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IZA DP No. 14417

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ABSTRACT

Are We Richer Than Our Parents Were? Absolute Income Mobility in Australia*

We conduct the first dedicated study of absolute income mobility in Australia, for 1950-2019. About two-thirds of 30-34 year-olds have higher real incomes than their parents did at the same age, and this has been stable for 25 years. This is among the highest levels of absolute mobility in the world. Nevertheless, mobility was considerably higher for baby-boomers (over 80% had higher incomes than their parents). About two-thirds of this decline in mobility is due to lower income growth. The remainder is due to rising inequality. The mobility estimate is higher (78%) when income is adjusted (equivalised) for family size.

JEL Classification: D31, H00, J62
Keywords: intergenerational mobility, absolute mobility, Australia

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Are we Richer than our Parents Were? Absolute Income Mobility in Australia

Tomas Kennedy and Peter Siminski

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28th of May, 2021

Abstract

We conduct the first dedicated study of absolute income mobility in Australia, for 1950-2019. About two-thirds of 30-34 year-olds have higher real incomes than their parents did at the same age, and this has been stable for 25 years. This is among the highest levels of absolute mobility in the world. Nevertheless, mobility was considerably higher for baby-boomers (over 80% had higher incomes than their parents). About two-thirds of this decline in mobility is due to lower income growth. The remainder is due to rising inequality. The mobility estimate is higher (78%) when income is adjusted (equivalised) for family size.

JEL Codes: D31; H00; J62

Keywords: Intergenerational Mobility; Absolute Mobility; Australia

1. Introduction

Australians seem pessimistic about their children's prospects. Prior to the Covid-19 pandemic, less than 30% of Australians believed that today's children will be better off financially than their parents. This percentage has been steady since 2015, and is amongst the lowest of countries surveyed (Pew Research Center, 2021).[1] This is despite strong long-run real income growth for at least 70 years (World Inequality Database, 2020). Such pessimism may reflect rising inequality overall (World Inequality Database, 2020), and between age groups (Wood & Griffiths, 2019). It may reflect stagnant wage growth in recent years (Bishop & Cassidy, 2017; Andrews et al. 2019), or perhaps broader concern over climate change or instability in global politics.

Pessimism may also reflect a lack of information. Absolute income mobility refers to the proportion of people whose real income is higher than their parents' income at the same age. Until recently, this proportion had never been estimated for Australia, nor indeed for any country in the world, mainly due to a lack of linked intergenerational income data.

The literature on absolute mobility remains sparse. But major contributions have been made in recent years. Chetty et al. (2017) proposed a methodological solution to the lack of linked data. They showed that absolute mobility can be estimated using cross-sectional income distributions, combined with knowledge on the extent of relative mobility. Manduca et al. (2020) confirmed the validity of Chetty et al.'s (2017) approach, by benchmarking to direct estimates using intergenerationally-linked data for a number of countries where such data are available.

Recently, Berman (2020) made several important contributions. He showed that the level of relative mobility has very little effect on absolute mobility estimates. Instead, absolute mobility is primarily a function of income growth between generations and the extent of inequality. He also proposed an approach for estimating absolute mobility with very limited data – drawing only on national income and inequality data from the World Inequality

[1] Respondents are asked "When children today in (survey country) grow up, do you think they will be better off or worse off financially than their parents?". The most pessimistic countries are Japan and a number of European countries.

Database. He demonstrated that the approach works reasonably well for many (but not all) countries for which more direct estimates exist.[2] As part of this exercise, Berman estimated absolute mobility for Australia to be 62.9% for the 1986 birth cohort, having declined from 80.7% for the 1950 cohort.

Our paper is the first dedicated study of absolute income mobility in Australia. For our main estimates, we closely follow the approach used by leading international studies. Our estimates are intended to be as comparable as practical to those of Chetty et al. (2017), as well as Manduca et al. (2020).[3] We adopt Chetty et al.'s 'copula and marginals' approach. We observe child income distributions directly at age 30-34 using all available household income data sources since 1982, covering cohorts born from 1950 to 1987. We observe the parent income distribution only for the 1984 child cohort. For other cohorts of parents, we assume that the distribution evolves proportionally to the national income distribution, in terms of mean income and inequality.

We estimate absolute mobility to be 68% for the most recent cohort. This puts Australia with a cluster of Scandinavian countries as having amongst the highest absolute mobility in the world (Manduca et al. 2020; Berman, 2020), and much higher than the US (50%) (Chetty et al. 2017). Absolute mobility is considerably higher again (78%) when using equivalised income instead.

Our absolute mobility estimates are stable across cohorts for the last 25 years. Nevertheless, absolute mobility has fallen, from 84% for the 1950 birth cohort. Our estimates are broadly similar to Berman's, though they are higher for the key cohorts.

Through a decomposition exercise, we estimate that about two-thirds of the decline in mobility is due to lower income growth. The remainder is due to rising inequality. This is consistent with results for other countries apart from the USA, where rising inequality is the major factor.

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[2] See also Manduca et al. (2020: Appendix 3) for a comparison of Berman's estimates with estimates from more conventional approaches.

[3] This focus on comparability follows the example of some Australian studies of relative income mobility, such as Leigh (2007), Mendolia & Siminski (2016) and Murray et al. (2018).

We also show that the estimates are robust to: measuring income at age 35-39, the imputation approach, inclusion of imputed rental income, different price indices, and using disposable (net of personal income tax) income.

The remainder of the paper is structured as follows. Section 2 details the methods and data while Section 3 presents the main results. Section 4 presents a decomposition of the drivers for falling mobility. Section 5 discusses robustness of the results to a number of factors and Section 6 concludes.

2. Methods and Data

2.1 Methods

Our approach is based on Chetty et al. (2017), with some departures necessitated by data limitations. We outline these methods and our departures below.

Let A_c denote the level of absolute income mobility for birth cohort c. A_c is simply the proportion of people whose income is higher than their parents, as depicted in Equation (1).

$$A_c = \frac{1}{N_c}\sum_i 1\{y_{ic}^k \geq y_{ic}^p\} \qquad (1)$$

Where y_{ic}^k is child i's own income, y_{ic}^p is their parent's income and N_c is the number of children in the cohort. The usual approach is to focus on annual household income (or more precisely, the sum of personal and spouse income) measured at around age 30 for both children and their parents. Migrant children are excluded on the grounds that their parents' income is often unobservable. With ideal linked intergenerational data, (1) can be measured directly. Manduca et al. (2020) use this direct approach to measure absolute mobility for Canada, Denmark, Finland, Norway, and Sweden, while Chetty et al. (2017) also use the direct approach for the USA, but only for recent cohorts.

For most countries and cohorts, data are not available to directly measure mobility as per equation (1). Chetty et al. (2017) proposed an alternate approach with less demanding data requirements. This is known as the 'copula and marginals' approach. Consider Equation (2), which is equivalent to equation (1).

$$A_c = \int 1\{Q_c^k(r^k) \geq Q_c^p(r^p)\} C(r^k, r^p)\, dr^k\, dr^p, \qquad (2)$$

where $Q_c^k(r^k)$ and $Q_c^p(r^p)$ are the rth quantile of the child and parent income distributions, and $C(r^k, r^p)$ is the density of the joint distribution of child income at rank r^k and parent income at r^p.

