New Estimates of Intergenerational Mobility in Australia

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New Estimates of Intergenerational Mobility in Australia[1]

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Abstract

We present new estimates of intergenerational earnings elasticity for Australia. We closely follow the methodology used by Leigh (2007), but use considerably more data (twelve waves of HILDA and four waves of PSID). Our adjusted estimates are intended to be comparable to those for other countries in Corak (2013). Our preferred estimate (0.35) is considerably higher than implied by Leigh's study, and is less subject to sampling variation. In an international context, intergenerational mobility in Australia is not particularly high, and is consistent with its relatively high level of cross-sectional inequality.

1. Introduction

Economic inequality has been the subject of debate for centuries, with research and analyses spanning from the code of Hammurabi, to the contributions of Plato and Aristotle, St. Thomas Aquinas, J.J. Rousseau, J.S. Mill, and many others. Nowadays, inequality is considered as one of the most urgent social problems. The President of the United States and the Managing Director of the International Monetary Fund Christine Lagarde have declared that tackling raising inequality is a top priority (Atkinson, 2015).

In debates on what can or should be done to address inequality, a key distinction is between equality of outcomes and equality of opportunities. Several political philosophers have discussed this distinction; including John Rawls, Robert Nozick, Amartya Sen, Ronald Dworkin, Richard Arneson, and G.A. Cohen (see Roemer and Trannoy, 2013 for a review).

Inequality (of outcomes) has been rising in most countries for around 30 years. Public opinion surveys suggest a lack of consensus on whether inequality of outcomes is desirable (Atkinson, 2015). This is probably because economic outcomes are partly a function of effort, talent and preferences for work versus leisure and many believe that some differences in economic rewards are justifiable (Atkinson, 2015). American citizens have traditionally been willing to tolerate a higher level of inequality than people living in other developed Western countries, because many people at the bottom of the income distribution believe that they, or at least their children, will be able to climb the income ladder (Benabou and Ok, 2001). On the other hand, a recent survey suggests that Australians would prefer a greater level of equality, and that the perceived level of inequality is lower than the actual level of inequality (Doiron, 2012).

Regardless of public opinion on its desirability, rising inequality has been linked to numerous instrumental concerns. In particular, there is evidence that rising inequality harms social cohesion, economic growth and, equality of opportunity (see OECD, 2015 and its references for a detailed discussion).

Egalitarian societies tend to be more socially cohesive, through lower levels of crime and higher levels of integration, and through social environments that are less hostile and more hospitable (Kawachi et al., 1997; Dunford, 2005). Some have argued that the link between inequality and social cohesion is a mechanism through which higher income inequality harms health, as measured by mortality and stress-related diseases (see for example Wilkinson, 2002, among others).

The relationship between inequality and economic growth stems from limited opportunities for human capital investment for children at the lower levels of the socio-economic distribution (Cingano, 2014). The rise of income inequality between 1985 and 2005 has been estimated to reduce economic growth of the OECD area by almost 5 percentage points (OECD, 2015).

The link between inequality of outcomes and opportunities has recently been studied intensely. Equality of opportunities is a concept frequently used in political speeches and public debates. Metaphors associated with this concept include "levelling the playing field" and "starting gate equality" (Roemer and Trannoy, 2013). Economic opportunities are partly determined by the circumstances of family background, such as parental education, occupation, marital status, region of birth – over which individuals have no control. Equality of opportunities is achieved when these factors do not play any role in achieving economic outcomes. Economists have engaged in debates around equality of opportunities for over three decades. John Roemer (1993, 1998) constructed an algorithm for analysing effectiveness of policies in equalizing opportunities for achieving a particular objective. Several empirical studies have estimated the extent to which opportunities are unequal in various countries (Roemer and Trannoy, 2013).

