-born children of immigrants, commonly referred to as second-generation immigrants, from diverse ethnic backgrounds, as well as Australian-born children of native-born individuals. The study focuses on the critical transition from mid-adolescence to early adulthood, a pivotal period in individual development that encompasses the shift from school to higher education or entry into the labour market (Becker 1965; Heckman & Mosso 2014).

Leveraging newly available, high-quality linked Australian census-administrative data, this study makes three key contributions to the literature on children's academic and labour market outcomes across diverse migration backgrounds. First, unlike existing Australian studies that primarily examine academic performance before school completion (Cobb-Clark & Nguyen 2012; Nguyen *et al.* 2020), this study investigates post-secondary educational attainment, including higher education qualifications and fields of study beyond the typical graduation age. Additionally, administrative higher education data offer granular insights into qualification levels and disciplines. Beyond education, this study also analyses early-career earnings using administrative income tax data.

Second, unlike previous research that often relies on survey datasets with relatively small sample sizes, our study leverages a comprehensive dataset encompassing the entire Australian population. This allows for a more detailed and robust analysis. For instance, the extensive sample size significantly enhances statistical power, enabling us to investigate outcomes at a granular level, such as by specific countries of origin, rather than relying on aggregated

regional classifications as seen in prior studies (Cobb-Clark & Nguyen 2012; Nguyen *et al.* 2020). Third, the longitudinal nature of our dataset presents a unique opportunity to examine educational and economic outcomes concurrently over time (Deutscher 2020). This dual-pathway approach provides valuable insights into how disparities in educational and economic trajectories develop and interact over an extended period, spanning a decade.

The evidence presented in this study holds significant relevance not only for Australia but also for other immigrant-receiving countries. As a nation with a substantial immigrant population, Australia ranks ninth globally for the proportion of its population born overseas (ABS 2024). However, the unique immigration composition and policy context in Australia mean that findings from countries like the United States may not be directly transferable. For instance, a much larger share of immigrants in Australia are admitted based on labour market skills compared to the U.S. (Antecol *et al.* 2003), and Australia has a higher proportion of its population born overseas (ABS 2024).

That said, consistent with Australian evidence (Cobb-Clark & Nguyen 2012; Nguyen *et al.* 2020), studies in the U.S. have also documented that children from certain immigrant groups achieve superior academic outcomes (Fryer & Levitt 2006; Figlio *et al.* 2019). However, due to data constraints (see Villarreal and Tamborini (2023) for a recent review), U.S. studies typically focus on a single outcome—most often educational achievements—rather than examining both educational and economic outcomes in tandem. By addressing these dual outcomes, this Australian study provides insights that may extend to other multicultural and immigrant-receiving nations.

This study presents three principal findings. First, among Australian-born children, those with Non-English Speaking Background (NESB) immigrant parents demonstrate the strongest academic outcomes. They achieve the highest Australian Tertiary Admission Rank (ATAR) scores and attain higher education qualifications. These outcomes are followed by children of Australian-born parents, with children of English-Speaking Background (ESB) immigrant parents ranking third. Notably, a compounding effect is observed, where children with both parents from NESB countries excel academically. These findings align with prior Australian research (e.g., Cobb-Clark and Nguyen (2012)) and are further substantiated in this study, which employs a longer time horizon and improved precision.

Second, this study reveals new evidence that the superior academic achievements of second-generation NESB immigrants are largely driven by children of parents from select Asian

countries. Their higher likelihood of completing higher education is primarily attributed to an increased probability of attaining bachelor's and master's degrees. Furthermore, these individuals are more likely to specialise in disciplines such as management and commerce, health, natural and physical sciences, engineering and related technologies, society and culture, information technology, and architecture and building.

Third, this study provides novel insights into the temporal dynamics of educational and financial disparities among children from diverse migration backgrounds. Consistent with their educational trajectories, children of NESB parents initially earn less than their peers with Australian-born parents at ages 21–22. However, this gap closes by ages 23–24 and reverses by ages 26–27, with children of NESB fathers out-earning their counterparts by ages 28–29. In contrast, children of ESB immigrant parents, who demonstrate weaker academic performance, also experience lower earnings relative to peers with Australian-born parents. This disparity becomes evident at ages 22–23 and continues to widen over time, reaching its peak at ages 28–29, where our follow-up ends.

Further analysis indicates that the earnings convergence—and eventual outperformance—of children of NESB parents, relative to both Australian-born children and those of migrants from other backgrounds, is primarily driven by their higher likelihood of pursuing higher education, partly due to their concentration in specific fields of study associated with substantial positive earnings returns.

The structure of this paper is organised as follows: Section 2 provides a concise review of the relevant literature. Section 3 describes the data employed in the analysis. Section 4 outlines the primary empirical findings, followed by Section 5, which delves into additional insights derived from our unique data and methodological approach. These include differences in completed levels of higher education and fields of study among children from diverse migration backgrounds, differences in educational and earnings outcomes by parental country of birth, and temporal trends in educational and financial trajectories. Finally, Section 6 concludes the paper by summarizing the key findings and offering directions for future research.

2. A brief review of related literature

This study, which investigates the educational and earnings pathways of second-generation migrants, contributes to two broadly defined lines of research. The first focuses on the educational performance of second-generation migrants, highlighting varying patterns across different ethnic backgrounds and countries (see comprehensive reviews by Dustmann and Glitz

(2011), Sweetman and van Ours (2015) or Duncan and Trejo (2018)). Within this area, the current study aligns closely with a growing body of Australian research. For instance, earlier work by Cobb-Clark and Nguyen (2012) utilised survey data from Youth in Focus linked to administrative data on parental income support receipts. They found that young Australians aged 20 from NESB immigrant families exhibit an educational advantage compared to their ESB immigrant and Australian-born peers. Their analysis focused on selected educational outcomes observed when individuals were approximately 20 years old, such as Year 12 completion, ATAR scores, and university enrolment.

Other studies have employed survey datasets like the Longitudinal Study of Australian Children (LSAC) to explore the academic outcomes of younger Australian-born individuals (Nguyen *et al.* 2020). These studies typically report that children of NESB immigrants outperform their peers, as measured by National Assessment Program - Literacy and Numeracy (NAPLAN) test scores through Year 9 (around ages 14–15). Nguyen *et al.* (2020) further highlight that children from NESB migrant families allocate more time to education-related activities, with these time investments substantially enhancing academic performance. Additionally, using LSAC data, Nguyen *et al.* (2019) demonstrate distinct temporal patterns in the development of non-cognitive skills among children of parents from various migration backgrounds.

Despite these contributions, prior Australian studies predominantly rely on survey datasets with limited sample sizes, constraining their ability to rigorously analyse the educational performance of children from diverse migration backgrounds beyond aggregated categories such as ESB or NESB.[1] Furthermore, these datasets typically focus on educational outcomes prior to higher education completion. By contrast, the linked census-administrative datasets used in this study enable a comprehensive exploration of post-school educational outcomes. The large sample size of these population-based datasets also facilitates more detailed and robust analyses than what was previously achievable with survey data.

This study also contributes to the extensive body of literature comparing the earnings of individuals from diverse migration backgrounds (Borjas 1985; Gregory 2015). This literature predominantly focuses on earnings disparities between first-generation migrants and native-

[1] An exception is the recent study by Zając *et al.* (2023), which utilises datasets largely similar to those employed in this study. However, their research focuses on the labour market trajectories of Australian graduates from advantaged and disadvantaged social backgrounds. In their analysis, the socioeconomic background index is constructed using various factors, including whether the individual was born overseas in an ESB or NESB country (i.e., as a first-generation immigrant).

born individuals, often documenting an initial income disadvantage for migrants that diminishes over time as they integrate into the labour market (for a U.S.-focused review, see Abramitzky and Boustan (2017)). In line with international findings, Australian studies consistently report wage gaps favouring native-born individuals, with NESB migrants experiencing the largest disadvantages. However, these gaps tend to narrow with migrant integration (Miller & Chiswick 1985; Beggs & Chapman 1988; Breunig *et al.* 2013; To *et al.* 2017). Additionally, similar to international evidence (Aydemir *et al.* 2009; Abramitzky *et al.* 2021), Australian research finds that while both first- and second-generation immigrants face disadvantages, second-generation migrants generally experience less pronounced disparities (Maani 1994; Deutscher 2020).

This study builds on prior Australian research by Maani (1994) and Deutscher (2020) to examine the relative earnings of second-generation immigrants. However, it advances the field through several unique contributions enabled by superior data and methodology. First, unlike Maani (1994), which utilised the Australian Longitudinal Survey (ALS) from 1985–1988 to document disadvantages among both young first- and second-generation immigrants, this study leverages more robust and detailed data to focus exclusively on the second generation. Similarly, Deutscher (2020), which relied on survey datasets such as Census, the Household, Income and Labour Dynamics in Australia (HILDA), and Youth in Focus to investigate intergenerational income mobility among second-generation Australians, does not analyse the relative earnings trajectories of second-generation immigrants in detail as this study does.

Moreover, previous Australian studies have been limited in their ability to examine educational and economic outcomes concurrently over extended periods due to data constraints. To our knowledge, this study is among the first in Australia—and rare internationally—to analyse disparities in educational and economic trajectories in tandem over a significant and important timeframe. For instance, a recent review of U.S. literature by Villarreal and Tamborini (2023) underscores that most studies tend to focus on either educational or earnings outcomes, but rarely both. By adopting a dual-focus approach, our study provides a more comprehensive and robust understanding of the interlinked pathways shaping the outcomes of second-generation immigrants. Leveraging population-wide administrative panel data, we trace how disparities in educational attainment and earnings evolve over more than a decade, from the end of secondary schooling into early adulthood. This unique approach also offers new insights into potential mitigating factors—such as investment in education, which is explicitly considered in this study—that may help reduce earnings disadvantages faced by certain migrant groups.

3. Data and sample

3.1. Data

This study utilises the Person Level Integrated Data Asset (PLIDA), developed and maintained by the Australian Bureau of Statistics (ABS). PLIDA is a secure and comprehensive integrated dataset that combines longitudinal information across multiple domains, including health, education, government payments, income, taxation, employment, and population demographics, such as Census data (ABS 2025).

The analysis draws upon three principal datasets. The first dataset is the 2011 Census, which provides extensive socio-demographic information, including gender, age, educational attainment, and country of birth. It also offers detailed data on family relationships, which are critical for identifying individuals' parental migration backgrounds. Additional variables derived from the Census include parental characteristics (e.g., age and education) and household attributes (e.g., tenure status and income), which serve as key explanatory variables in the empirical models.[2]

The second dataset is the Higher Education Information Management System (HEIMS), an administrative resource provided by the Department of Education, Skills, and Employment. HEIMS encompasses nationwide data on higher education enrolments and completions spanning 2005 to 2019. This dataset contributes variables such as Australian Tertiary Admission Rank (ATAR) scores,[3] higher education qualification completion, qualification levels, and fields of study.

The third dataset, the Personal Income Tax (PIT) records, is sourced from the Australian Taxation Office (ATO). PIT data includes comprehensive information on total personal taxable income for each financial year (FY),[4] serving as the primary measure of earnings in this study. The PIT data span the 2011/12 to 2018/19 financial years.