Expressing A_c in this way highlights that absolute mobility can be calculated differently, using a combination of data inputs that are usually more accessible. $Q_c^k(r^k)$ and $Q_c^p(r^p)$ are the 'marginals' - the cross-sectional income distributions of children and their parents. $C(r^k, r^p)$ is the 'copula' – the intergenerational transition matrix, which summarises relative income mobility.

Of these three inputs, the copula is most difficult to compile, as it too requires linked intergenerational income data. Fortunately, absolute mobility estimates are relatively insensitive to variations to the copula. Whilst Chetty et al. (2017) take an extremely conservative approach to alternate copulas, Berman (2020) asserts that realistic copulas are well approximated by simple bivariate log-normal distributions. He shows that absolute mobility estimates do not vary greatly with assumed levels of relative mobility if copulas are modelled in this way.

In practice, studies which use the copula and marginals approach have assumed stable copulas between cohorts (e.g. Chetty et al., 2017, Berman, 2020). This involves obtaining one copula for each country, and using this to estimate absolute mobility for all cohorts whose marginals are available. We too assume copula stability in our analysis, and demonstrate that the results are insensitive to alternative realistic copulas. Manduca et al. (2020) demonstrate the effectiveness of this approach, through comparisons to the direct estimation benchmark.

2.2 Data

Copula

The 'copula' is the intergenerational transition matrix - which contains the proportion of children in each quantile of the child income distribution, by quantile of the parent income distribution. For our main estimates, we draw on the copula published by Deutscher & Mazumder (2020: Figure A.3). It was constructed using linked income tax data for the 1978-1982 birth cohorts. Child income was measured across a five-year period 2011-2015 (at approx. age 29-37) and parent income over an eleven-year window (1991-2001). On one hand, this copula is not ideal as it does not directly match the data in the marginals.[4] On the other hand, it is quite similar to that used by Chetty et al. (2017) and hence aids in comparability. We emphasise again that the results are largely insensitive to alternate copulas, as will be shown.

Deutscher & Mazumder's (2020) copula is published as a ventile transition matrix. We use an interpolation procedure to approximate a percentile transition matrix.[5]

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[4] Parent income is measured at older ages than child income, whereas the marginals are constructed for parent and child at the same age. The copula is for multi-year income, whereas annual income is used in the marginals. Deutscher & Mazumder show how summary measures of relative mobility (2020: especially Figure A.3b) vary using different income window lengths. Using single-year income for either generation would reduce the rank correlation, but not sufficiently to meaningfully change our absolute mobility results, as will be shown.

[5] To elaborate, each ventile transition probability is divided by five and used as the transition probability for the percentiles at the midpoints of those ventiles. Probabilities for other percentiles are linearly interpolated. Probabilities for the two bottom percentiles are set equal to the third percentile, and similarly for the two top percentiles. Each probability is then rescaled to sum 100% for each parental percentile, to account for rounding error. For example, the original ventile matrix shows that 14.6% of children from the top parent ventile have income in the top ventile, while 9% are in the next ventile. In the first step of our procedure, the probability of moving from the 98th parent percentile to the 98th child

Child Marginals

Child marginal income distributions are sourced from each ABS household income survey conducted since 1982, as well each wave of HILDA since 2001, for a total of 36 marginal income distributions. In each case, we use annual 'income unit' income.[6] The income concept includes income from all sources.[7]

In each data source, we keep Australian-born people aged 30-34, and weight them by the cross-sectional population weights provided with each file. Since 32 years is the midpoint age, we refer to the cohort born 32 years earlier. For example, the 1982 file yields income data for the 1950 cohort of children. Beginning with Chetty et al. (2017), most absolute mobility estimates have used income measured at age 30. There are two reasons for our departure. It is unavoidable as many of our data sources only provide age in 5-year bands. Also, using a 5-

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percentile is set to 14.6%/5 = 2.92%, and 9%/5 = 1.8% for the 93rd child percentile. Interpolating yields probabilities of 2.024%, 2.248%, 2.472%, and 2.696% for moving from the 98th parent percentile to the 94th-97th child percentiles. A similar procedure is used to interpolate parent percentiles.

[6] For this age group, 'income unit' income is essentially the same as personal income plus spouse income, although it also includes any income earned by dependent children. The specific variables used in HILDA are (_tifeftp -_tifeftn), summed across persons in each income unit). For the Income Surveys, the variable names are uuu0015 for 1982, uuu0141 for 1986, inctotpu for 1990-2007, and inctopu8 from 2008 onwards. For 2008 onwards, the variable inctotpu is also available, and is more comparable to the income definition used in earlier years. Using inctotpu instead of inctopu8 in those years has little impact on the results – for the four affected cohorts, the estimates are between 0.0 and 0.3 percentage points lower when using inctotpu.

[7] The methodology used in ABS income surveys has not stayed constant over time (Siminski et al., 2003; Wilkins, 2014). In our view, the changes documented by Siminski et al. (2003) are unlikely to greatly impact the distribution of total annual income across the years they discuss. The implications of the issues raised by Wilkins (2014) for later years are less clear, but the use of HILDA as well helps to triangulate the results.

year window ensures adequate sample sizes, since we rely on household survey data, rather than Census data.[8]

Parent Marginals

To construct parent marginals, we begin with the 1984 birth cohort. This is the only cohort whose parent income distribution is observed directly. We construct this distribution in a way that resembles Chetty et al.'s approach. The procedure is more complicated than for child income, simply because parents have children at different ages. Therefore, parents are in the appropriate age group (30-34) at different points in time, and in some cases, the children have not actually been born yet. To construct this distribution, we use data from five ABS Income Surveys, held approximately five years apart: 1982; 1986; 1990; 1996, 2000, as well as the Household Expenditure Survey in 1975-76. From each year, we keep income units whose head is aged 30-34, weighted by the population weights provided with each file, multiplied by the number of children they have who were born in 1982-86.[9] To include parents whose children were not yet born, we use the surveys held in 1975-76 and 1982. We cannot identify which of these 30-34 year-olds would later become parents. Therefore, we use all such income units, weighted by the average number of 0-4 year-old children amongst income units in the 1986 income survey whose head was aged 40-44 & 35-39, respectively,. Again, this mirrors the approach of Chetty et al. (2017). Most of the resulting (weighted) sample of parents is

[8] The Census of Population and Housing data could also be used for this analysis, with microdata available since 1981. However, income is collected crudely (in broad categories) in the Australian census. Using census data would hence rely heavily on income imputation for both generations.

[9] More precisely, we rely on variables which record the number of children in the household of certain ages at the time of the survey, typically in 5-year age ranges. For example, in the 1986 survey, this is the number of children aged 0-4 years, while for 1990 we use children aged 5-9 (although ideally this would be 4-8 years if they were identifiable).

observed in 1986 (35.0%), 1990 (26.0%) and 1982 (20.6%). Data from 1975-76 accounts for 5.2% of the sample, while 9.6% and 3.6% are from the 1996 and 2000 surveys, respectively.[10]

We do not observe the parental income distribution for other cohorts. Instead, we assume that between 1952 and 1989, the parental income distribution followed the same trend (in terms of the mean and the level of inequality) as the overall income distribution. Appendix 1 describes this procedure in detail. In Section 3.3, we apply the same procedure to also impute child income distributions, as a test of whether the procedure is likely to be reliable.