Whilst equality of opportunity is difficult to directly operationalise and is not equivalent to intergenerational mobility, the two are closely related. In Corak's words "if one number is to summarize the degree to which inequality is transmitted across the generations, just as sometimes

one number, like a Gini coefficient, is used to summarize the degree of inequality at a point in time, then the intergenerational elasticity is an appropriate statistic to use" (Corak, 2013: p. 83).[2]

A clear cross-sectional relationship between inequality and intergenerational mobility has been found by several authors in cross-country analyses (Andrews and Leigh, 2009; Bjõrklund and Jäntti, 2009; Blanden, 2013; Corak; 2006; 2013, Ermisch et al. 2012). This relationship was popularized by Alan Krueger in his role as a U.S. presidential adviser, dubbing it the 'Great Gatsby Curve'. The 'Great Gatsby Curve' (reproduced in Figure 1 with our own estimate also included) depicts countries along two dimensions, income inequality (measured by the Gini coefficient) and intergenerational economic mobility (measured by the elasticity between paternal earnings and son's earnings). Countries like Finland, Denmark and Norway show very low levels of inequality as well as a very small intergenerational elasticity of earnings. On the other hand, Italy, United Kingdom and United States are among the most unequal societies, and at the same time are characterised by a very high degree of transmission of economic advantage and disadvantage between fathers and sons.

As suggested by Corak (2013), more income inequality in the present affects the mobility of young people, as family background is likely to play a bigger role in determining adult outcomes, while individual characteristics, such as ability, talent and hard work play a much smaller role. This concept has been expanded by the OECD in several policy documents, emphasising the idea that investments in promoting equality of opportunities, such as education policies, can foster higher economic mobility and, ultimately, economic growth (OECD, 2015). High levels of inequality have been found to have a strong negative effect on levels of education achieved, skills developed, and labour market outcomes of individuals from low-income families and therefore significantly increase inter-generational education persistence (OECD, 2015).

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[2] Some argue the merits of intergenerational *correlation* as a better measure of mobility than intergenerational elasticity (see for example Jäntti and Jenkins, 2014). Nevertheless, elasticity is the measure usually used in international comparisons. However, we also show estimates of intergenerational correlation in Section 5.

Inequality has been analysed and debated in Australia in many studies (Saunders, 2004; Leigh, 2013; Wilkins 2014, among many others). Despite a general belief that Australia is an egalitarian society, international comparisons suggest that Australia's level of inequality is slightly higher than the OECD average (OECD, 2015). There are far fewer studies of Australian intergenerational mobility. Of these, Leigh (2007) has been the most influential, and has been used as the basis of numerous intergenerational comparisons (D'Addio, 2007; Ichino et al., 2011; Blanden, 2013; Corak, 2013). Leigh's estimate suggests that Australia is particularly mobile, given its level of inequality. Figure 1 (Corak's version of the Great Gatsby curve) shows Australia as an outlier when Leigh's estimate is used.[3]

We follow Leigh's approach closely in deriving estimates of intergenerational earnings' elasticity, but we use considerably more data, yielding more precise estimates. Specifically, we use twelve waves (2001-2012) of the Household, Income and Labour Dynamics Australia (HILDA) survey rather than one to construct raw Australian estimates. Importantly, Wave 4 (2004), which Leigh used, yields an elasticity estimate that is lower than for any other wave apart from Wave 1. We also use four waves (2001, 2003, 2005 and 2007) of the Panel Study of Income Dynamics (PSID) study rather than one. Our estimated elasticity (0.35) is about 34% larger than implied by Leigh's study, and is less subject to sampling variation. This suggests that Australia's level of mobility is consistent with its level of inequality. And economic mobility in Australia is not particularly high in an international context.

The remainder of the paper is structured as follows. Section 2 reviews previous Australian work on intergenerational mobility. Section 3 outlines methods and data. Section 4 presents the main results. Section 5 presents some additional results, including the intergenerational correlation and the

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[3] Andrews and Leigh (2009) present the first version of the 'Great Gatsby Curve' of which we are aware. In their results, Australia does not have an outlying low intergenerational elasticity. Indeed, the elasticity is slightly higher than the fitted value based on its level of inequality. However, the results in that paper do not seem to have been influential in the subsequent literature, possibly due to the limitations of the data used.

probabilities of moving between specific parts of the earnings distribution between generations. Section 5 concludes.