[2] The 2011 Census also includes information on Year 12 completion status, which could serve as an additional educational outcome variable. However, we do not include this variable in our analysis, as only a small proportion of individuals in our sample—approximately 11% (see sample selection details below)—had completed Year 12 by 2011. Nonetheless, additional results indicate that the pattern of Year 12 completion does not vary markedly by migration background, which consistent with findings from prior Australian research (Cobb-Clark & Nguyen 2012).

[3] In Australia, domestic students aspiring to attend university typically require an ATAR, a percentile ranking ranging from 0.00 to 99.95. Students generally receive their ATAR score upon completing Year 12, the final year of secondary school. Most students are 17 or 18 years old at this stage, depending on their birthdate and the state or territory in which they studied. In our regression analysis of ATAR score, we additionally include a dummy variable to indicate the year in which an individual left school. It is important to note that ATAR scores are only observed for individuals who enrolled in higher education and appear in the HEIMS dataset.

[4] The financial year in Australia spans from July 1 to June 30 of the following year.

These datasets are linked through the Person Linkage Spine, a system designed to integrate records for all individuals residing in Australia during the reference periods. The linkage process employs a deterministic method using identifiers such as names, date of birth, gender, and address (ABS 2025).

3.2. Sample

This study focuses on individuals born in Australia to examine the influence of parental immigrant backgrounds on those who were born and raised domestically. These individuals are commonly referred to as second-generation immigrants. Following methodologies employed in previous studies (Cobb-Clark & Nguyen 2012; Nguyen *et al.* 2020), this approach allows for a clearer attribution of differences in children's outcomes to variations in their parents' migration backgrounds.

We focus on individuals aged 15 to 18 as of the Census month in August 2011 for three primary reasons. First, we rely on household relationships reported in the 2011 Census to identify connections between household members. Specifically, we determine the country of birth of parents for individuals residing with both natural or adopted parents at the time of the census.[5] Consequently, we can only link children to their parents if they were co-residing during the 2011 Census. This approach allows us to directly observe parental age, education, and income as reported by the parents themselves, facilitating an examination of their potential influence on the subsequent educational and income trajectories of their children.

Second, by focusing on 15- to 18-year-olds, most of whom co-reside with their parents, we mitigate the issue of older children leaving the parental home for education- or work-related reasons. Such patterns of leaving home may differentially affect observations across migration backgrounds.

Third, this age range allows us to track these individuals through to potential completion of higher education within the timeline of our higher education dataset, which extends to 2019. Since a typical undergraduate degree takes around four years, by 2019, individuals in our sample would have reached 23 to 26 years of age, providing an adequate timeframe to capture

[5] While the 2011 Census provides an indicator of whether an individual's mother or father was born overseas, we chose to use the direct reports from the individuals instead. This is because parental information does not provide the exact country of birth of the overseas-born parent, and as demonstrated further in the paper, a more detailed classification of country of birth is crucial. Furthermore, our approach, using country of birth as directly reported by the individual, provides greater precision than relying on information reported by another household member (Nguyen *et al.* 2023).

higher education outcomes. In subsequent sections, we will examine older cohorts and show that our results remain consistent across age groups.

We further refine the sample by excluding individuals with missing data on key variables, such as parental country of birth and education. This restrictive sample criterion, made possible by the extensive size of our original population datasets, allows for a nuanced examination of how variations in parental background, specifically the educational attainment and country of birth of both mothers and fathers, may differentially influence the educational and earnings outcomes of individuals. This approach is essential for understanding the potential moderating effects of parental characteristics on socioeconomic outcomes, consistent with findings in the literature on intergenerational transmission of advantage (Dustmann *et al.* 2012; Sweetman & van Ours 2015; Zając *et al.* 2023; Haeck & Laliberté 2025).

4. Main results

4.1. Descriptive results

Table 1 presents summary statistics for key variables, disaggregated by parental migration status, highlighting notable differences in socioeconomic, educational, and earning outcomes among children from different migration backgrounds.[6] While there is minimal variation in the age of children, parents born overseas are, on average, older than their Australian-born counterparts. This trend is consistent for both mothers and fathers and suggests a positive association between international migration and higher childbearing ages among immigrants.

Additionally, consistent with Australia's skill-based migration policies, immigrant parents demonstrate higher levels of educational attainment, with a significantly greater likelihood of holding a bachelor's degree or higher compared to Australian-born parents (Antecol *et al.* 2003; Gregory 2015). This pattern is evident for both mothers and fathers. In terms of homeownership, children of migrant parents are more likely to live in outright-owned homes and less likely to reside in homes with mortgages. However, they are associated with lower household income compared to children of Australian-born parents.[7] The final rows of Table 1 reveal that children of migrant parents achieve statistically significantly higher educational

[6] For brevity and demonstration purposes, we categorise whether the mother or father was born overseas without more detailed disaggregation. Unreported results show that the top ten countries of birth for migrant mothers are: England, Vietnam, New Zealand, Lebanon, China (excluding Hong Kong and Taiwan), the Philippines, India, Malaysia, Scotland, and Italy. The list for fathers is similar, with Sri Lanka replacing Malaysia.

[7] Similar patterns have been observed in other Australian studies. Immigrants tend to have higher qualifications than native-born Australians, largely due to Australia's skilled migration policies (Antecol *et al.* 2006). However, despite these higher qualifications, immigrants—particularly in the initial years after arrival—often earn less than their Australian-born counterparts (Breunig *et al.* 2013; Nguyen & Duncan 2017).

outcomes but exhibit lower income levels, regardless of whether the mother or father is a migrant.

4.2. Regression model

To investigate the factors associated with outcome Y for individual i at time t, we employ the following regression model:

$$Y_{i,t=2011+k} = \alpha + D_i\beta + X_{i(t=2011)}\gamma + \varepsilon_i \qquad (1)$$

where D_i is a vector of two categorical variables, each indicating the country of birth of the individual's mother or father. $X_{i(t=2011)}$ is a set of explanatory variables derived from the 2011 Census. These variables are measured at the time of the 2011 Census for two primary reasons. First, they are constructed using Census data and are not widely available in other datasets. Second, for certain time-varying variables, such as household income, measuring them at the beginning of the study period helps mitigate concerns about reverse causality—for instance, the possibility that children's income may influence household income.

In the main analysis, we focus on three primary outcomes: two educational outcomes—ATAR scores and attainment of a higher education qualification—and personal income tax. Subsequently, we also examine the level and field of study among university graduates. The outcome variable, Y, is measured at different points in time, denoted by $t = 2011 + k$, where k ranges from 0 (indicating the outcome is measured in 2011) to 8 (indicating measurement at the end of the study period in 2019). The value of k is determined by the specific outcome under analysis and whether the analysis is static or temporal in nature. As noted above, outcomes are measured after the time the explanatory variables are observed, in order to align with data availability and to address concerns about reverse causality. In Equation (1), ε_i denotes the usual idiosyncratic term and α, β and γ are vectors of parameters to be estimated.

Following the approach commonly adopted in the literature (Fryer & Levitt 2006; Cobb-Clark & Nguyen 2012; Figlio *et al.* 2019; Nguyen *et al.* 2020), the vector X_i includes a range of individual and household characteristics potentially correlated with the outcome of interest. These variables encompass individual attributes (e.g., gender and age, included flexibly as month-of-birth dummies), parental characteristics (e.g., age and age squared, and highest qualifications for both mother and father), and household features (e.g., residential tenure

indicators and household income[8]). Additionally, state/territory dummy variables are included to account for geographic and institutional differences in observed outcomes.

In Equation (1), the coefficients in β are of particular interest, as they capture differences in the outcome associated with individuals from various migration backgrounds, consistent with previous studies (Fryer & Levitt 2006; Cobb-Clark & Nguyen 2012; Figlio *et al.* 2019; Nguyen *et al.* 2020). Following the existing literature, we leverage the richness of our linked census–administrative data to control for a comprehensive set of variables typically associated with educational and earnings outcomes, thereby reducing the influence of unobservable factors on the estimated gap (β). Additionally, this study improves upon prior work by exploiting the panel structure of our linked datasets to measure certain time-varying explanatory variables at the beginning of the study period, helping to mitigate concerns about reverse causality. By combining both approaches, this study provides robust evidence on gaps in educational and earnings outcomes among children from different migration backgrounds, conditional on observables. Moreover, we apply this empirical model to examine both cross-sectional gaps at a specific point in time—consistent with most prior studies—as well as the dynamics of these gaps over a longer, decade-long period.

For binary outcomes, such as the attainment of a higher education qualification, a logit model is employed to appropriately account for the dichotomous nature of the dependent variable. The results are reported as marginal effects to facilitate interpretation. When multiplied by 100, these marginal effects represent percentage changes in the probability of the outcome. For continuous outcomes, such as ATAR scores or annual income, we utilise an Ordinary Least Squares (OLS) regression, which provides estimates of the average effect of the explanatory variables on the dependent variable.

In our baseline regression, to allow sufficient time for certain outcomes to materialise, we measure outcomes such as higher education completion and income at the latest available time point in the dataset. Moreover, for interpretative simplicity, we follow prior Australian studies (Cobb-Clark & Nguyen 2012; Nguyen *et al.* 2020) by categorizing each parent's country of birth into three broad groups: Australian-born (the reference category), born overseas in an

[8] Household income in the Census is reported in brackets, such as $65,000 to $80,000. For ease of presentation and interpretation, we follow the common practice of treating income as a continuous variable by using the midpoint of each bracket. Unreported results are largely consistent when household income is included as a categorical variable.

English-speaking background (ESB) country, or born in a non-ESB (NESB) country.[9] The emphasis on English-speaking backgrounds is particularly pertinent, given that Australia—an English-speaking nation—reported in the 2021 Census that 22% of its population speaks a language other than English at home (ABS 2024). This categorization also reflects the well-documented substantial economic benefits associated with greater English language proficiency (Bleakley & Chin 2010).

4.3. Main regression results

Table 2 presents regression estimates for two migration background groups for each parent, controlling for variables specified in Equation 1. The findings reveal significant differences in children's educational attainment and earnings based on parental migration background. Specifically, children of ESB immigrant parents underperform academically relative to their peers with Australian-born parents, as reflected in lower ATAR scores and a decreased likelihood of obtaining a higher education qualification by 2019. Within this group, paternal migration background demonstrates a stronger association with ATAR scores, whereas maternal migration background has a greater impact on higher education attainment, with estimates approximately 50% larger for mothers (-2.16 compared to -1.42 for fathers, as shown in Column 4 of Table 2).

In contrast, children of NESB immigrants outperform children of Australian-born parents across all educational outcomes considered. Within the NESB group, maternal migration background exerts a significantly greater influence on ATAR scores and the probability of obtaining higher education qualifications. For instance, the estimated effect of NESB maternal migration background on ATAR scores is nearly three times greater than that of paternal migration background (1.81 compared to 0.62, as presented in Column 1). Similarly, the estimate for NESB maternal migration background on the likelihood of obtaining a higher education qualification is over 15% higher than that for paternal migration background (9.46 compared to 8.27, as shown in Column 4).

Column 6 of Table 2 indicates that children of immigrant parents have statistically significantly lower taxable incomes compared to children of Australian-born parents, with a difference ranging from 1.48 to 1.81 thousand AU$ per year (measured in the 2018/19 financial year). This pattern is consistent regardless of whether the parents are from ESB or NESB countries.

[9] Building on previous Australian studies (Cobb-Clark & Nguyen 2012; Nguyen *et al.* 2020), this study classifies ESB countries as Canada, England, New Zealand, Northern Ireland, Scotland, South Africa, Wales, and the United States. Countries of origin not included in this classification are categorised as NESB.