2.3 Descriptive Statistics

Table 1 shows descriptive statistics for each sample of children, as well as the directly observed sample of parents. For most cohorts, the sample size is around 1000, or greater. Table 1 shows the increase of mean child income across cohorts, in both data sources. The child data are also characterised by a marked fall in the size of income units in the 1980s and 1990s, reflecting the declining fertility rates of women at ages less than 30 (ABS, 2014).

A comparison of the parent sample (observed around 1986 on average) with the contemporaneous sample of children (not their own children) also yields interesting insights. Since children are not necessarily parents themselves, their income unit size is smaller. Their gross income is also higher, due to higher labour force participation. For both reasons, their equivalised income is considerably higher. This suggests we should expect absolute mobility to be relatively high for somewhat mechanical reasons, even with no change in the economy or demographic factors over time. This does not invalidate the approach, it simply reflects that circumstances of parents and non-parents differ.[11]

[10] The 1975-76 survey does not have annual income (it only has current weekly income), which we multiplied by 52.

[11] Berman's (2020) approach does not account for such factors, although adjustments could perhaps be made to accommodate them.

Table 1 – Descriptive Statistics

Year(s)	Mean Income unit size	Mean Gross income $2020	Mean After-tax income $2020	Mean Equivalised income $2020	Sample size
			Parents		
1976-2000	4.06	73685	58189	38364	1081*
			Children (ABS Income Surveys)		
1982	3.54	80077	.	45817	2449
1986	3.38	81101	64498	48043	1376
1990	3.23	83582	64259	50503	2410
1994	2.96	79277	61870	50002	1090
1995	2.97	81185	63227	51081	1041
1996	3.01	79223	62012	49649	1026
1997	2.95	83484	64674	52161	958
1999	2.81	92530	70668	59990	902
2000	2.66	87737	67275	58099	905
2002	2.81	95172	73912	60967	1373
2003	2.79	92204	77123	58954	1517
2005	2.73	103683	85717	66001	1304
2007	2.70	99425	84688	64382	1053
2009	2.69	105087	90985	68281	1809
2011	2.63	104247	90250	68032	1477
2013	2.64	112431	95043	72971	1467
2015	2.68	112982	95773	72501	1731
			Children (HILDA)		
2001	2.70	91657	71877	60181	1103
2002	2.71	97119	75734	63138	1019
2003	2.72	90069	70368	58708	944
2004	2.70	93940	73423	61390	892
2005	2.67	99057	77870	65333	901
2006	2.71	110173	87394	73207	896
2007	2.71	116734	91965	77384	878
2008	2.72	116617	92270	78338	818
2009	2.69	122524	98910	80732	815
2010	2.58	118001	94693	80181	804
2011	2.61	116404	94314	76773	1039
2012	2.62	117941	94703	77863	1062
2013	2.69	117209	94347	75646	1094
2014	2.68	113569	91641	73570	1145
2015	2.62	114431	92289	74836	1223
2016	2.52	113052	90762	75040	1289
2017	2.52	112221	89983	74762	1332
2018	2.52	113729	90656	75977	1404
2019	2.58	117072	95416	77285	1446

Notes: All Incomes are expressed in constant $2020 prices. *The listed parent sample size excludes 589 and 1963 observations from the 1975-76 HES and the 1982 ABS Income Survey. As discussed in the text, observations from those years are assigned much lower weights than other observations, since those without children cannot be excluded, accounting for a combined 26% of the weighted parent sample.

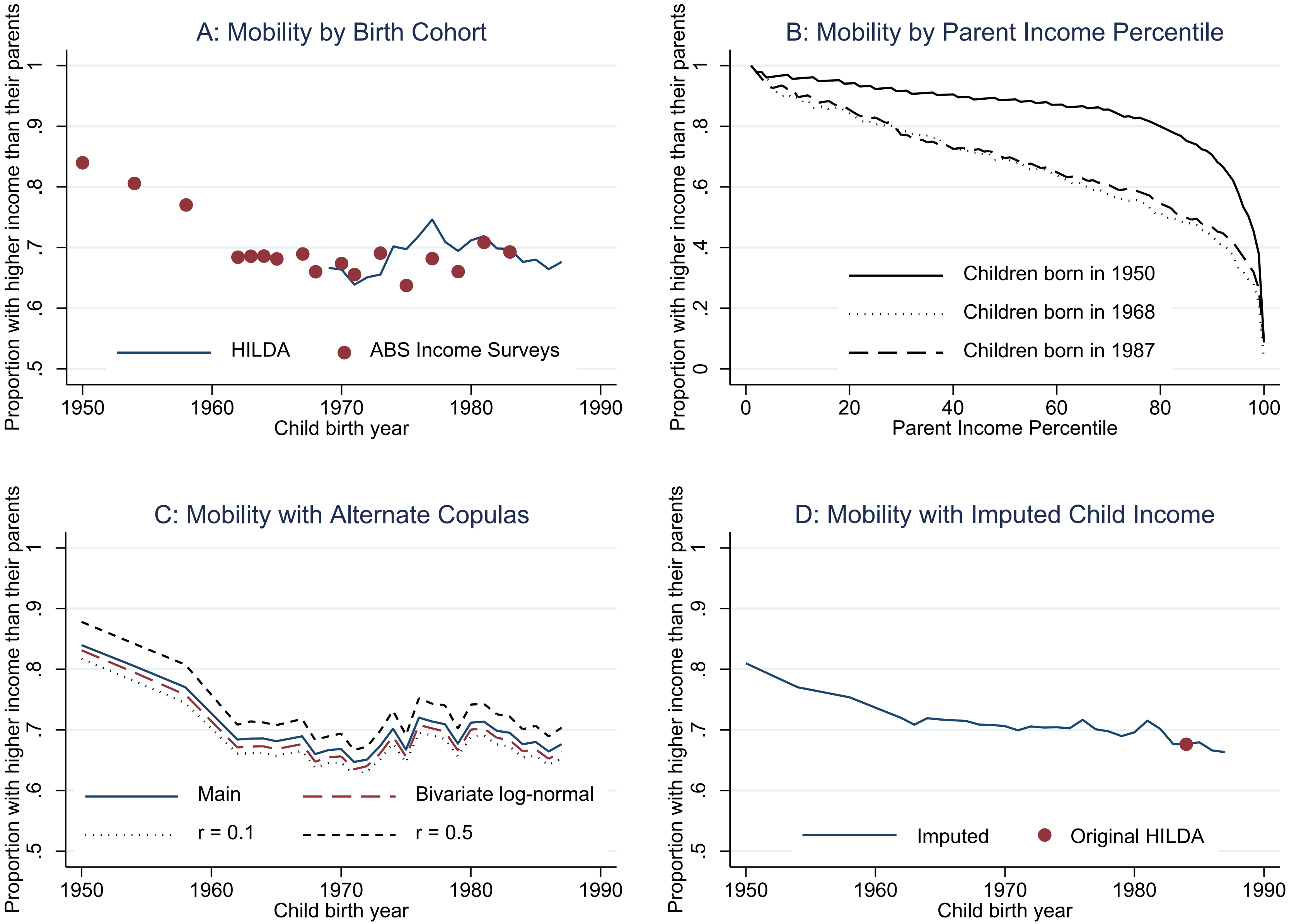
3. Results

3.1 Main Results

Figure 1 Panel A shows the main results – estimated percentages of people whose income around age 32 was higher than their parents' income around the same age. Appendix Table A.1 shows these same results. For the majority of these cohorts, around two-thirds of children had higher incomes than their parents (Panel A), including 68% for the latest (1987) cohort. These estimates are stable across birth cohorts from the early 1960s cohorts onwards. Nevertheless, mobility is estimated to be considerably higher for earlier birth cohorts, as high as 84% for the 1950 birth cohort, and 81% for the 1954 cohort.