2. Previous Australian Work on Inequality and Intergenerational Mobility

There is a substantial empirical literature on inequality in Australia. Recent contributions include Saunders (2004), Johnson and Wilkins (2006), Saunders and Bradbury (2006), Atkinson and Leigh (2007), Doiron (2012), Leigh (2013), Whiteford (2013) and Wilkins (2014). Many of these studies document rising inequality over time. Factors contributing to this increase include demographic changes, labour market trends, earning gaps, education inequality, and the disparity between the income share of the individuals at the top of the income distribution and the rest of the population (Atkinson and Leigh, 2007; Doiron, 2012; Leigh, 2013; Whiteford, 2013). Some studies have considered the roles the tax and transfer system (Whiteford, 2013), the role of housing (Siminski and Saunders, 2004; Saunders and Siminski, 2005), and the role of non-cash government benefits (e.g. Garfinkel *et al.*, 2006).

The emergence of high quality panel data has enabled studies of short-run (year-to-year) mobility. Wilkins and Warren (2012) use HILDA to analyse income mobility between 2001 and 2009. They show that, on average, individuals moved slightly more than two deciles in that period, and over 55% of people that were in the bottom quintile in 2001, remained in the same quintile in 2009. A similar proportion did not move from the top quintile of the income distribution (46%). Overall, few people moved by more than one quintile in the analysed period of time.

However, very limited work has linked income inequality to intergenerational mobility (Andrews and Leigh, 2009; Leigh, 2013) and the analysis of transmission of economic advantage between generations of Australians has received little attention, especially from economists. Most of the

existing research comes from literature in sociology, which has focused on mobility across occupations, rather than earnings, and on the determinants of this phenomenon. Some examples are Marks and McMillan (2003), Chester (2015), Redmond et al. (2014).

Cobb-Clark (2010) presents evidence from the Youth in Focus project, a large project on the intergenerational transmission of disadvantage, and looks in particular at the transmission of income support across generations. Research based on Youth in Focus has shown that young people who grew up in families that receive intense income support are more likely to engage in risky behaviours (Cobb-Clark et al., 2012), have low education and various health problems (e.g. asthma or depression), and these factors are likely to have a negative effect on people's income.

Leigh (2007) calculates intergenerational earnings elasticity combining four surveys conducted in 1965, 1973, 1987 and 2001-2004 and using parental occupation to predict earnings, and compares the level of intergenerational income mobility in the 2000s with the degree observed in the 1960s, and with socio-economic mobility observed in the United States. This work suggests that intergenerational earnings elasticity in Australia has been relatively constant over time and is likely to be in the range of 0.2- 0.3. This is similar to estimates for other OECD countries such as New Zealand, Canada and Sweden, which have substantially higher intergenerational earnings mobility than other countries such as Italy, the US and the UK (d'Addio, 2007).

In a recent study, Huang et al. (2015) use HILDA and the Longitudinal Labour Force Survey (LLFS) in a two-stage panel regression model. They estimate the intergenerational earnings elasticity in Australia for the period 2001-2013 to lie between 0.11 and 0.30. The major limitation of their approach is to not address the issue of attenuation bias stemming from measurement error that comes with imputing father's income (father's income is not directly observed in any available Australian data source). This implies that their elasticity estimates are likely to be severely biased towards zero and are not internationally comparable. Our own approach to deal with this form of bias, drawing on Leigh (2007) and Corak (2006, 2013), is detailed below.

3. Methods and Data

Intergenerational earnings elasticity is a simple and commonly used indicator of the intergenerational persistence of economic advantage. Given microdata on earnings for a representative sample of adult males and for their fathers, intergenerational elasticity β can be estimated from the following regression model:

$$\ln Y_i^{son} = \alpha + \beta \ln Y_i^{father} + \varepsilon_i, \tag{1}$$

where Y_i^{son} is a measure of the (usually hourly) earnings of each working-age male i and Y_i^{father} is a measure of earnings for the father of each member of the sample. A larger elasticity indicates greater intergenerational persistence. For example, an elasticity of 0.4 suggests that a 10% increase in a father's earnings is associated with a 4% increase in his son's earnings. An elasticity of zero would suggest that individual earnings are unrelated to their father's earnings. The focus on males is motivated by concerns over the complications related to female selection into labour market participation, including differences in participation rates over time and between countries.