However, children of NESB immigrant parents face a slightly greater disadvantage in taxable income compared to children of ESB immigrant parents. For example, children of NESB immigrant mothers earn approximately $270 less annually than children of ESB immigrant mothers.

Table 2 also presents results from a modified regression based on Equation (1), which includes an interaction term between the categorical variables capturing the migration backgrounds of both parents. The findings from this extended regression (shown in Columns 2, 5, and 7) indicate some compounding effects of having both parents from specific migration background combinations. Notably, the statistically significant and positive coefficient (at the 1% level) for the interaction term between NESB mother and NESB father variables suggests that children of parents who both originate from a NESB country achieve better outcomes both academically and financially. For example, compared to children of two Australian-born parents, children of two NESB immigrant parents have ATAR scores that are 2.52 points higher. Furthermore, these children earn 1.25 thousand AU$ more annually than their counterparts with two Australian-born parents.[10]

4.4. Other regression results

The estimates for other important variables, presented in Appendix Table A1, align largely with expectations.[11, 12] For example, consistent with prior Australian research, males typically

[10] For representational purposes, we do not report marginal effects following the logit regression in this extended model, as the marginal effect for the interaction term is not defined.

[11] Appendix Table B1 presents results from two regression specifications: one including only the categorical variables indicating the country of birth of the individual's mother or father (reported in the even-numbered columns), and another that adds a full set of control variables (reported in the odd-numbered columns). Two key patterns emerge. First, the R-squared values increase substantially with the inclusion of controls, indicating that these factors are important in explaining educational and earnings outcomes. Second, the estimated effects of parental migration background change considerably with the addition of controls, particularly for educational outcomes. For example, in the ATAR score regressions, the coefficients on indicators for having an ESB migrant mother or an ESB or NESB migrant father change sign. Similarly, in the regressions for any higher education qualification, the coefficients for having an ESB migrant mother or an ESB migrant father also change sign. These substantial shifts in direction, and in some cases magnitude, underscore the importance of accounting for observable socio-economic characteristics when analysing educational disparities by migrant background.

[12] In theory, the contribution of each explanatory variable to the observed educational and earnings gaps between children of different migration backgrounds can be analysed using the Oaxaca-Blinder (OB) decomposition method (Blinder 1973; Oaxaca 1973). This approach has been used, for example, by Nguyen *et al.* (2022) to assess the role of children's time use—among other factors—in explaining gender-based test score gaps. The OB decomposition relies on regression estimates—such as those presented in Appendix Table A1—and differences in average values of explanatory variables across groups.

However, we refrain from applying this method in the present study for two main reasons. First, OB decomposition is best suited for comparing two groups, while our baseline regression classifies parental country of birth into three categories: Australian-born, ESB, and NESB, resulting in six mutually exclusive child groups. Exhaustively reporting decomposition results for all pairwise comparisons would be overly complex. Second, we analyse three key educational and financial outcomes and include a rich set of controls. Presenting decomposition

underperform academically (Booth & Kee 2011; Le & Nguyen 2018a; Nguyen *et al.* 2022), whereas they exhibit stronger financial performance in line with international findings (Blau & Kahn 2017; Le & Nguyen 2018b). Additionally, children's educational attainment, measured by ATAR scores and higher education completion, as well as earnings, increase with parental age, albeit at a decreasing rate. This is evidenced by statistically significant and positive coefficients for parental age, contrasted with statistically significant and negative coefficients for parental age squared.

The relationship between parental education and children's outcomes varies by outcome type. Specifically, children of more highly educated parents—whether maternal or paternal—demonstrate higher academic achievement, reflected in higher ATAR scores and a greater likelihood of completing higher education. However, no consistent relationship is observed between parental education and children's earnings, as children of parents with the highest educational qualifications do not necessarily earn more. This pattern holds for both maternal and paternal education.

Household wealth and income are also significant predictors of children's academic and financial outcomes. Children from wealthier households, as indicated by homeownership status, and those from higher-income households tend to perform better academically and financially. Moreover, the stronger statistical significance of household income estimates on children's earnings suggests that children's financial outcomes are more closely correlated with parental income than with parental education. These findings are consistent with broader research on intergenerational transmission, which highlights the critical role of parental education, health, and income in shaping children's outcomes (Black & Devereux 2011; Mendolia & Siminski 2016; Le & Nguyen 2017; Hancock *et al.* 2018; Le & Nguyen 2018c; Page 2024).

5. Additional results

Overall, our findings thus far corroborate much of the prior literature while offering enhanced precision due to the use of exceptionally large and high-quality datasets. This robust data foundation allows us to expand upon existing research by addressing previously underexplored dimensions of intergenerational outcomes.

results for each outcome and explanatory variable across multiple group comparisons would considerably increase the length of the paper.

5.1. Level and field of higher education completion

First, we examine differences in completed levels of higher education and fields of study among children from diverse migration backgrounds. For the analysis of completed higher education levels, we classify outcomes into five mutually exclusive categories: no higher education qualification (the reference group), diploma, bachelor's degree, graduate diploma, and master's degree or higher. For fields of study, we adopt the Australian two-digit classification system for fields of education, categorizing individuals into 11 mutually exclusive groups: no higher education qualification (the reference group); natural and physical sciences; information technology; engineering and related technologies; architecture and building; agriculture and environmental studies; health; education; management and commerce; society and culture; and creative arts.[13]

We employ a multinomial logit regression model where the dependent variable is a categorical indicator representing either the completed level of education or the field of study. These outcomes, as noted above, are measured at the end of the study period in 2019. The regression controls for the same set of explanatory variables outlined in Equation (1), ensuring consistency in the modelling framework and comparability with prior analyses.

Table 3 presents the marginal effects of parental migration background on the likelihood of attaining different levels of higher education. The findings indicate notable differences in educational outcomes for children based on the migration background of their parents. Specifically, children of ESB parents exhibit lower probabilities of completing a bachelor's or graduate diploma degree compared to children of Australian-born parents. This pattern appears more pronounced for maternal migration background, as reflected in larger absolute values or greater statistical significance for maternal estimates relative to paternal ones.

In contrast, children of NESB parents are more likely to achieve higher education qualifications across all levels compared to their peers with Australian-born parents. Specifically, children of NESB mothers are 7.66 percentage points (pp) more likely to complete a bachelor's degree,

[13] For a small proportion of higher education graduates (less than 3% in our dataset) who obtained multiple degrees in a given year, we assigned the degree with the highest educational level. The field of study corresponding to this highest-level degree was also attributed to these individuals. In rare cases where individuals completed multiple degrees of the same level within the same year, the field of study was determined based on the order of classification in the Australian two-digit system for fields of education. For example, if an individual completed degrees of the same level in both natural and physical sciences, and information technology, the field listed first in the classification system (natural and physical sciences) was selected. Observations where individuals completed a field in food, hospitality, and personal services are grouped with those who completed a degree in management and commerce due to the insufficient sample size for separate analysis.

1.22 pp more likely to attain a master's degree or higher, 0.36 pp more likely to obtain a graduate diploma, and 0.21 pp more likely to earn a diploma. Similarly, children of NESB fathers demonstrate a 6.38 pp higher probability of completing a bachelor's degree, a 1.24 pp higher likelihood of attaining a master's degree or higher, a 0.47 pp higher probability of earning a graduate diploma, and a 0.17 pp increased likelihood of completing a diploma.

The predominance of bachelor's and master's degrees in these results is especially noteworthy, as these qualifications represent the majority of higher education outcomes among graduates in the dataset (84% and 8%, respectively). These patterns suggest that the superior academic performance observed among children of NESB parents is primarily driven by achievements in these two educational categories. Conversely, the lower academic performance of children of ESB parents is largely attributable to their reduced likelihood of attaining bachelor's or graduate diploma qualifications.

Table 4 presents the estimated effects of parental migration background on the likelihood of attaining higher education qualifications across various fields of study. The findings indicate that, compared to children of Australian-born parents, children of ESB parents exhibit distinct educational patterns. Specifically, children of ESB parents are significantly less likely to complete degrees in engineering and related technologies, health, education, and management and commerce, as evidenced by negative and statistically significant estimates ($p < 0.1$) for both maternal and paternal migration backgrounds. Notably, children of ESB fathers are 0.43 pp more likely to complete a degree in creative arts, as indicated by a positive and statistically significant estimate at the 1% level.

In contrast, children of NESB parents generally exhibit a higher likelihood of attaining higher education qualifications across most fields of study compared to children of Australian-born parents, with patterns remaining relatively consistent between maternal and paternal migration backgrounds. Specifically, children of NESB parents are more likely to complete degrees in fields such as management and commerce, health, natural and physical sciences, engineering and related technologies, society and culture, information technology, and architecture and building. Conversely, children of NESB mothers are less likely to complete degrees in education compared to their counterparts with Australian-born mothers. Furthermore, children of NESB parents are less likely to attain qualifications in agriculture and environmental studies, as indicated by statistically significant ($p < 0.1$) and negative estimates. Notably, the negative association in this field is more pronounced for paternal migration background than for maternal migration background.

5.2. Detailed country of birth of each parent

This subsection utilises the extensive sample size of our dataset to investigate variations in educational outcomes and earnings by the detailed country of birth of each parent, focusing on the top 30 countries of origin for immigrant mothers in the sample. Figure 1 illustrates significant differences in ATAR scores by the country of birth of each parent. Panel A highlights that children of immigrant mothers born in China, Sri Lanka, Hong Kong, Malaysia, Vietnam, South Korea, Singapore, Cambodia, India, and South Africa achieve the highest ATAR scores. In contrast, children of mothers originating from Chile, Lebanon, Turkey, Fiji, and the Philippines exhibit the lowest performance. Similarly, Panel B demonstrates that children of fathers from China, Hong Kong, Vietnam, Cambodia, and Malaysia attain the highest ATAR scores, whereas those with fathers born in former Yugoslavia, Chile, the Philippines, Turkey, Fiji, Scotland, and Egypt achieve the lowest scores.

Figure 2 – Panel A demonstrates that children of mothers born in China, Hong Kong, Cambodia, Vietnam, Sri Lanka, Indonesia, Malaysia, India, Poland, and Singapore exhibit the highest likelihood of completing a higher education qualification by 2019. Conversely, children of mothers from New Zealand and England show the lowest probability of attaining a higher education qualification within the same timeframe.

Similarly, Panel B of Figure 2 indicates that children of fathers originating from Cambodia, Hong Kong, Vietnam, China, Malaysia, Singapore, South Korea, Sri Lanka, India, and Lebanon are most likely to complete higher education by 2019. By contrast, children of fathers from major English-speaking background (ESB) countries, including the U.S., New Zealand, and England, have the lowest likelihood.

In terms of annual taxable income, Figure 3 – Panel A shows that children of immigrant mothers from South Korea, the U.S., Singapore, Lebanon, Turkey, Germany, Cambodia, and Scotland have the lowest income as of the 2018/19 financial year. However, for children of mothers from other major source countries, there are no statistically significant differences in income compared to children of Australian-born mothers. Similarly, Panel B in Figure 3 demonstrates that children of fathers immigrating from Turkey, Chile, Lebanon, the U.S., Papua New Guinea, Fiji, Germany, England, and New Zealand earn less than those with Australian-born fathers. For children of fathers from other major source countries, no statistically significant income differences are observed compared to those of Australian-born fathers.