Panel B shows these estimates by parent income percentile for the earliest, latest, and middle cohorts. For the 1950 birth cohort, upward mobility was high across most of the parent income distribution. Children whose parents' income was at the 20th percentile had a 94% probability of having a higher income than their parents. Those with parents at the 50th percentile had a 89% probability of a higher income, while even those with parents at the 80th percentile had an 80% chance of a higher income. Only children whose parents' incomes were above the 97th percentile had less than 50% chance of a higher income themselves. For the youngest (1987) birth cohort, we observe the same downward-sloping pattern, but with lower probabilities throughout. Children whose parents' incomes were at the 20th, 50th and 80th percentiles, respectively, had a 85%, 69% and 55% probability of upward mobility. Those with parents at the 95th percentile had a 39% probability of higher income. Unsurprisingly, the patterns for the 1968 and 1987 cohorts are similar.

Figure 1 Estimated Proportions of Children with Higher Income Than their Parents (at age 30-34)



Notes: Panel A shows the preferred estimates of absolute mobility by birth cohort. Panel B shows absolute mobility for three cohorts, by percentile of parent income. Panel C shows the original estimates alongside three alternate series, each derived using bivariate lognormal copulas, including bounds with extreme high and low relative mobility. Panel D shows alternate estimates derived using child incomes derived using the same imputation approach as used for the parent income distributions. For cohorts where estimates from HILDA and an ABS Income Survey are both available, Panel C shows the average of the two.

3.2 Robustness to Alternate Copulas

As discussed earlier, the main results are contingent on the assumed copula and its stability across cohorts. We now explore sensitivity of key results to alternate copulas, similar to Berman's (2020) approach. We only consider realistic copulas, which are well-approximated by bivariate log-normal distributions (Berman, 2020). For this purpose, we construct three alternate series of absolute mobility estimates. For each alternate series, we impose copulas derived from assumed bivariate log-normal distributions of parent-child income pairs, each with a different correlation (ρ).

In the first alternate series, ρ is set to 0.2247, which corresponds with a rank-correlation of 0.215 - the same as in the original copula. Figure 1 Panel C shows the main results again, alongside this alternate series.[12] These alternate estimates closely resemble the original series, they are one percentage point lower for every cohort. This confirms that the original copula is well-approximated by a bivariate log normal distribution for the purpose of estimating absolute mobility.

The other two series in Figure 1 Panel C form bounds. Following Berman (2000), these also use bivariate log-normal copulas, but with extreme low and high correlations, respectively. The low correlation (ρ = 0.1047) copula produces a rank-correlation of 0.1. The high correlation (ρ = 0.5178) copula has a rank correlation of 0.5. This range (0.1 to 0.5) encompasses all of the known estimated rank correlations of parent-child income for any country or cohort (Berman, 2020). The resulting range of absolute mobility estimates is relatively small for each cohort. Each range is also approximately centred around the original estimates. For example, the range is 65% to 70% for the youngest cohort, and 82% to 88% for the oldest cohort. Overall these results strongly suggest that the main estimates are robust to the assumption of copula stability.

It is noteworthy that the series with high relative mobility corresponds with relatively low absolute mobility, and vice versa (Berman, 2020). This highlights a paradox of desirable mobility outcomes. Absolute mobility is enhanced by persistence in income rankings between

[12] Here we show the average of estimates derived from HILDA data and ABS Income Survey data for those cohorts for which both data sources are available.

generations (assuming some economic growth between generations). Nevertheless, as pointed out, the extent of relative mobility is a small factor in the extent of absolute mobility.

3.3 Validity of Parent Income Imputations

As a test of whether the parent imputation procedure is likely to be reliable, we now apply the same procedure to also impute child income distributions. In the main analysis, child income distributions are directly observed for each cohort. Here, we only use the observed distribution for the 1984 birth cohort, and impute the distributions for other years. The results generated with this procedure are shown in Figure 1 Panel D. The main features here are the same as the main estimates – a pattern of declining absolute mobility between the first and last cohort. Here, however, the decline is smaller, mainly due to lower mobility estimates for the early cohorts. The trend is also more stable, as it abstracts from the (appropriate) sampling error inherent in the estimate for each cohort in the main analysis.

4. Why has Absolute Mobility Declined in Australia?

As outlined by Berman (2020), absolute mobility can be seen as a function of three factors. The extent of relative mobility is one of these. Second, economic growth may 'lift all boats' if all other factors stay constant. The third factor is inequality. Assuming positive growth between generations, high inequality (in either generation) reduces the prevalence of upward mobility.

Which of these factors drove the decline in absolute mobility? There are strong reasons to believe that change in relative mobility is not a major factor. We do not have data on changes in relative mobility in household income. But Leigh (2007, Figure 1) suggests that relative mobility in male earnings has been relatively stable since the 1960s. Also, as shown in Figure 2 and by Berman (2020), even large changes in the assumed level of relative mobility have a modest impact on absolute mobility estimates.

There have been large changes in economic growth and in inequality over the period of interest. Figure 2 Panel A shows growth in mean income between parents and children. We directly observe parent income only for the 1984 birth cohort. For this cohort, mean income at age 30-34 was 53% higher than parental income at the same age. This is shown with a triangle marker. For other cohorts, we observe mean child income, whilst assuming that mean parental income changed proportionally with overall mean income, in line with the methods used in the main analysis. Panel A also shows 30-year growth of per adult income, as used by Berman (2020) to approximate income growth between generations. The two series have similarities, but also substantial differences. For both series, growth was highest for the earliest birth cohorts. However, income growth for 30-34 year-olds appears to have followed a different path to national income. At first glance, the mining boom is a candidate explanation. The mining boom has lifted total Australian income since about 2005 (Downes et al., 2014). The patterns we show would be consistent with people aged 30-34 benefiting more from the mining boom than average adults. However, the pattern of average incomes by age and year in HILDA does not provide strong evidence for this. It seems that trends in national income per adult may not be a close proxy for trends in average household income, not for this age group, nor overall.[13]

Figure 2 Panel A also raises conceptual and practical issues. Our adopted approach may identify changes in annual incomes amongst 30-34 year-olds more accurately than relying on national income trends. But such income measures are likely to experience transient fluctuations, which may be misleading if the real focus is lifetime income. These issues have not yet been explored sufficiently in the absolute mobility literature. Panel A also highlights the key role of observed parent income for the 1984 birth cohort. Since parent income for other cohorts is assumed proportional to this cohort, sampling error here will affect estimated mobility for every cohort. Partly for this reason, we show alternate results in Section 5 for which parental income is directly observed for a different birth cohort.