Ideally, the measure of earnings (for both fathers and sons) used is 'permanent' earnings – i.e. a measure which summarises earnings capacity across each person's entire working life. Whilst conceptually straightforward, the estimation of such elasticities is complicated by measurement issues and data availability. To estimate permanent earnings, longitudinal data are required which follow two generations across their entire working lives. Such data are available for few countries. But estimates which rely on a single observation of father's current earnings are likely to suffer badly from attenuation bias (i.e. bias towards zero). This is due to two factors which both lead to measurement error in fathers' earnings. The first factor is the strong systematic variation in earnings over the life cycle. Recorded fathers' earnings at a point in time strongly depend on the age of the father at that time. The second source of measurement error is transitory variation in current earnings, which again leads to attenuation bias.

In the Australian context (as for many other countries), adequate data do not exist to directly estimate intergenerational earnings elasticity – not even with a single observation of father's earnings, let alone for permanent earnings. [4] Given this, a common strategy in this literature is to estimate the elasticity using the best available alternative approach for the country of interest and also for the United States using a comparable approach. Whilst both estimates are flawed, they are arguably comparable and hence the relative extent of intergenerational mobility can be inferred. Finally, the estimate for Australia is re-scaled in an attempt to account for the apparent bias due to the inferior data. This scaling factor is equal to an externally derived benchmark elasticity estimate for the USA, divided by the estimate derived for the USA using the inferior approach that was also adopted to derive the Australian estimate. This approach is now described in further detail, as applied for our Australian estimates.

Given the characteristics of Australian data, a credible strategy is to impute each father's earnings on the basis of their reported occupation, since occupation data are available as will be described below. Following Leigh (2007), the coefficients of the following model can be estimated using a cross-sectional sample of *sons*:

$$\ln Y_i = \alpha + \mathbf{\theta'Occ_i} + \pi_1 Age_i + \pi_2 Age_i^2 + e_i \,, \tag{2}$$

Where Occ is a vector of mutually exclusive occupational category indicators. The estimated coefficients from this regression are then used to impute earnings for each father ($\ln \widehat{Y_i^{father}}$) on

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[4] Sons' and fathers' earnings are both directly observed in HILDA only for those who were co-residing in at least one wave of the survey, and both have reported earnings in at least one wave. Given the relatively short length of the HILDA panel, there are few such cases. It would be possible to select a sample of younger sons (say, men aged 25-29) whose own earnings are observed in later waves and whose fathers are also included in the respondent sample. Direct estimates of intergenerational elasticity could be calculated for such a sample. Such estimates would be subject to large sampling variability due to the small sample size, and they may not be indicative of intergenerational mobility for the broader population. This strategy has not been pursued here, but it will become more attractive as HILDA continues to mature.

the basis of the fathers' occupation. Father's age is held constant at 40 in the imputation in order to remove any life-cycle variation from the measure of father's earnings. That is,

$$\ln \widehat{Y_i^{father}} = \hat{\alpha} + \hat{\theta} \mathbf{Occ}_i^{father} + \hat{\pi}_1 40 + \hat{\pi}_2 1600 \,, \tag{3}$$

using the estimated parameters ($\hat{\alpha}$, $\hat{\theta}$, $\hat{\pi}_1$ and $\hat{\pi}_2$) from (2). This imputed value ($\ln \widehat{Y_i^{father}}$) is then used as a regressor in the intergenerational earnings regression. Since a credible measure of permanent child earnings is also unavailable, current earnings is used. And since current earnings are recorded at various ages, we also control for a quadratic in sons' age to improve precision and to remove any bias caused by a correlation between child's age and father's occupation. The estimating equation is therefore:

$$\ln Y_i^{son} = \alpha + \beta \ln \widehat{Y_i^{father}} + \gamma_1 Age_i^{son} + \gamma_2 (Age_i^{son})^2 + \varepsilon_i, \tag{4}$$