Overall, while patterns vary slightly depending on specific educational outcomes and the parents' country of birth, the findings indicate that children of immigrants from Asian countries—notably China, Hong Kong, Cambodia, Vietnam, Sri Lanka, Indonesia, Malaysia, Singapore, and India—consistently achieve superior academic outcomes. Our observation that children of Asian immigrants outperform both children of non-immigrant parents and children of other immigrant parents aligns with evidence from other multicultural Anglo-Saxon countries (Dustmann & Glitz 2011; Duncan & Trejo 2018). Furthermore, this study introduces a novel finding: by the ages of approximately 23 to 26, these children earn at least as much as their counterparts with Australian-born parents or parents from other immigrant backgrounds, underscoring their strong academic and economic achievements.

5.3. Temporal differences in educational and financial outcomes

This subsection examines the educational and financial disparities over time among children from various migration backgrounds. To explore these differences, we apply Equation (1) to two key time-varying outcomes: higher education attainment and annual individual taxable income. For educational attainment, separate regressions are conducted for each calendar year from 2013 to 2019, using a sample of individuals aged 17 or 18 at the time of the 2011 Census. For earnings, we focus on an older cohort of individuals aged 21 or 22 at the time of the 2011 Census, ensuring sufficient observation of their earnings outcomes for each financial year from 2011/12 to 2018/19. Additionally, we intentionally employ a smaller sample of individuals with similar ages (i.e., individuals no more than two years apart, as opposed to the four-year age difference in the baseline analysis) to minimize the effect of age on outcomes, providing a more meaningful temporal analysis. This approach also ensures that we observe the earnings outcomes of older individuals, particularly for NESB children, who are more likely to enrol in higher education and enter the labour market later. Furthermore, to ensure clarity and manageability of the results, this subsection focuses on two migration background groups for each parent, as defined in the baseline regression.

Table 5 presents the estimates of parental migration background on the likelihood of completing any higher education degree over time, revealing distinct temporal patterns. For children of ESB immigrant mothers, a reduced probability of completing higher education compared to children of Australian-born mothers emerges at ages 21–22, widens until ages 24–25, and then plateaus. Similarly, for children of ESB immigrant fathers, a disadvantage in higher education attainment appears at ages 22–23 but diminishes in later years. In contrast, Table 5 shows that the pattern of higher education attainment favouring children of NESB

immigrant mothers and fathers relative to children of Australian-born parents begins at ages 19–20, accelerates through ages 24–25, and subsequently levels off.

Turning to earnings, Table 6 reveals distinct patterns associated with parental migration background over time.[14] For children of ESB migrant parents, lower earnings compared to children of Australian-born mothers emerge at ages 23–24, widen by ages 27–28, and slightly decrease by ages 28–29. Similarly, children of ESB migrant fathers exhibit lower earnings than their counterparts with Australian-born fathers, with this disparity appearing earlier, at ages 22–23, and progressively increasing through the end of the study period at ages 28–29.

In contrast, children of NESB migrants exhibit a different trajectory. Initially, they earn less than children of Australian-born parents at ages 21–22, but this gap narrows by ages 23–24 and becomes statistically insignificant thereafter. This trend aligns with earlier findings that children of NESB migrants tend to spend more time pursuing higher education, delaying labour market entry and resulting in temporarily lower earnings. By ages 26–27, children of NESB fathers begin to out-earn their peers with Australian-born fathers, with an average annual earnings advantage of AU$1,300—a 2.5% increase relative to the sample mean. This gap becomes even more pronounced at ages 28–29, where children of NESB fathers earn AU$1,550 more annually—a 2.8% increase relative to the sample mean.

5.4. Early returns to level and field of education

Earlier in Section 4.3, we found that children of migrants—regardless of whether their parents are from English-speaking backgrounds—tend to have lower taxable incomes compared to children of native-born parents. We also observed that children of NESB parents are more likely to participate in higher education, which typically takes a longer time to complete (Sections 4.3 and 5.1). It is therefore of interest to examine whether the earnings gap, or "disadvantage", observed among children of migrants—particularly those with NESB parents—is attributable to a higher likelihood of pursuing higher education qualifications or to the selection of fields of study, such as medicine, which involve longer training durations.

To investigate this, we estimate a model similar to Equation (1), additionally and separately controlling for: (1) completed level of education; (2) completed field of study; and (3) the

[14] We have run additional sensitivity analyses, testing interactions between completed education levels and fields of study as additional explanatory variables in the earnings regressions and found that the results are largely consistent with those presented here.

interaction between completed level of education and field of study.[15] As in the baseline analysis, this subsection focuses on taxable income measured at the end of the study period (i.e., the 2018/19 financial year). As previously noted, this time point is chosen to allow sufficient time to observe higher education outcomes, when most individuals in our baseline sample would be between 23 and 26 years of age and are expected to have completed their tertiary education.

The results of this analysis, presented in Table 7, indicate that the earnings gap within this age group persists even after controlling for completed education level (Column 2), field of study (Column 3), and their interaction (Column 4). The magnitude and statistical significance of the estimated gaps remain broadly consistent with the baseline estimates (reproduced in Column 1). These earnings differentials are considerable, ranging from 2.61% of the mean earnings in our sample—as observed for children of ESB migrant mothers in Column 4—to 6.58%, as recorded for children of NESB migrant fathers.

Table 7 also reports early career earnings returns to completed levels of education and fields of study, measured for individuals aged 23 to 26 years.[16] The results in Column 2 indicate that, compared to individuals with no higher education qualification (the reference group), those with a graduate diploma earn the highest average annual income (approximately $16,000 more), followed by individuals with a master's or higher degree ($11,000 more), and those with a bachelor's degree ($10,000 more). In contrast, individuals with a diploma earn about $2,000 less than the reference group.

Column 3 presents earnings by field of study for those who have completed a higher education qualification. Among individuals aged 23 to 26, those who studied engineering earn the highest

[15] We refrain from including ATAR score as an additional explanatory variable in the earnings equation because, as noted earlier in Section 3, ATAR scores are only available for individuals who enrolled in higher education. Including this variable would introduce a sample selection issue, as children of NESB migrants are disproportionately more likely to have an ATAR score and, consequently, to be included in the estimation sample. Moreover, it would result in a reduction of the sample size by more than half.

[16] It is important to note that the estimated earnings returns to education level and field of study presented in this study, while representing an improvement over some previous Australian studies—such as Daly *et al.* (2015), which relies on 2006 Census data and self-reported income to estimate returns to field of study, and Leigh (2025), who uses HILDA data to examine returns to education level without controlling for parental socio-economic background, as this study does—should not be interpreted as causal due to potential confounding factors (Card 1999). Furthermore, differences in data sources and empirical methodologies mean that the results are not directly comparable across studies. Given concerns regarding the endogeneity of education level and field of study, these variables are excluded from the baseline earnings regressions. Additionally, the analysis focuses solely on early career outcomes and does not capture long-term or lifetime returns. Moreover, the primary earning outcome measured in this study is individual taxable income, which does not account for total working hours. For brevity and clarity, results concerning interactions between education level and field of study are not reported in Column 4 of Table 7.

returns—approximately $18,000 more than the reference group without a higher education qualification—followed by graduates in education ($17,000), health ($16,000), management and commerce ($14,000), information technology ($13,000), architecture and building ($9,000), and agriculture and environmental studies ($7,000). Returns for graduates in natural and physical sciences are negative (about -$2,000), while those in creative arts earn roughly the same as the reference group; the estimate for creative arts is less than $500 and is statistically significant only at the 10% level.

These early-career returns to education level and field of study—broadly consistent with previous Australian research (Daly *et al.* 2015; Leigh 2025)—suggest that children of NESB parents, who are more likely to pursue higher education, tend to enrol in qualifications associated with substantial positive earnings returns. In particular, they are overrepresented in programs such as graduate diplomas, bachelor's degrees, and master's or higher degrees, which are linked to significantly higher earnings. These educational choices and their associated returns may help offset the observed earnings disadvantage faced by second-generation migrants with NESB backgrounds, thereby facilitating convergence in earnings with children of native-born parents. These results underscore the critical role of education in supporting the economic integration of migrants in the host country, particularly in terms of labour market outcomes, as highlighted in the existing literature (Dustmann & Glitz 2011; Duncan & Trejo 2018).

However, it is less clear how field of study contributes to narrowing the overall earnings gap between children of NESB and native-born parents. As discussed in Section 5.1, children of NESB parents are more likely to enrol in certain high-return fields—such as management and commerce, health, engineering, and information technology—but are also more likely to choose fields with lower initial returns, such as natural and physical sciences, and less likely to enrol in high-return fields such as education.

5.5. Gender differences in educational outcomes and earnings

This subsection examines potential gender differences in the educational and earnings outcomes of children from different migration backgrounds. To investigate this, we estimate separate specifications of Equation (1) for males and females. For clarity and brevity, we focus on three key outcomes: ATAR scores, attainment of any higher education qualification, and total taxable income. These outcomes are measured at the end of the study period, allowing sufficient time for them to be fully observed. This approach is consistent with the main analysis.

As before, migration background is defined based on the language background of the parents' country of birth, comparing outcomes for children of native-born parents with those of ESB and NESB parents.

Table 8 suggests limited gender differences in the educational outcomes of children from different migration backgrounds, as the estimates for males and females are broadly similar in both magnitude and statistical significance (Columns 1–4). One notable exception is in ATAR scores: sons of ESB fathers have significantly lower ATAR scores (by 0.87 points) compared to sons of Australian-born fathers, whereas no statistically significant difference is observed between daughters of ESB and Australian-born fathers. Unreported results confirm that this gender difference is statistically significant at the 5% level for this particular outcome and subgroup.

By contrast, Columns 5 and 6 of Table 8 reveal more substantial gender differences in earnings among children from different migration backgrounds.[17] Specifically, children of migrant parents earn less taxable income than children of Australian-born parents, regardless of whether their parent's country of birth is English-speaking or not. These findings are consistent with the baseline results reported in Table 2 (Column 6).

Further examination of Table 8 reveals that among daughters, those with NESB parents are somewhat less disadvantaged than those with ESB parents, although both groups earn less than daughters of Australian-born parents. Among sons, however, the pattern is reversed: those with ESB parents are less disadvantaged than those with NESB parents, although again, both groups earn less than sons of Australian-born parents.

Moreover, the earnings gap by migration background appears more pronounced for males than for females. For instance, daughters of NESB migrant mothers earn $610 less per year than daughters of Australian-born mothers, while sons of NESB migrant mothers earn $2,910 less than sons of Australian-born mothers. Similarly, daughters of NESB migrant fathers earn $580 less, compared to a $2,940 shortfall for their male counterparts. Daughters of ESB migrant fathers earn $1.260 less, while sons earn $2,130 less than the respective native-born comparison group.

[17] These gender differences in earnings persist even when additionally and separately controlling for (1) completed level of education, (2) completed field of study, and (3) the interaction between level and field of study, as outlined in Section 5.4.

The gender disparity in earnings disadvantage is particularly pronounced for children of NESB parents. The relative earnings gap for males is over four times greater than for females in the case of NESB mothers (−2,910 ÷ −610 ≈ 4.77). In contrast, for children of ESB fathers, the relative gap is less than twofold (−2,130 ÷ −1,260 ≈ 1.69). Moreover, the earnings difference for children of ESB migrant mothers is not statistically significant.