There have also been large changes in cross-sectional inequality, as shown in Figure 3 Panel B. The horizontal axis here is the year in which incomes were observed. On the vertical axis is

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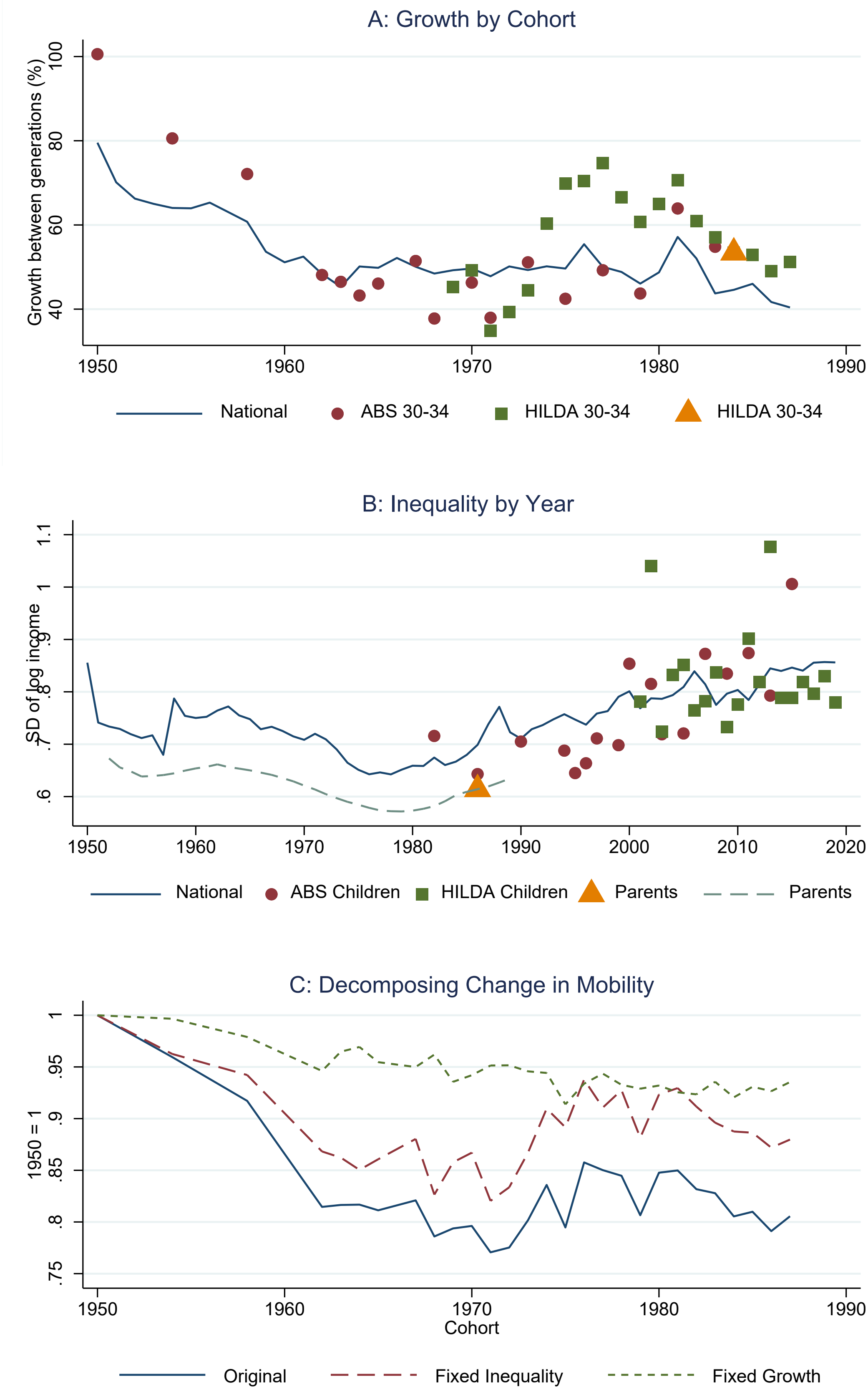
[13] See Manduca et al. (2020) for a related analysis of growth and inequality for other countries.

a summary measure of inequality – the standard deviation of log annual income. For each cohort, we show inequality of child income, which we observe directly. Whilst there is fluctuation (noise) in this series, there is a strong upward trend in inequality across all of the cohorts we consider. Figure 2 Panel B also shows a series for national income inequality, derived from top-income shares in the WID. This series follows the same strong upward trend in 1978-2019, after trending downward in earlier years. Inequality in parental income is also shown in Panel B. Again, this is only observed directly for one birth cohort (the 1984 birth cohort) – which we show at 1986. As discussed earlier, inequality in parental income is assumed to have evolved proportionally with changes in national income inequality. Consequently, estimated inequality in parental income does not vary as much between cohorts as it does for child income. It is also noteworthy that for the earlier cohorts, income inequality is similar for parental income as for child income.

To explore the roles of changing growth and inequality, we conduct a simulation exercise in which economic growth and inequality are respectively held constant, similar to Berman (2020). The results are shown in Figure 2 Panel C. This panel shows three series: one is the original series, normalised to equal 1 for the 1950 cohort. In the second series, we recalculate absolute mobility for each cohort after imposing a constant annual growth rate in mean income of 2.4%, whilst retaining original levels of inequality. This (2.4%) is the actual annualised real growth between parent and child income that we estimated for the first cohort. For the third series, we instead impose a constant level of inequality across all of the income distributions, whilst retaining original means. The chosen level of inequality is equal to the observed inequality of parental income for the first cohort.

The results suggest that declining economic growth and rising inequality both contributed to the observed fall in mobility. Overall, declining growth explains 65% of the observed fall in mobility over the period. Rising inequality, which has also steadily contributed to falling mobility, accounts for the remaining 35%.

Figure 2 Drivers of Change in Absolute Mobility



Notes: Panel A shows estimates of real income growth between generations. Child and parent income at age 30-34 are both observed directly for the 1984 birth cohort (marked with a triangle). For other cohorts, child income is observed directly while mean parent income is assumed to follow the same trend as the national income distribution. The national income distribution is growth over 30 years in national income per adult (World Inequality Database, 2020). Panel B shows estimates of inequality by year. Inequality is measured by the standard deviation of log income. All estimates for child birth cohorts are from directly observed child income distributions. The income distribution of the parents of the 1984 birth cohort is also directly observed (and is centred on 1986). Inequality of parent income for other years is assumed to follow the same trend as the smoothed estimates of inequality in national income, shown in Appendix Figure A.1, Panel B. The series for national income is the unsmoothed equivalent of Figure A.1, Panel B, more akin to the series used by Berman (2020). Panel C shows the main estimates (scaled to 1 for the earliest cohort), alongside two alternate series. In these alternate series, growth and inequality are respectively held constant. Where growth is held constant, it is set equal to that observed for the first cohort (2.4% per annum). Where inequality is held constant, it is set equal to that of the parent distribution from the first cohort. Where estimates from HILDA and an ABS Income Survey are both available, Panel C shows the average of the two.