$\ln \widehat{Y_i^{father}}$ should be seen as a crude approximation of fathers' earnings. Its derivation assumes that the occupational earnings structure amongst the sample of children is the same as the occupational earnings structure a generation earlier. It also ignores: variation in earnings within occupation; changes in occupation across fathers' life course; and possible misreporting of fathers' occupation. Direct use of this measure, for example in intergenerational transition matrices, should be done very cautiously and arguably should be avoided completely. But if the same approach is used to generate corresponding US estimates, then perhaps the bias will be similar for both countries. The adjusted estimate for Australia (IGE_{AUS}) is thus:

$$\widehat{IGE}_{AUS} = \hat{\beta}_{AUS} \frac{IGE_{USA\ benchmark}}{\hat{\beta}_{USA}} \tag{5}$$

This estimate of IGE_{AUS} can be compared to published estimates derived by Corak (2013) for numerous other countries, if one uses the same $IGE_{USA\ benchmark}$ as used by Corak, which is 0.473, based on Grawe's (2004) estimate.

Whilst there is a substantial literature which uses such methods, the issue of statistical inference has arguably been insufficiently discussed. The appropriate method for calculating standard errors for $\widehat{IGE}_{AUS}$ perhaps depends on its purpose. $\hat{\beta}_{AUS}$ and $\hat{\beta}_{USA}$ are both subject to sampling variation. $IGE_{USA\ benchmark}$ was also estimated in an empirical study and that estimate is itself subject to sampling variation. If one is primarily interested in the size of $\widehat{IGE}_{AUS}$, then all three sources of sampling variation should be taken into account in deriving its standard error. However, we argue that the absolute magnitude of this estimate is not of primary importance. More important is how it compares with those of other countries. Therefore we treat $IGE_{USA\ benchmark}$ as an arbitrary scalar (which was applied to each of Corak's estimates for various countries). For this reason, we show standard errors that account for the variance of both $\hat{\beta}_{AUS}$ and $\hat{\beta}_{USA}$, but not the variance in the estimate of $IGE_{USA\ benchmark}$. The standard error of $\widehat{IGE}_{AUS}$ is derived using a 'delta-method' approach, which draws on a first-order Taylor Series expansion to estimate the variance of the ratio of two independent random variables: $Var\left(\frac{\hat{\beta}_1}{\hat{\beta}_2}\right) = \frac{Var(\hat{\beta}_1)}{\hat{\beta}_2^2} + \frac{\hat{\beta}_1^2 Var(\hat{\beta}_2)}{\hat{\beta}_2^4}$ Standard errors for the Australian and US estimates which draw on pooled data (across waves) also account for clustering within individuals.

The Australian component of the analysis draws on the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is a representative longitudinal study of the Australian population that commenced in 2001. A total of 13,969 individuals in 7,682 households were interviewed in wave 1 through a combination of face-to-face interviews and self-completion questionnaires, for all members of households aged 15 years old and over. Members of households included in wave 1 have subsequently been survey annually, along with any new members of any households which they form. A general top-up sample of around 2000 new households was added in 2011 (Wave 11).

The results for the United States are derived using the same methods, applied to the 2001, 2003, 2005 and 2007 waves of the Panel Study of Income Dynamics (PSID). The PSID is the longest running

longitudinal household survey in the world. This study began in 1968 with a sample of over 18,000 individuals living in 5,000 families and selected to be representative of the United States population. The PSID followed these individuals and their descendants. The initial PSID sample also included a low-income oversample from the Survey of Economic Opportunities (SEO). We followed Lee and Solon (2006) and Leigh (2007) and excluded this sample from our analysis. In 1990 and 1992, a Latino sample was added to the PSID, and in 1997 and 1999, an immigrant sample was added. Following Leigh (2007), these additional samples were included in our analysis. Consistent with the analysis conducted in Leigh (2007), we used the Cross-National Equivalent File version of the PSID (see Burkhauser et al., 2001 for an explanation of the background of the CNEF) and merged it with the information from PSID where respondents were asked for their fathers' occupation when they were growing up. Occupations were 3-digit codes, using the 1970 occupational coding system and fathers were spread across 465 occupations. The analysis used individual labour earnings (coded as i11110 by the CNEF), divided by hours worked.

For both the Australian and US analysis, responding person sampling weights are applied and the sample is limited to men (sons) aged between 25 and 54 years of age, with positive earnings. Also excluded are observations which have a non-positive sampling weight, and those with missing occupation or missing father's occupation.