6. Discussion

One of the main findings of this study is that children of immigrants from selected countries—particularly those with non-English speaking or Asian backgrounds—tend to achieve better academic outcomes than both children of Australian-born parents and children of immigrants from other countries. Understanding the factors that contribute to this academic success is of significant interest. However, robustly identifying and quantifying the role of these factors remains challenging due to data limitations and methodological constraints (Sweetman & van Ours 2015; Figlio *et al.* 2019; Nguyen *et al.* 2020)).

A notable exception is the recent work by Nguyen *et al.* (2020), which specifically investigates the role of children's time allocation in explaining ethnic differences in academic test scores. Using Australian panel data that link time-use diaries to academic test scores through Year 9, and employing various panel data methods to address the potential endogeneity of children's time allocation, the study finds that children of Asian immigrants devote more time to educational activities than their peers. Their analysis shows that this difference in time investment—rather than parental socio-demographic characteristics or parenting styles—accounts for a substantial portion of the academic advantage observed among children of Asian immigrants.

When considered alongside our findings, this earlier Australian evidence for a younger cohort suggests that differences in childhood time investment, particularly in educational activities, may contribute to the superior academic achievement and post-school attainment observed in our sample, as measured by ATAR scores and higher education completion. Unfortunately, the currently available data do not allow for a rigorous analysis of this hypothesis, as such an investigation would require panel data tracking both time allocation and academic outcomes over an extended period, similar to the approach used by Nguyen *et al.* (2020). Therefore, exploring the underlying drivers of academic success among children from selected immigrant backgrounds, using alternative datasets or empirical strategies remains an important avenue for future research.

Another key finding of this study is that second-generation immigrants in Australia, irrespective of their parents' English language background, experience earnings disadvantages at the early stages of their careers (i.e., ages 23 to 26). This result aligns with both international and Australian evidence (Maani 1994; Aydemir *et al.* 2009; Deutscher 2020; Abramitzky *et al.* 2021). Furthermore, our more detailed and dynamic analyses using an older cohort (Section 5.3) reveal that the earnings gap for children of NESB migrants disappears by ages 23–24, whereas it persists for children of ESB migrants until ages 28–29. This emerging dynamic pattern—enabled by our unique data and empirical approach—indicates differing earnings trajectories across selected migrant groups. However, this finding warrants further examination with longer panel data, as current datasets do not capture the full period over which earnings may eventually converge. If the earnings gap among children of ESB migrants persists, it holds important policy implications, particularly regarding the underlying factors contributing to this disparity. While such an investigation lies beyond the scope of the present study, it represents a promising avenue for future research using more comprehensive data and refined methods.

This study (Subsection 5.5) also finds that sons of migrant parents—particularly those from NESB—experience a more pronounced earnings disadvantage in early adulthood (ages 23 to 26). To the best of our knowledge, this pattern has not been previously documented in the literature (Deutscher 2020; Villarreal & Tamborini 2023). This contribution is made possible by the rich data and large sample size employed in our analysis. However, as noted above, it remains important to investigate whether this disadvantage persists later in life. If the gender disparity continues, it would be valuable to examine the underlying sources of these gaps. One plausible explanation is the influence of unobservable factors systematically associated with parental migration backgrounds—such as prevailing gender norms in parents' countries of origin—which may differentially affect sons and daughters in terms of labour market outcomes (Marianne 2011). Similar mechanisms have recently been explored in the context of gender gaps in educational outcomes among second-generation immigrants in the United States (Nollenberger *et al.* 2016; Huber & Paule-Paludkiewicz 2024). While our dataset allows us to control for a wide range of observable characteristics—including parental education and income, as well as children's academic achievement—it is not well suited to identifying such unobserved influences. As with most previous studies, the precise mechanisms underlying these earnings disadvantages remain difficult to quantify (Abramitzky & Boustan 2017). Future research should investigate these mechanisms more thoroughly, using alternative datasets and empirical strategies better suited to capturing long-term and intergenerational dynamics.

Finally, this study focuses on parents' home country English language background when examining the educational and earnings pathways of Australian-born children. As documented earlier, this classification follows prior Australian studies (Cobb-Clark & Nguyen 2012; Nguyen *et al.* 2020) and reflects the well-established economic benefits associated with higher English language proficiency (Bleakley & Chin 2010). Our detailed country-level analysis further reveals that the superior academic performance among children from non-English-speaking backgrounds (NESB) is primarily driven by those with Asian heritage. For brevity and clarity, this study focuses on two main country groupings—based on parental English language background and geographic region—which are more granular than those used in previous Australian studies (Cobb-Clark & Nguyen 2012; Deutscher 2020; Nguyen *et al.* 2020). However, it is important to acknowledge that these classifications are not exhaustive, and alternative groupings may provide additional insights (Nollenberger *et al.* 2016; Figlio *et al.* 2019; Huber & Paule-Paludkiewicz 2024). Further exploration of such alternative classifications—an endeavour best pursued through dedicated future research—may deepen our understanding of the factors driving superior outcomes among specific migrant groups. Some preliminary observations are available from the detailed country-level results presented in Subsection 5.2.

7. Conclusion

Leveraging newly available linked 2011 Census-administrative datasets, this study investigates disparities in educational attainment and earnings trajectories among children from diverse parental migration backgrounds in Australia, tracing their development from mid-adolescence to early adulthood. By adopting an extended time horizon and enhanced analytical precision, the study corroborates established findings, such as the superior academic performance of second-generation NESB immigrants, while also uncovering several novel insights.

Specifically, the study reveals that the strong academic outcomes of NESB second-generation immigrants are largely attributable to children of parents from select Asian countries, including China, Hong Kong, Cambodia, Vietnam, Sri Lanka, Indonesia, Malaysia, Singapore, and India. Their higher likelihood of completing higher education is predominantly driven by increased probabilities of attaining bachelor's and master's degrees. Furthermore, they tend to specialise in fields such as management and commerce, health, natural and physical sciences, engineering, society and culture, information technology, and architecture and building.

The study also highlights temporal patterns in educational and financial trajectories. For children of NESB immigrant parents, the academic advantage—reflected in their higher likelihood of completing higher education—emerges around ages 19–20, accelerates until ages 24–25, and then plateaus. This educational pathway aligns with financial outcomes: while these individuals initially earn less than their peers with Australian-born parents at ages 21–22, the earnings gap narrows by ages 23–24 and disappears thereafter. By ages 26–27, children of NESB fathers begin to out-earn their counterparts with Australian-born fathers, with this advantage becoming more pronounced by ages 28–29. Further analysis reveals that this convergence in earnings is partly explained by the greater likelihood of children of NESB parents enrolling in higher education fields associated with substantial positive earnings returns.

In contrast, children of ESB immigrant parents, who demonstrate weaker academic performance, also experience lower earnings compared to peers with Australian-born parents. This disparity becomes evident as early as ages 22–23 and continues to widen throughout the study period, peaking at ages 28–29, where our follow-up ends. Overall, the findings emphasise the strongest academic and economic outcomes among second-generation NESB immigrants, while highlighting comparatively weaker outcomes for second-generation ESB immigrants within the Australian context.

While our study makes significant contributions, several limitations warrant consideration and present opportunities for future research. First, due to current data constraints, the analysis does not extend to income outcomes in later life stages from age 30 years and beyond. Expanding income data integration within the PLIDA framework could enable longitudinal studies on income disparities beyond early adulthood. Second, while this study focuses on human capital in terms of educational attainment and monetary outcomes, future research should explore additional dimensions, such as non-cognitive skills and health outcomes, to provide a more comprehensive understanding of integration metrics. Third, further investigation is needed into the factors driving the superior outcomes observed among specific migrant groups. Future studies addressing these areas would contribute to a more nuanced understanding of immigrant integration within Australia's multicultural context.

Despite the above limitations, our study provides clear contributions to the literature, by presenting novel evidence based on unique data. Specifically, it is the first study to leverage linked census and administrative population-based datasets on higher education and income to examine the dynamics of educational attainment and earnings trajectories during early

adulthood for individuals with diverse migration backgrounds in Australia. Our findings underscore the critical role of education in facilitating the economic integration of migrants and their descendants in the host country. As such, this study provides a foundation for future research aimed at deepening our understanding of socio-economic disparities among individuals from different migrant backgrounds—not only in Australia, but also in other multicultural societies.

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Table 1: Summary statistics by parental migration background

Variable	Mother born			Father born		
	In Australia	Overseas	Difference (Australia – Overseas)	In Australia	Overseas	Difference (Australia – Overseas)
	(1)	(2)	(3)	(4)	(5)	(6)
SC male	0.52	0.51	0.01**	0.52	0.51	0.00
SC age (years)	16.51	16.52	-0.01**	16.51	16.51	0.00
Mother age (years)	46.14	47.27	-1.13***	46.21	47.02	-0.81***
Mother born in Australia	1.00	0.00	1.00***	0.88	0.38	0.50***
Mother ESB migrant	0.00	0.31	-0.31***	0.07	0.11	-0.04***
Mother NESB migrant	0.00	0.69	-0.69***	0.05	0.52	-0.47***
Mother Year 11 or lower	0.37	0.31	0.06***	0.37	0.32	0.04***
Mother Year 12	0.16	0.23	-0.07***	0.16	0.22	-0.06***
Mother Certificate	0.13	0.10	0.04***	0.13	0.10	0.03***
Mother Diploma	0.12	0.13	0.00***	0.12	0.13	0.00
Mother Bachelor degree or higher	0.22	0.24	-0.02***	0.22	0.23	-0.01***
Father age (years)	48.53	50.55	-2.02***	48.53	50.46	-1.94***
Father born in Australia	0.87	0.35	0.52***	1.00	0.00	1.00***
Father ESB migrant	0.07	0.12	-0.04***	0.00	0.32	-0.32***
Father NESB migrant	0.06	0.54	-0.48***	0.00	0.68	-0.68***
Father Year 11 or lower	0.25	0.25	0.01**	0.25	0.26	0.00
Father Year 12	0.10	0.16	-0.06***	0.10	0.16	-0.06***
Father Certificate	0.34	0.23	0.11***	0.34	0.23	0.11***
Father Diploma	0.09	0.10	0.00	0.09	0.10	0.00***
Father Bachelor degree or higher	0.21	0.26	-0.05***	0.21	0.25	-0.04***
Renter	0.12	0.12	0.00	0.12	0.12	-0.01***
Mortgage owner	0.64	0.59	0.05***	0.63	0.59	0.04***
Outright owner	0.25	0.29	-0.05***	0.25	0.28	-0.03***
Household income ($1,000)	106.29	98.80	7.48***	106.44	98.73	7.71***
ATAR scores	78.77	79.74	-0.97***	78.95	79.35	-0.40***
SC completed a HE degree by 2019	0.36	0.49	-0.14***	0.36	0.48	-0.13***
SC taxable income in 2018/19 FY ($1,000)	42.18	38.94	3.25***	42.26	38.88	3.38***
Observations	198,695	67,668		195,337	71,026	

Notes: Figures are sample mean. SC denotes Study Child. Tests are performed on the significance of the difference between the sample mean for "In Australia" and "Overseas" sub-group. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 2: Educational and financial outcomes by parental migration background