This contrasts with Berman (2020), who finds that rising inequality is the main driver of falling mobility in Australia. Berman's approach differs from ours in numerous ways. The discrepancy is partly explained by the higher growth for the 1950 cohort in our analysis (as shown in Panel Figure 2 B). If we drop this cohort and repeat the decomposition, increasingly inequality accounts for 45% of the fall in mobility. Similarly, growth and inequality contribute equally if we exclude the youngest five cohorts. Nevertheless, our conclusion differs from Berman's – our best estimates are that lower growth accounts for the majority (65%) of the decline in absolute mobility.

5. Robustness

5.1 Other Measures of income

Our main approach is based on the preferred approach used by previous leading studies. However, it ignores the effects of the taxation system and its changes over time. It also ignores family composition, which affects living standards. Figure 3 Panel A shows alternate estimates, which instead draw on after-tax (disposable) income, and equivalised income, alongside the main estimates.[14]

Disposable income is not available in the 1982 (or 1975) data. Thus we exclude the 1950 birth cohort. We also drop parent observations drawn from the 1975 and 1982 data. Using disposable income increases the mobility estimates for each cohort by 1-4 percentage points. This reflects the progressive taxation system, which equalises the income distribution for each generation and each cohort.[15] Otherwise, the series follows a very similar trend to the main estimates.

Analysing equivalised income comes with complications for parent income. As discussed, the parent income distribution is directly observed only for the 1984 birth cohort. The imputation procedure (described in Appendix 1) used for other cohorts does not account for changes in family composition over time. This has no bearing on the main results, but likely has important implications for equivalised income. The total fertility rate declined from around 3 in 1950 to less than 1.9 in 1984, and age of birth also increased (Australian Bureau of Statistics, 2014). For both reasons, mean parental equivalised income is likely overestimated considerably in the early cohorts, and hence absolute mobility is underestimated. Therefore, those estimates, which are already quite high, should be seen as lower bounds. The estimates for younger cohorts are unaffected by these issues. These also exhibit high rates of absolute mobility – at around 78% - much higher than the baseline estimates. Chetty et al. (2017) and Manduca et al. (2020) find similar increases in mobility for other countries when adjusting for family composition.

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[14] Equivalised income is income adjusted for family size and composition. Equivalising accounts for the different needs of income units of different sizes, taking into account economies of scale. We use the square root of n equivalence scale, which follows Chetty et al. (2017), and many other studies. Equivalised income is hence equal to income divided by the square root of the number of people in the income unit.

[15] For example, inequality (as measured by the standard deviation of log income) is 10% lower for disposable income than for gross income for the 1984 child birth cohort.

The higher estimates with equivalised income are due to two factors. They are due to equivalised income being more equally distributed than unequivalised income.[16] They also reflect the much smaller income unit size of people aged 30-34 compared to the family size of their parents at the same age (Table 1). This in turn is driven by several factors including demographic factors: delayed fertility and higher propensity of living without a partner. It also reflects that not all children are parents and hence that children on average have smaller family size as adults than as children for purely mechanical reasons independent of demographic change. Whether equivalised income or unequivalised income is most appropriate for studying absolute income is an open question. A detailed exploration of such issues is worthy of further work.

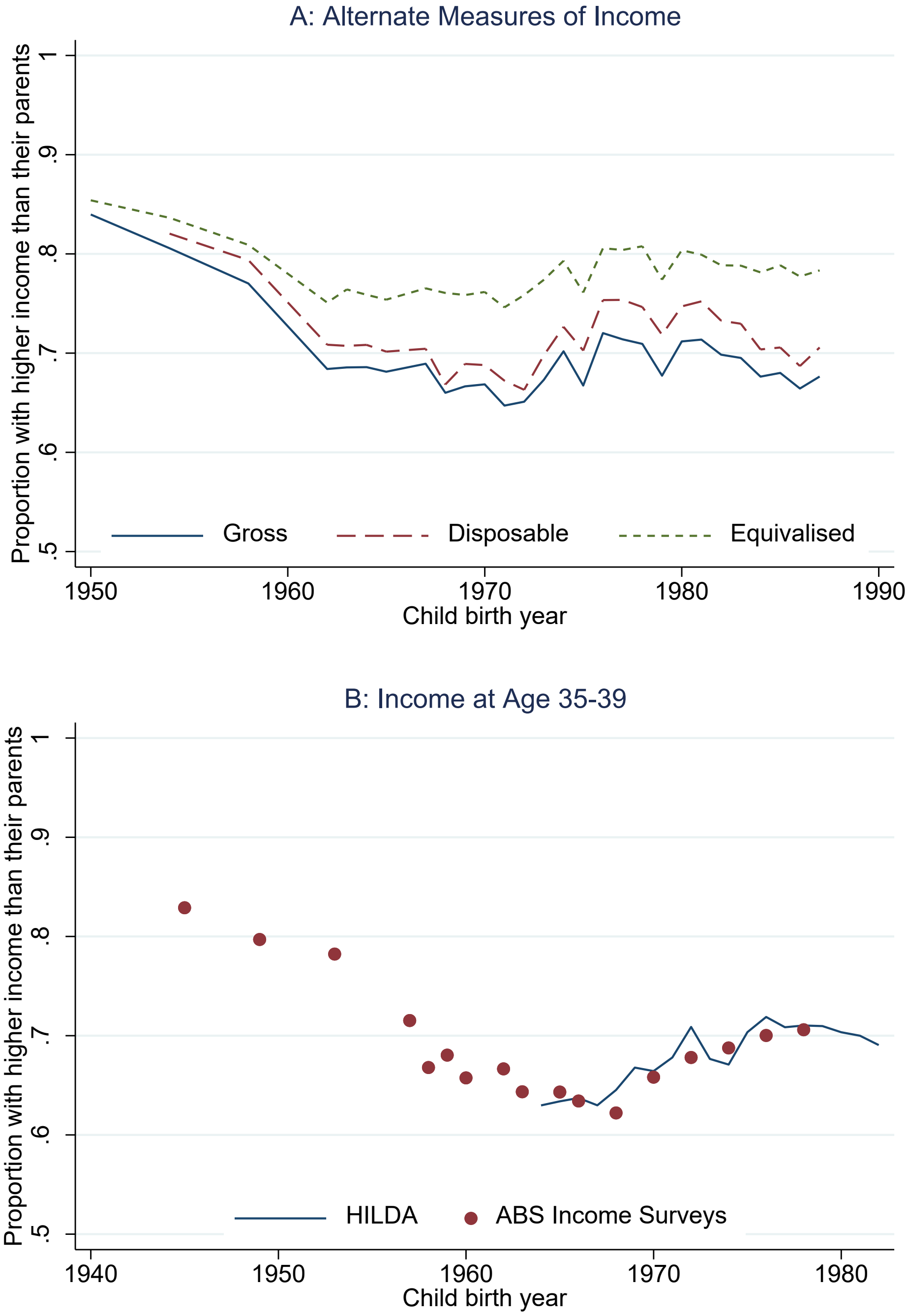
5.2 Age at which income is measured

Absolute mobility research has focussed on income observed around age 30, presumably for data availability reasons. One can also analyse income observed at other ages. Here we show results using income measured at age 35-39. Lifecycle bias is not yet well understood in the context of absolute income mobility. But the relative mobility literature suggests that income around 40 is a better indicator of lifetime income than income at earlier ages (Nybom & Stuhler, 2017). In our context, using ages 35-39 also allows cleaner identification of parents.[17]

[16] For example, inequality (as measured by the standard deviation of log income) is 7% lower for equivalised income than for unequivalised income for the 1984 child birth cohort.