In HILDA, the full sample of 25-54 years old men is 44,952 observations across waves. Of these, 15,421 have no recorded earnings (due mainly to self-employment and non-employment). Of the remaining sample, 2,520 have no recorded father's occupation and an additional 139 have a non-positive sampling weight. After applying the exclusions, we are left with 26,872 observations in the estimation sample, or 60% of all 25-54 males in the full HILDA sample.

In PSID, the full sample of 25-54 years old men is 12,259 observations across waves. After excluding individuals without recorded earnings, father's occupation or sample waves, we are left with 5,767 observations, or 47% of all 25-54 males in the full PSID sample.

4. Results

The main results are conveyed in Figure 2. Table 2 shows these same results in more detail. The upper panel of Figure 2 shows raw estimates of the intergenerational earnings elasticity using each wave in HILDA separately and with all waves pooled. These are estimated using the imputed father's earnings approach.[5],[6] The far-right data point is the preferred estimate, derived from the pooled sample, shown with a robust 95% confidence Interval that accounts for within-individual error correlation. This pooled estimate (0.227) is 30% higher than the Wave 4 estimate (0.174).

The middle panel shows comparable estimates for the USA using the PSID. These are estimated using the 2001, 2003, 2005 and 2007 waves individually, and with the four waves pooled.[7] Our sample size is around four times larger than Leigh's (2007) in each wave, or sixteen times larger overall.[8] Our estimates vary little between waves. Our preferred estimate is 0.306, from the pooled analysis.

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

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

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

[8] In personal correspondence, Dr Leigh indicated that he restricted the PSID sample to the cohort born between 1951 and 1959. This was for consistency with Solon (1992), which he used as the benchmark U.S. estimate. We do not make this sample restriction because we think that consistency in the analysis of HILDA and PSID is of first-order importance. The comparison between the raw Australian estimate and the similarly-derived U.S. estimate determines Australia's elasticity estimate relative to those for other countries shown in Corak (2013). In practice, this discrepancy in sample selection criteria is not a major factor, since our estimates for PSID are not markedly different to Leigh's, especially for 2001.

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

The lower panel of Figure 2 shows the HILDA estimates for each wave after applying the Corak-style (2006; 2013) adjustment (described in Section 3), which draws on our pooled PSID elasticity estimate of 0.306 instead of Leigh's 0.325. The 95% Confidence Intervals shown are based on a standard error calculation which accounts for the variance of both the HILDA and PSID estimates.

These results suggest that Australia's intergenerational elasticity is considerably higher than previous studies. Our preferred estimate (0.35) is the pooled estimate, since it draws on the most data and hence is less subject to sampling error. This is close to the fitted line in Figure 1, and is 34% larger than Corak's published estimate drawing on Leigh. This means that 10% higher earnings for a father are associated with 3.5% higher earnings for his son.

5. Other Measures of Mobility

Our main focus has been to estimate the intergenerational earnings elasticity for Australia. This is primarily motivated by a desire for a summary measure that is easily compared to those for other countries. We now consider how our estimate translates to other meaningful summary indicators of mobility. To do this, we need to make a number of reasonable, but non-trivial assumptions.

Some argue that intergenerational correlation is a better summary measure than elasticity, if earnings inequality has changed considerably between generations (Jantti and Jenkins, 2013). The intergenerational correlation more directly summarises to a child's ability to move up (or down) the earnings distribution with respect to their ranking in the distribution. A relatively high elasticity, on the other hand, may reflect an increase in the dispersion of the earnings distribution between generations.

The intergenerational correlation (ρ) can be expressed as:

$$\rho = \beta \frac{\sigma_f}{\sigma_s} \tag{6}$$

Where β is the intergenerational elasticity of the logarithm of permanent earnings, σ_f is the standard deviation of permanent earnings in the father's generation, and σ_s is the standard deviation of permanent earnings in the son's generation. We do not have data on the distribution of permanent earnings for fathers so we cannot calculate ρ directly. However there is evidence that male earnings inequality has increased markedly over the period of interest. In fact, Coelli and Borland's (2016) estimates suggest that the standard deviation of log earnings increased by around 50% over this generation.[9] For our calculations we assume that this also applies to permanent earnings.[10] Drawing on equation (6), we thus estimate the intergenerational earnings correlation (ρ) to equal $\beta \frac{\sigma_f}{\sigma_s} = 0.35 \frac{\sigma_f}{1.5\sigma_f} = 0.35 \frac{1}{1.5} = 0.233$.