	ATAR scores		Any higher education qualification by 2019			Taxable income (2018/19 FY; in AU$1,000)	
	Estimate	Interaction	Estimate	ME	Interaction	Estimate	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mother ESB migrant	-0.31*	-0.46**	-11.27***	-2.16***	-9.94***	-1.48***	-1.46***
	(0.16)	(0.20)	(1.69)	(0.32)	(2.03)	(0.26)	(0.33)
Mother NESB migrant	1.81***	0.62***	47.20***	9.46***	26.04***	-1.75***	-2.35***
	(0.15)	(0.21)	(1.58)	(0.32)	(2.33)	(0.22)	(0.32)
Father ESB migrant	-0.49***	-0.54***	-7.37***	-1.42***	-6.86***	-1.72***	-1.72***
	(0.16)	(0.19)	(1.64)	(0.31)	(1.96)	(0.22)	(0.26)
Father NESB migrant	0.62***	-0.52**	41.44***	8.27***	24.61***	-1.81***	-2.30***
	(0.15)	(0.20)	(1.56)	(0.32)	(2.14)	(0.21)	(0.29)
Mother ESB migrant – Father ESB migrant		0.29			-1.47		0.02
		(0.39)			(3.99)		(0.58)
Mother ESB migrant – Father NESB migrant		1.08*			-14.63**		-0.31
		(0.62)			(6.55)		(0.87)
Mother NESB migrant – Father ESB migrant		0.44			0.63		-0.01
		(0.57)			(6.05)		(0.80)
Mother NESB migrant – Father NESB migrant		2.52***			43.90***		1.25***
		(0.31)			(3.35)		(0.46)
Observations	102,730	102,730	266,363	266,363	266,363	266,363	266,363
R-squared	0.161	0.162				0.039	0.039
Mean dependent variable	79.07	79.07	39.22	39.22	39.22	41.36	41.36

Notes: Results from an Ordinary Least Squares (OLS) regressions for continuous outcomes and from a Logit model for binary outcomes. Marginal effects (ME) are reported for Logit model. Results (coefficients and standard errors) for the Logit model are multiplied by 100 for aesthetic purposes. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Remaining results are reported in Appendix Table A1. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 3: Differences in level of education by parental migration background

Parental migration background:	Mother ESB migrant	Mother NESB migrant	Father ESB migrant	Father NESB migrant
Child's level of education	(1)	(2)	(3)	(4)
Diploma or lower	-0.03	0.21***	-0.10	0.17**
	(0.07)	(0.07)	(0.07)	(0.07)
Bachelor	-1.70***	7.66***	-0.99***	6.38***
	(0.32)	(0.32)	(0.31)	(0.31)
Graduate diploma	-0.25***	0.36***	-0.17*	0.47***
	(0.09)	(0.09)	(0.09)	(0.09)
Master or higher	-0.18	1.22***	-0.16	1.24***
	(0.12)	(0.12)	(0.12)	(0.12)

Notes: Results (coefficients and standard errors) are from a multinomial model, reported in marginal effects, and multiplied by 100 for aesthetic purposes. Outcome variable: Level of higher education by 2019. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Number of observations: 266,363. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 4: Differences in field of study by parental migration background

Parental migration background:	Mother ESB migrant	Mother NESB migrant	Father ESB migrant	Father NESB migrant
Child's field of study	(1)	(2)	(3)	(4)
Natural and physical sciences	0.19	1.68***	0.09	0.73***
	(0.13)	(0.13)	(0.13)	(0.12)
Information technology	-0.03	0.72***	-0.04	0.45***
	(0.07)	(0.08)	(0.07)	(0.07)
Engineering and related technologies	-0.20*	1.48***	-0.25**	0.93***
	(0.10)	(0.12)	(0.10)	(0.11)
Architecture and building	-0.11	0.20***	0.06	0.43***
	(0.07)	(0.07)	(0.07)	(0.08)
Agriculture and environmental studies	-0.10**	-0.09*	0.04	-0.18***
	(0.05)	(0.05)	(0.05)	(0.04)
Health	-0.45**	2.31***	-0.78***	1.71***
	(0.19)	(0.19)	(0.18)	(0.18)
Education	-0.70***	-1.14***	-0.70***	0.02
	(0.15)	(0.13)	(0.14)	(0.15)
Management and commerce	-0.56***	3.10***	-0.64***	3.00***
	(0.17)	(0.18)	(0.17)	(0.18)
Society and culture	-0.30*	0.98***	0.34*	1.09***
	(0.18)	(0.18)	(0.18)	(0.18)
Creative arts	0.08	-0.03	0.43***	-0.03
	(0.14)	(0.14)	(0.14)	(0.14)

Notes: Results (coefficients and standard errors) are from a multinomial model, reported in marginal effects, and multiplied by 100 for aesthetic purposes. Outcome variable: Field of higher education study by 2019. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Number of observations: 266,363. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 5: Difference in higher education attainment by parental migration background over time

Calendar year:	2013	2014	2015	2016	2017	2018	2019
Age of individuals in the respective year:	19-20	20-21	21-22	22-23	23-24	24-25	25-26
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mother ESB migrant	0.10	-0.23	-1.14***	-1.76***	-1.89***	-2.07***	-2.03***
	(0.13)	(0.29)	(0.43)	(0.51)	(0.53)	(0.54)	(0.54)
Mother NESB migrant	0.40***	2.10***	4.42***	6.92***	8.67***	9.18***	9.43***
	(0.12)	(0.30)	(0.45)	(0.51)	(0.54)	(0.54)	(0.55)
Father ESB migrant	-0.10	0.03	-0.52	-1.65***	-1.41***	-0.90*	-1.16**
	(0.11)	(0.29)	(0.43)	(0.50)	(0.53)	(0.54)	(0.54)
Father NESB migrant	0.57***	2.51***	5.17***	6.79***	7.53***	8.01***	8.07***
	(0.13)	(0.31)	(0.45)	(0.51)	(0.53)	(0.54)	(0.54)
Observations	93,771	93,771	93,771	93,771	93,771	93,771	93,771
Mean dependent variable	0.01	0.07	0.18	0.29	0.35	0.39	0.42

Notes: Results (coefficients and standard errors) are from a Logit model, reported in marginal effects, and multiplied by 100 for aesthetic purposes. Outcome variable: higher education attainment. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 6: Difference in annual individual taxable income by parental migration background over time

Financial year:	2011	2012	2013	2014	2015	2016	2017	2018
Age of individuals in the respective year:	21-22	22-23	23-24	24-25	25-26	26-27	27-28	28-29
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mother ESB migrant	-0.26	-0.43	-0.94**	-0.89*	-1.37***	-1.45***	-1.61***	-1.48**
	(0.37)	(0.40)	(0.44)	(0.49)	(0.51)	(0.54)	(0.60)	(0.65)
Mother NESB migrant	-2.68***	-1.70***	-1.09***	0.01	-0.02	0.27	0.59	0.92
	(0.32)	(0.36)	(0.42)	(0.60)	(0.54)	(0.54)	(0.61)	(0.66)
Father ESB migrant	-0.70*	-1.38***	-1.30***	-1.40***	-1.38***	-1.86***	-1.85***	-2.32***
	(0.37)	(0.39)	(0.46)	(0.49)	(0.51)	(0.52)	(0.59)	(0.62)
Father NESB migrant	-1.76***	-1.43***	-0.88**	-0.18	0.80	1.30**	0.95	1.55**
	(0.32)	(0.36)	(0.40)	(0.52)	(0.51)	(0.52)	(0.58)	(0.63)
Observations	56,868	56,868	56,868	56,868	56,868	56,868	56,868	56,868
R-squared	0.05	0.06	0.06	0.04	0.04	0.04	0.04	0.03
Mean dependent variable	28.32	33.10	38.02	42.35	46.96	50.24	53.53	56.05

Notes: Results are from an OLS regression. Outcome variable: annual individual taxable income (in AU$1,000). Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 7: Early returns to level and field of education

Specification:	Baseline	Educational levels	Field of study	Interaction
	(1)	(2)	(3)	(4)
Mother ESB migrant [a]	-1.48***	-1.23***	-1.11***	-1.08***
	(0.26)	(0.26)	(0.26)	(0.26)
Mother NESB migrant [a]	-1.75***	-2.66***	-2.66***	-2.64***
	(0.22)	(0.21)	(0.21)	(0.21)
Father ESB migrant [a]	-1.72***	-1.61***	-1.43***	-1.42***
	(0.22)	(0.22)	(0.22)	(0.22)
Father NESB migrant [a]	-1.81***	-2.60***	-2.72***	-2.72***
	(0.21)	(0.21)	(0.21)	(0.21)
Diploma or lower [b]		-1.91***		
		(0.63)		
Bachelor [b]		10.12***		
		(0.14)		
Graduate diploma [b]		15.63***		
		(0.50)		
Master or higher [b]		11.11***		
		(0.41)		
Natural and physical sciences [b]			-2.23***	
			(0.32)	
Information technology [b]			13.12***	
			(0.68)	
Engineering and related technologies [b]			18.38***	
			(0.47)	
Architecture and building [b]			8.74***	
			(0.58)	
Agriculture and environmental studies [b]			7.47***	
			(0.95)	
Health [b]			15.62***	
			(0.24)	
Education [b]			16.53***	
			(0.26)	
Management and commerce [b]			14.28***	
			(0.31)	
Society and culture [b]			5.07***	
			(0.24)	
Creative arts [b]			-0.46*	
			(0.27)	
Observations	266,363	266,363	266,363	266,363
R-squared	0.039	0.059	0.075	0.077
Mean dependent variable	41.36	41.36	41.36	41.36

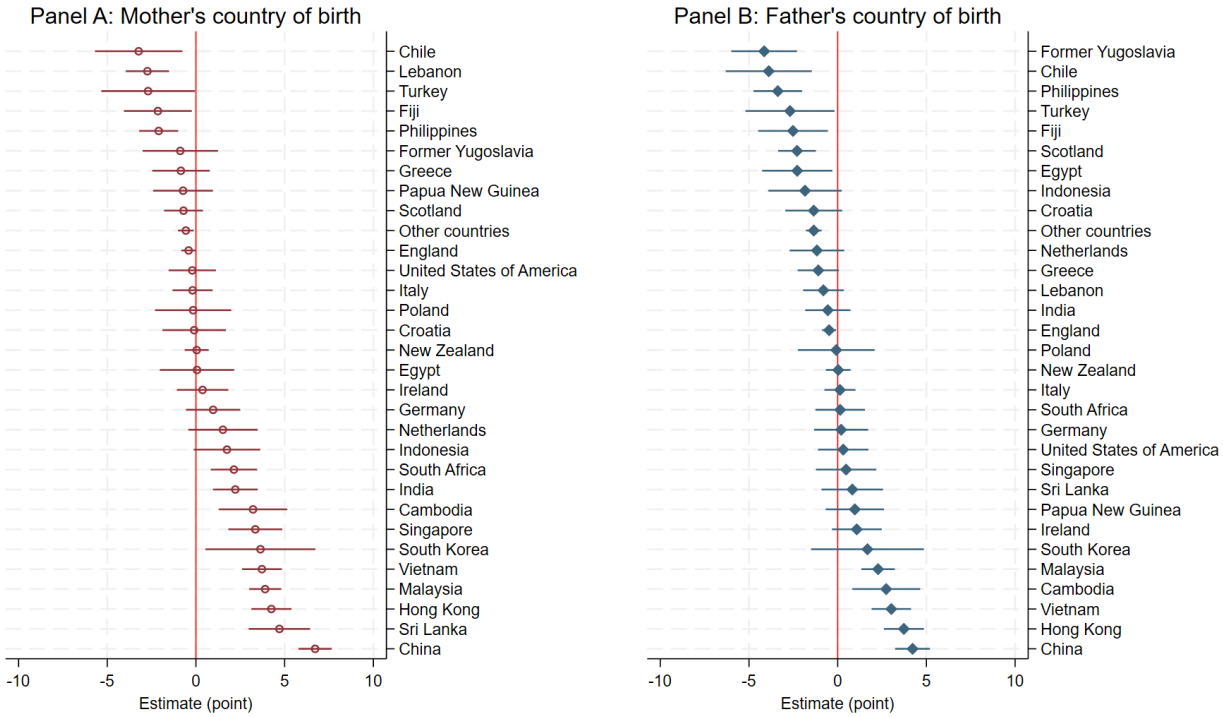
Notes: Results are from an OLS regression. Outcome variable: annual individual taxable income (in AU$1,000) recorded in 2018/19 financial year. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. [b] and [b] indicates Australian-born mothers and fathers, and "No higher education qualification" are set as the respective base groups. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 8: Gender difference in educational and financial outcomes by parental migration background