[17] Using similar methods to identify parents as the main analysis, the parent sample here consists of parents aged 35-39 with 0-4 year-old children. As discussed in Section 2, we are unable to explicitly identify parents who had children at ages older than when income is measured – affecting around 26% of the weighted sample of parents in the main analysis. This falls to 5.5% of the parent sample when income at age 35-39 is used instead, since few parents had children at older ages.

Figure 3 Alternate Estimates of Absolute Mobility by Birth Cohort



Notes: Panel A shows estimates of absolute mobility using alternate measures of income – gross (pre-tax) income, disposable (after-tax) income, and equivalised gross income. Each is 'income unit' income, which for this population is essentially the sum of personal income and spouse income. The equivalence scale is the square root of the number of people in the income unit. The gross income estimates correspond with the 'preferred' estimates shown in Figure 1. Disposable income (and tax paid) are not available in the 1982 income survey or the 1976 Household Expenditure Survey. The 1950 cohort is hence excluded from the disposable income series. Observations from the 1976 and 1982 surveys are also hence excluded from the parent disposable income distributions. Where estimates from HILDA and an ABS Income Survey are both available, Panel A shows the average of the two. Panel B shows absolute mobility estimates with income measured at age 35-39 for both generations. The approach used for Panel B otherwise follows the same approach as the main estimates shown in Figure 1 Panel A.

The absolute mobility estimates using income at ages 35-39 are shown in Figure 3 Panel B. The results (which pertain to cohorts five years older than the main analysis) are similar to the main analysis. The main difference is that these estimates seem to follow a smoother trend. This trend suggests a recent increase in absolute mobility.

5.3 Housing

Housing plays a particularly important role in Australian living standards and income distribution (Saunders & Siminski, 2005; Saunders, 2017). Recently, Alexeev (2020) showed that including imputed rent (IR) as a component of income has a substantial impact on relative income mobility estimates for Australia, though not for USA or Germany. He finds the intergenerational rank correlation to be around 20% higher after including IR, even though the study population was young - around age 30 at the time income was measured.

Therefore, it is worth considering whether imputed rent also has important implications for absolute mobility estimates. We address this by separately considering the implications of imputed rent for the three drivers of absolute mobility: relative mobility, income growth, and inequality.

Alexeev finds that including IR increases the rank correlation by around 0.05. While this is a large change, the results shown in Figure 2 suggest this, on its own, would only increase absolute mobility by around half of one percentage point.

Including imputed rent also has little effect on income inequality for this age group. Alexeev's Table 1 shows the ratio of standard deviation/mean child income to be 49%, and almost exactly the same (50%) if IR is included. For their parents, the change is also small and in the opposite direction, from 55% to 52%. Therefore, including IR is unlikely to affect estimates of absolute mobility through the channel of measured inequality.

Finally, including IR increases mean household income only slightly for this age group. Alexeev (2020: Table 1) shows a mean IR/income ratio of 6.8% for 26-32 year-olds. Our own analysis using CNEF suggests this is stable over the length of the HILDA period. For 30-34 year olds, the ratio of mean IR to pre-government household income is 6.3% in 2001, and 5.6% in 2019.

It is clear that including IR in income is unlikely to meaningfully impact on our estimates of absolute mobility through any of the three drivers of absolute mobility. Nevertheless, the role of housing is worthy of further investigation. All of the conclusions we have made in this assessment of IR are with reference to the annual income of relatively young (30-34 year olds) children and parents. This reflects the primary purpose of the paper- to produce estimates comparable to those for other countries, for which the focus has been on income at around age 30. IR is larger for older age groups. For example, the mean IR:income ratio is much larger at about 23% for 60-64 year olds in HILDA. Also, alternate approaches may focus explicitly on lifetime income rather than annual income. In that context, IR may be more important.

5.4 Alternate Cost of Living Indices

The CPI may not adequately capture changes in the purchasing power of income over time for the group of interest, potentially distorting estimates of absolute mobility. The ABS produces an alternate series of Selected Living Cost Indices (SCLIs) for four types of households (Australian Bureau of Statistics, 2021). The two household types of relevance are employee households (households whose principal source of income is from wages and salaries); and other government transfer recipient households (households whose principal source of income is a government pension or benefit other than the age pension or veterans affairs pension).

Unfortunately, these series cannot be applied to re-estimate mobility for any of the cohorts studied here, since they only commenced in 1998. However, the evolution of these series has been quite similar to the CPI, providing reassurance of the validity of the main estimates. Between June 1998 and June 2019, the CPI increased by 70.3%, while the SCLI increased by 68.9% for employee households and 79.6% for government transfer recipient households. Since most households in the age groups considered are employee households, changes in the CPI have closely aligned with changes in the costs of living for the period where data are available.

6. Conclusion

Our results imply that absolute income mobility in Australia (68%) is amongst the highest in the world, at least for countries where such estimates are available. This contrasts with an apparent pessimism for our children's future. Of course there is much uncertainty for how people's lives will play out in the future, and past trends need not be good indicators of the future. Nevertheless, the estimates shown reveal an Australia whose children have a high chance of a better standard of living than their parents, especially those whose parents have relatively low incomes.

Despite this, the level of absolute mobility is considerably lower than it was for baby boomers, as 84% of those born in 1950 had a higher income that their parents. This decline in absolute mobility had two drivers: lower average growth in recent decades, and rising cross-sectional income inequality. We estimate that 65% of the decline in mobility over the period studied is due to lower growth, while higher inequality accounts for the remaining 35%. However, this is somewhat sensitive to which cohorts are included in the analysis. For example, if we exclude the first cohort, the estimated contribution of rising inequality becomes 45%. If income inequality continues to rise, this will clearly further reduce the proportion of children having a higher income than their parents.

We qualify these findings by noting that the absolute income mobility literature is still in its infancy. There are many avenues for further research. Presumably, absolute mobility of lifetime income is more interesting that income received in a single year. Little is known about potential bias from using single-year measured income (such issues are well understood in the *relative* mobility literature). For instance, post-WW2 economic growth not only benefited baby boomers' lifetime incomes, but also that of their parents. This has not been accounted for in our study, nor in any other study that we are aware of. The complicated role of family composition in mobility estimates is also worthy of further study. Future work may also explore differences in absolute mobility by sex and for other subpopulations. Analysis of equivalised income may be particularly informative for analysis by sex, since most single parents are women. Future work may also explore the impact of non-cash government benefits such as Medicare, and public education, which have evolved dramatically. The role of housing is also worthy of more extensive study. The focus on income may also be broadened to study absolute mobility of consumption, or of wealth. In all of these realms, the potential impact of policy reforms could be simulated using structural models or other approaches.