Child's outcome:	ATAR scores		Any higher education qualification by 2019 (Logit, ME)		Taxable income (2018/19 FY, in AU$1,000)	
Child's gender:	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Mother ESB migrant	-0.28	-0.35	-2.37***	-1.95***	-1.46***	-1.51***
	(0.21)	(0.25)	(0.48)	(0.42)	(0.29)	(0.42)
Mother NESB migrant	1.75***	1.85***	9.12***	9.71***	-0.61**	-2.91***
	(0.19)	(0.22)	(0.48)	(0.43)	(0.28)	(0.32)
Father ESB migrant	-0.14	-0.87***	-1.58***	-1.24***	-1.26***	-2.13***
	(0.21)	(0.24)	(0.48)	(0.42)	(0.28)	(0.33)
Father NESB migrant	0.51***	0.75***	8.55***	7.96***	-0.58**	-2.94***
	(0.19)	(0.22)	(0.47)	(0.42)	(0.28)	(0.32)
Observations	56,648	46,082	129,111	137,252	129,111	137,252
R-squared	0.176	0.147			0.041	0.038
Mean dependent variable	79.28	78.82	47.49	31.44	39.40	43.20

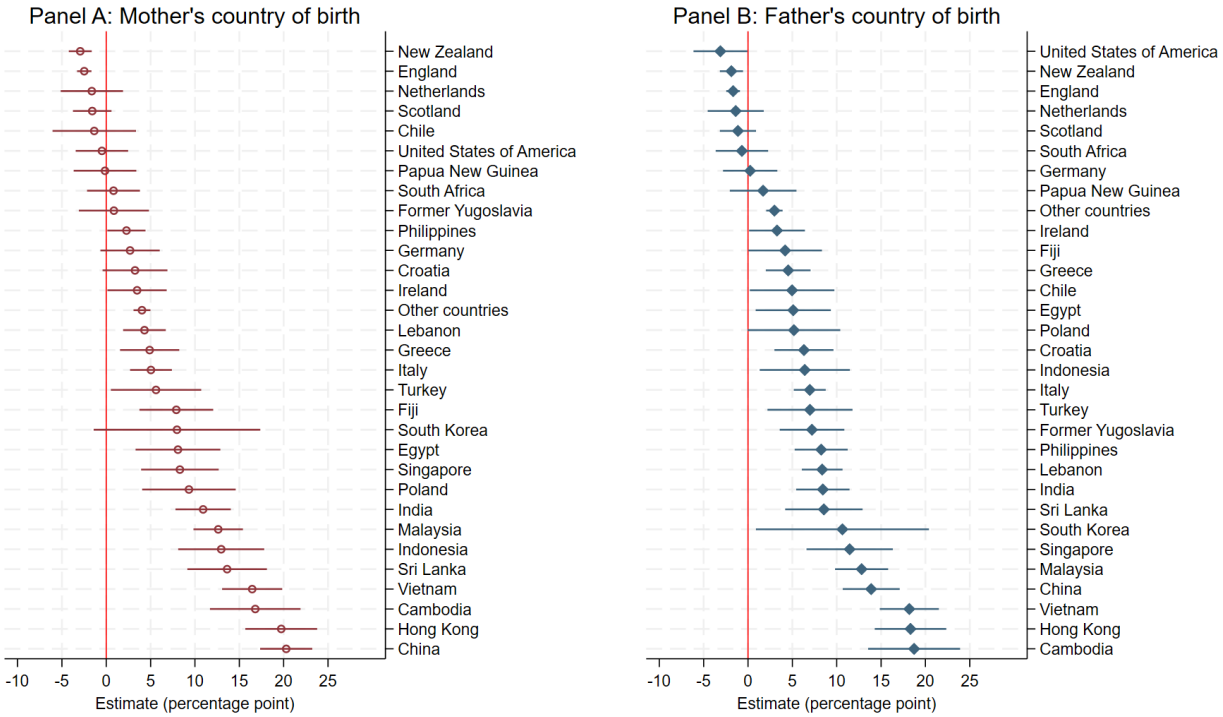
Notes: Results from an Ordinary Least Squares (OLS) regressions for continuous outcomes and from a Logit model for binary outcomes. Marginal effects (ME) are reported for Logit model. Results (coefficients and standard errors) for the Logit model are multiplied by 100 for aesthetic purposes. Other explanatory variables include SC month of birth dummies, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Figure 1: Differences in ATAR scores by the top 30 parental countries of birth



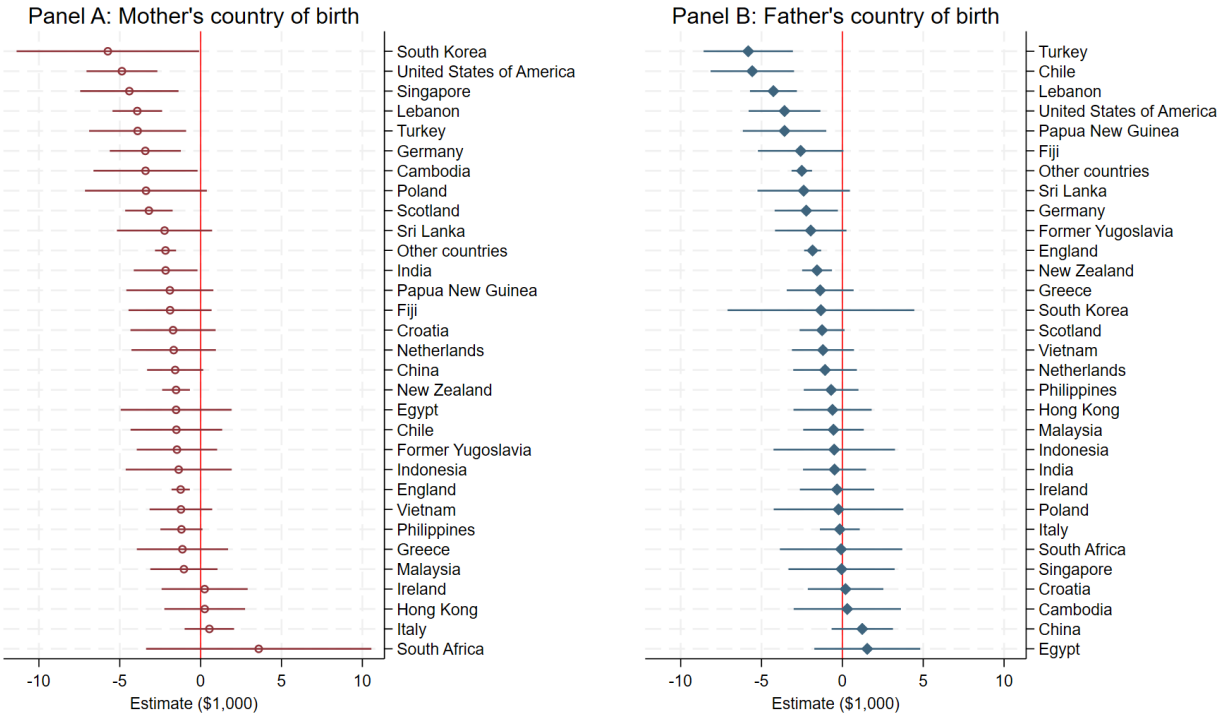
Notes: Results (coefficients and 95% confidence intervals) are from an OLS model. Outcome variable: ATAR scores. Other explanatory variables include SC month of birth dummies, SC gender, year left school, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Detailed regression results are presented in Appendix Table B2.

Figure 2: Differences in higher education attainment by the top 30 parental countries of birth



Notes: Results (coefficients and 95% confidence intervals, multiplied by 100 for aesthetic purposes) are from a Logit model and are reported in marginal effects. Outcome variable: higher education attainment by 2019. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Detailed regression results are presented in Appendix Table B2.

Figure 3: Differences in annual taxable income by the top 30 parental countries of birth



Notes: Results (coefficients and 95% confidence intervals) are from an OLS model. Outcome variable: annual taxable income in 2018/19 FY. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Detailed regression results are presented in Appendix Table B2.

Appendix A

Appendix Table A1: Factors influencing educational attainment and earnings outcomes (remaining results)

	ATAR scores		Any higher education qualification by 2019			Taxable income (2018/19 FY)	
	Estimate	Interaction	Estimate	ME	Interaction	Estimate	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Male	-1.17***	-1.17***	-80.35***	-15.57***	-80.44***	3.75***	3.75***
	(0.09)	(0.09)	(0.89)	(0.16)	(0.89)	(0.12)	(0.12)
Mother age	1.56***	1.56***	27.03***	0.51***	27.35***	2.62***	2.63***
	(0.17)	(0.17)	(1.69)	(0.03)	(1.69)	(0.19)	(0.19)
Mother age squared	-0.01***	-0.01***	-0.26***		-0.26***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.02)		(0.02)	(0.00)	(0.00)
Mother Year 12 [(a)]	2.04***	2.05***	46.17***	9.13***	46.28***	0.82***	0.82***
	(0.14)	(0.14)	(1.31)	(0.26)	(1.31)	(0.18)	(0.18)
Mother Certificate [(a)]	0.72***	0.75***	21.32***	4.10***	21.75***	-0.26	-0.25
	(0.17)	(0.17)	(1.51)	(0.29)	(1.51)	(0.19)	(0.19)
Mother Diploma [(a)]	3.01***	3.03***	59.19***	11.85***	59.62***	-0.62***	-0.61***
	(0.15)	(0.15)	(1.47)	(0.30)	(1.47)	(0.20)	(0.20)
Mother Bachelor degree or higher [(a)]	5.67***	5.70***	92.67***	18.98***	93.16***	-1.35***	-1.34***
	(0.13)	(0.13)	(1.34)	(0.28)	(1.34)	(0.19)	(0.19)
Father age	0.85***	0.81***	14.67***	0.15***	13.96***	0.41***	0.40***
	(0.10)	(0.10)	(1.08)	(0.02)	(1.08)	(0.12)	(0.12)
Father age squared	-0.01***	-0.01***	-0.14***		-0.13***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.01)		(0.01)	(0.00)	(0.00)
Father Year 12 [(a)]	2.42***	2.43***	61.38***	12.19***	61.41***	0.79***	0.79***
	(0.17)	(0.17)	(1.58)	(0.32)	(1.58)	(0.21)	(0.21)
Father Certificate [(a)]	0.75***	0.77***	28.98***	5.52***	29.50***	2.18***	2.19***
	(0.15)	(0.15)	(1.26)	(0.24)	(1.26)	(0.16)	(0.16)
Father Diploma [(a)]	3.04***	3.07***	75.16***	15.13***	75.68***	0.76***	0.77***
	(0.18)	(0.18)	(1.70)	(0.35)	(1.70)	(0.23)	(0.23)
Father Bachelor degree or higher [(a)]	6.76***	6.77***	123.36***	25.63***	123.80***	-0.22	-0.21
	(0.15)	(0.15)	(1.46)	(0.30)	(1.47)	(0.20)	(0.20)