Finally, the new literature on absolute mobility has focussed on measurement, without addressing its link to social welfare. That link is needed to validate any claims for absolute mobility as an explicit social goal. Early work in economics by Markandya (1982; 1984) on the relationship between mobility and social welfare draws on earlier work from sociology. It distinguishes between 'exchange mobility' and 'structural mobility', which are related to relative and absolute mobility. An explicit articulation of the relationship between absolute mobility and social welfare would be worthwhile.

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Appendix 1 – Imputation of Parent Income Distribution

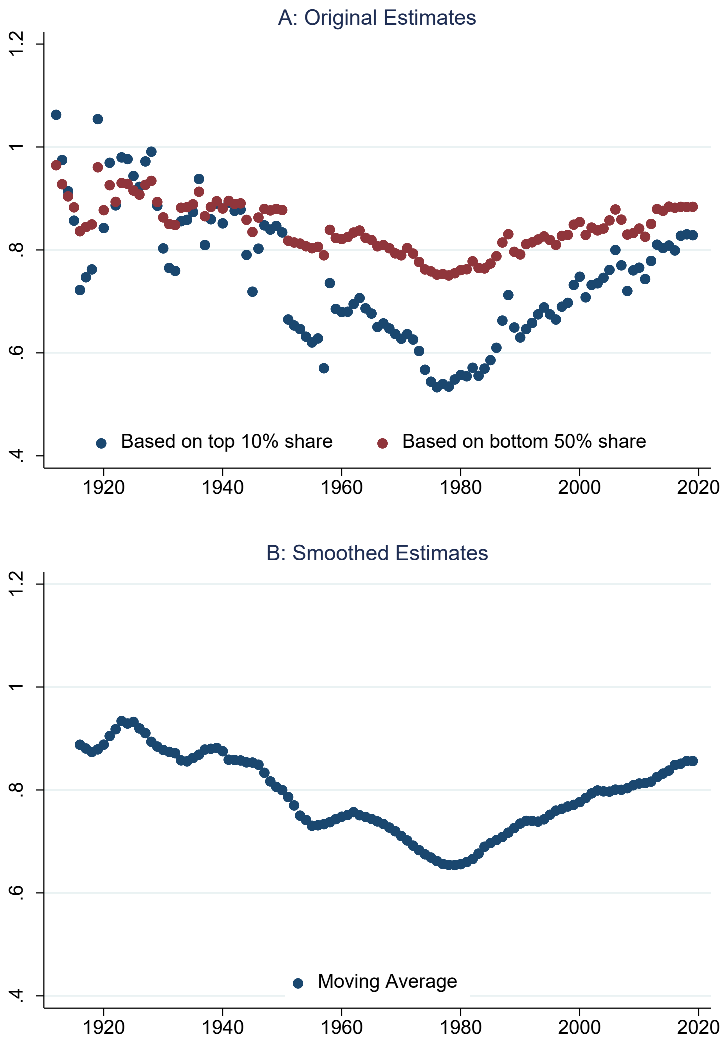
This appendix outlines the procedure for imputing parent income distributions. As discussed in Section 2, the parent income distribution is observed directly for the 1984 birth cohort. For other cohorts, we assume that between 1952 and 1989, the parental income distribution evolved proportionally (in terms of growth and inequality) to the overall income distribution. For this, we draw on data from the World Inequality Database (WID). The WID includes national income per adult at constant Australian prices, as well as summary indicators of inequality – including top 10% and bottom 50% income shares of pre-tax national income.

Using the WID income share data, we approximate the standard deviation of the national log income distribution in each year. For a lognormal distribution, the relationship between income shares and the standard deviation is given by the following formula (Berman 2020):

$$S_q = 1 - \Phi(\Phi^{-1}(1-q) - \sigma) \tag{A.1}$$

Where S_q is the share of total income held by the top q of the distribution. Using this formula, we first generate two estimates of σ for each year – using the top 10% share, and the bottom 50% share, respectively. These estimates are shown in Figure A.1 Panel A. They follow a similar trend, but are different, which reflects that the true distributions are not quite lognormal. These estimates are also somewhat unstable, especially for earlier years. To create a single smooth series, we take the average of the two estimates for each year, and then calculate a 9-year moving average (using four years either side of the base year). This is justified on the grounds that the parental income distribution we are interested in (at around age 30-34) does not pertain to a single year, but a range of years, depending on parents' age when their child was born. The resulting smoothed series is shown in Panel B.

Figure A.1 Estimated Standard Deviation of Log income from World Inequality Database



Notes: This figure shows estimates of inequality of the Australian national income distribution. In both panels, the vertical axis shows estimates of the standard deviation of log income. In Panel A, these are derived using equation (A.1) and income shares (top 10% and bottom 50%) accessed from the World Inequality Database (2020). Panel B shows a 9-year moving average of the mean of the estimates in Panel A.

Beginning with the observed percentiles of the parental income distribution for the 1984 birth cohort (whose income observations are centred around 1986), we impute parent income at each percentile for other cohorts using:

$$Y_c^q = \exp\left[\left(\log Y_{1984}^q - \lambda_{1984}\right) \times \frac{\sigma_{(c+2)}}{\sigma_{1986}} + \lambda_{1984}\right] \times \frac{\mu_{(c+2)}}{\mu_{1986}} \qquad \text{(A.2)}$$

Where Y_c^q is parent income at quantile q for cohort c; μ and σ are the mean income and standard deviation of log income from the WID data in each year; and λ_{1984} is mean log income of the observed parental income distribution for the 1984 cohort. This ensures that that both mean income and the standard deviation of log income follow the same trends for the imputed parental income distributions as those observed for the WID income distributions.[18]

[18] The observed parent income distribution is negative at the first percentile, so $Y_c^{.01}$ is undefined in equation A.2. To account for this, we set $Y_c^{.01}$ to $Y_{1984}^{.01} \times \frac{\mu_{(c+2)}}{\mu_{1986}}$, before rescaling each distribution again to ensure the mean income trend exactly follows the target trend.

Appendix 2 – Detailed Results

Table A.1 Main Estimates of Absolute Mobility by Birth Cohort and Source of Data for Child Income Distribution

Child Birth Year	ABS Income Surveys	HILDA
1950	0.840	
1954	0.806	
1958	0.770	
1962	0.684	
1963	0.686	
1964	0.686	
1965	0.681	
1967	0.689	
1968	0.660	
1969		0.667
1970	0.674	0.664
1971	0.655	0.639
1972		0.651
1973	0.691	0.655
1974		0.702
1975	0.637	0.697
1976		0.720
1977	0.682	0.746
1978		0.709
1979	0.660	0.694
1980		0.712
1981	0.708	0.719
1982		0.698
1983	0.693	0.698
1984		0.676
1985		0.680
1986		0.664
1987		0.676

Notes: This table contains the same estimates shown in Figure 1 Panel A