	ATAR scores		Any higher education qualification by 2019			Taxable income (2018/19 FY)	
	Estimate	Interaction	Estimate	ME	Interaction	Estimate	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mortgage owner [(b)]	1.55***	1.55***	57.19***	10.54***	57.40***	6.18***	6.19***
	(0.18)	(0.18)	(1.59)	(0.28)	(1.60)	(0.18)	(0.18)
Outright owner [(b)]	4.06***	4.07***	92.06***	17.57***	92.35***	9.62***	9.63***
	(0.19)	(0.19)	(1.73)	(0.31)	(1.74)	(0.22)	(0.22)
Total household income (yearly, $ mil)	4.24***	4.41***	-2.07	-0.40	0.24	33.93***	33.99***
	(0.84)	(0.84)	(8.17)	(1.58)	(8.17)	(1.18)	(1.18)

Notes: Results from an Ordinary Least Squares (OLS) regressions for continuous outcomes and from a Logit model for binary outcomes. Marginal effects (ME) are reported for Logit model. Results (coefficients and standard errors) for the Logit model are multiplied by 100 for aesthetic purposes. Other explanatory variables include SC month of birth dummies and state/territory dummies. [(a)] and [(b)] denotes "Under Year 12", and "Renters" as the base group, respectively. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix B

for refereeing purposes and to be published online

Appendix Table B1: Educational and financial outcomes by parental migration background – Regressions with and without additional controls

	ATAR scores		Any higher education qualification by 2019		Taxable income (2018/19 FY)	
	With controls	Without controls	With controls	Without controls	With controls	Without controls
	(1)	(2)	(3)	(4)	(5)	(6)
Mother ESB migrant	-0.31*	0.96***	-2.16***	0.72**	-1.48***	-1.34***
	(0.16)	(0.18)	(0.32)	(0.36)	(0.26)	(0.26)
Mother NESB migrant	1.81***	1.60***	9.46***	12.98***	-1.75***	-2.38***
	(0.15)	(0.16)	(0.32)	(0.35)	(0.22)	(0.22)
Father ESB migrant	-0.49***	0.55***	-1.42***	0.49	-1.72***	-2.02***
	(0.16)	(0.17)	(0.31)	(0.35)	(0.22)	(0.22)
Father NESB migrant	0.62***	-0.72***	8.27***	9.10***	-1.81***	-2.31***
	(0.15)	(0.16)	(0.32)	(0.34)	(0.21)	(0.21)
Observations	102,730	102,730	266,363	266,363	266,363	266,363
R-squared	0.161	0.001			0.039	0.003
Mean dependent variable	79.07	79.07	39.22	39.22	41.36	41.36

Notes: Results from an OLS regressions for continuous outcomes and from a Logit model for binary outcomes. Marginal effects (ME) are reported for Logit model. Results (coefficients and standard errors) for the Logit model are multiplied by 100 for aesthetic purposes. "Without controls" refers to regressions that include only the categorical variables indicating the country of birth of the individual's mother or father, whereas "With controls" refers to regressions that additionally include a full set of control variables. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix Table B2: Educational and financial outcomes by the top 30 parental countries of birth

	ATAR scores	Any higher education qualification by 2019	Taxable income (2018/19 FY)
	(1)	(2)	(3)
Mother - England	-0.41*	-2.48***	-1.23***
	(0.21)	(0.41)	(0.29)
Mother - Vietnam	3.72***	16.45***	-1.22
	(0.57)	(1.73)	(0.99)
Mother - New Zealand	0.04	-2.94***	-1.52***
	(0.34)	(0.66)	(0.44)
Mother - Lebanon	-2.74***	4.31***	-3.92***
	(0.62)	(1.23)	(0.78)
Mother - China (excludes SARs and Taiwan)	6.72***	20.29***	-1.57*
	(0.48)	(1.50)	(0.88)
Mother - Philippines	-2.10***	2.28**	-1.19*
	(0.56)	(1.10)	(0.67)
Mother - India	2.22***	10.92***	-2.17**
	(0.64)	(1.59)	(1.01)
Mother - Malaysia	3.90***	12.62***	-1.03
	(0.46)	(1.42)	(1.06)
Mother - Scotland	-0.70	-1.58	-3.20***
	(0.56)	(1.11)	(0.75)
Mother - Italy	-0.19	5.04***	0.54
	(0.58)	(1.20)	(0.78)
Mother - Sri Lanka	4.70***	13.63***	-2.23
	(0.88)	(2.29)	(1.50)
Mother - Hong Kong	4.25***	19.73***	0.25
	(0.58)	(2.06)	(1.27)
Mother - Turkey	-2.70**	5.61**	-3.90**
	(1.35)	(2.60)	(1.53)
Mother - Fiji	-2.15**	7.90***	-1.89
	(0.98)	(2.12)	(1.31)
Mother - Cambodia	3.22***	16.80***	-3.41**
	(0.99)	(2.60)	(1.64)
Mother - South Africa	2.14***	0.82	3.59
	(0.67)	(1.52)	(3.55)
Mother - Former Yugoslavia	-0.88	0.86	-1.47
	(1.09)	(2.02)	(1.27)
Mother - United States of America	-0.21	-0.49	-4.87***
	(0.68)	(1.51)	(1.12)
Mother - Greece	-0.85	4.89***	-1.13
	(0.83)	(1.70)	(1.44)
Mother - Ireland	0.37	3.47**	0.25
	(0.74)	(1.70)	(1.36)
Mother - Egypt	0.06	8.08***	-1.52
	(1.07)	(2.44)	(1.75)
Mother - Germany	0.97	2.68	-3.42***
	(0.78)	(1.71)	(1.12)
Mother - Croatia	-0.10	3.24*	-1.70
	(0.91)	(1.87)	(1.34)
Mother - Papua New Guinea	-0.73	-0.14	-1.90
	(0.86)	(1.80)	(1.37)

	ATAR scores	Any higher education qualification by 2019	Taxable income (2018/19 FY)
	(1)	(2)	(3)
Mother - Poland	-0.16	9.32***	-3.38*
	(1.10)	(2.69)	(1.92)
Mother - Indonesia	1.75*	12.96***	-1.36
	(0.96)	(2.47)	(1.67)
Mother - Netherlands	1.52	-1.63	-1.66
	(1.00)	(1.79)	(1.33)
Mother - Chile	-3.23**	-1.35	-1.50
	(1.26)	(2.40)	(1.45)
Mother - South Korea	3.64**	7.97*	-5.74**
	(1.58)	(4.79)	(2.88)
Mother - Singapore	3.35***	8.30***	-4.41***
	(0.78)	(2.23)	(1.55)
Mother - Other countries	-0.57**	4.03***	-2.17***
	(0.23)	(0.49)	(0.33)
Father - England	-0.49**	-1.67***	-1.84***
	(0.20)	(0.40)	(0.27)
Father - Vietnam	3.02***	18.19***	-1.20
	(0.57)	(1.70)	(0.98)
Father - New Zealand	0.03	-1.87***	-1.57***
	(0.35)	(0.67)	(0.47)
Father - Lebanon	-0.81	8.36***	-4.26***
	(0.58)	(1.17)	(0.74)
Father - China (excludes SARs and Taiwan)	4.22***	13.89***	1.23
	(0.50)	(1.64)	(0.97)
Father - Philippines	-3.37***	8.25***	-0.70
	(0.70)	(1.53)	(0.86)
Father - India	-0.56	8.44***	-0.49
	(0.65)	(1.54)	(0.99)
Father - Malaysia	2.28***	12.81***	-0.55
	(0.48)	(1.53)	(0.96)
Father - Scotland	-2.29***	-1.14	-1.26*
	(0.54)	(1.04)	(0.71)
Father - Italy	0.13	6.97***	-0.16
	(0.45)	(0.92)	(0.63)
Father - Sri Lanka	0.82	8.55***	-2.39
	(0.89)	(2.23)	(1.46)
Father - Hong Kong	3.73***	18.32***	-0.61
	(0.57)	(2.06)	(1.23)
Father - Turkey	-2.69**	6.99***	-5.82***
	(1.28)	(2.45)	(1.41)
Father - Fiji	-2.52**	4.19**	-2.58*
	(1.00)	(2.11)	(1.35)
Father - Cambodia	2.73***	18.72***	0.30
	(0.98)	(2.64)	(1.69)
Father - South Africa	0.14	-0.69	-0.08
	(0.71)	(1.51)	(1.93)
Father - Former Yugoslavia	-4.14***	7.21***	-1.96*
	(0.94)	(1.86)	(1.13)
Father - United States of America	0.31	-3.11**	-3.58***
	(0.72)	(1.55)	(1.13)

	ATAR scores	Any higher education qualification by 2019	Taxable income (2018/19 FY)
	(1)	(2)	(3)
Father - Greece	-1.09*	4.53***	-1.37
	(0.59)	(1.28)	(1.06)
Father - Ireland	1.07	3.27**	-0.33
	(0.72)	(1.60)	(1.17)
Father - Egypt	-2.28**	5.10**	1.54
	(1.01)	(2.16)	(1.67)
Father - Germany	0.19	0.25	-2.23**
	(0.78)	(1.56)	(1.00)
Father - Croatia	-1.35*	6.31***	0.20
	(0.82)	(1.70)	(1.19)
Father - Papua New Guinea	0.97	1.70	-3.58***
	(0.84)	(1.92)	(1.32)
Father - Poland	-0.08	5.18*	-0.24
	(1.10)	(2.67)	(2.05)
Father - Indonesia	-1.84*	6.40**	-0.50
	(1.05)	(2.59)	(1.92)
Father - Netherlands	-1.17	-1.38	-1.07
	(0.79)	(1.61)	(1.00)
Father - Chile	-3.89***	4.97**	-5.57***
	(1.24)	(2.43)	(1.32)
Father - South Korea	1.68	10.64**	-1.33
	(1.62)	(4.98)	(2.95)
Father - Singapore	0.47	11.46***	-0.05
	(0.87)	(2.48)	(1.68)
Father - Other countries	-1.35***	2.98***	-2.51***
	(0.23)	(0.47)	(0.32)
Observations	102,730	266,363	266,363
R-squared	0.189		0.040
Mean dependent variable	79.07	39.22	41.36

Notes: Results from an Ordinary Least Squares (OLS) regressions for continuous outcomes and from a Logit model for binary outcomes. Marginal effects (ME) are reported for Logit model. Results (coefficients and standard errors) for the Logit model are multiplied by 100 for aesthetic purposes. Other explanatory variables include SC month of birth dummies, SC gender, maternal age, maternal education, paternal age, paternal education, household residential tenue status, total household income, and state/territory dummies. Australian-born mothers and fathers are set as the respective base groups. Robust standard errors are reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.