Also of interest is the probability that a son achieves high (low) earnings, as a function of his father's earnings. Again, it is not possible to examine this directly with available data. But we can make a reasonable attempt at this following the approach of Solon (1989; 1992). This approach only requires an estimate of the intergenerational correlation, under the assumption that log permanent earnings in the two generations are bivariate normally distributed. As discussed by Solon (1992) this assumption does not allow for the extent of upward mobility to differ from the extent of downward mobility. Nevertheless, it allows for reasonable suggestive estimates.

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[9] Coelli and Borland (2016) show time series of summary statistics for the distribution of earnings for full time male workers for 1975 to 2011. Their estimates suggest that the log 90/50 percentile log wage gap increased by around 50% over a generation, similarly for the log 90/50 percentile log wage gap. This is approximately equivalent to a 50% increase in the standard deviation of the log earnings distribution as well.

[10] This seems to be a reasonable assumption, but it is not trivial. It is possible that the increase in cross-sectional earnings inequality reflects a greater variance in the transitory (rather than the permanent) component of earnings – although Coelli and Borland's (2016) restriction to full time workers perhaps lessens this concern.

Key results of this exercise are shown in Table 3. Corresponding estimates based on Leigh's elasticity estimate are also shown for comparative purposes. Columns (1) and (2) show the assumed intergenerational elasticities and correlations, respectively. The remaining columns show the estimated probability for a son's permanent earnings to lie in a given interval of the population distribution.

Panel A shows estimates for sons whose fathers' earnings were at the 5th percentile of the distribution. Our estimates suggest that the almost two thirds (65.3%) of such sons had earnings in the bottom half of the distribution (Column 5). They also suggest that the probability of these sons' earnings being in the lowest decile is 17.8%, more than four times larger than probability of being in the top decile (4.3%). Using Leigh's estimate, the corresponding probabilities are 15.3% and 5.7%, or 2.7 times higher.

Panel B shows similar estimates for sons whose father's earnings were at the 20th percentile of the distribution. The probability of the son's earnings being in the lowest decile is 13.2%, more than twice as high as the probability of being in the top decile (6.4%). Using Leigh's estimate, the corresponding probabilities are 12.3% and 7.5%, or 1.7 times higher.

The results for sons of fathers whose earnings lie at the median of the distribution are in Panel C. Due to the intergenerational correlation in earnings, these sons are slightly less likely than average to be in the top or bottom decile of the distribution (9.4% in each case).

The results for fathers at the 80th and 95th percentiles (Panels D and E) are symmetrical to those in Panels A and B, due to the assumed bivariate normal distribution.

6. Conclusion

This study has analysed intergenerational mobility in Australia, and has generated new estimates of earnings elasticity using HILDA data. We have updated the estimates of Leigh (2007) by following the

same approach but using considerably more data, yielding more precise estimates. Specifically, we used twelve waves (2001-2012) of HILDA, rather than one, to construct estimates of intergenerational mobility and we also use four waves of the Panel Study of Income Dynamics (PSID) study rather than one.

Our analysis is performed by imputing father's earnings on the basis of their reported occupation, since detailed occupation data are available in HILDA. The estimates for Australia are re-scaled in order to account for likely attenuation bias due to the imputation. The scaling factor is constructed in a way that makes the estimates comparable to those estimated by Corak (2013) for other countries. We have also proposed an approach to statistical inference that is appropriate for international comparisons of intergenerational elasticity.

Our preferred estimate for the intergenerational earnings elasticity in Australia is 0.35, which is considerably higher than the estimate in Leigh (2007), which was in turn the basis of Corak's (2013) estimate. Our higher estimate is consistent with Australia's level of income inequality, as depicted in the so-called 'Great Gatsby Curve' (Figure 1). It suggests that a 10 percent increase in father's earnings is associated with a 3.5 percent increase in son's earnings. Combining this result with the estimates reported in Corak (2013), we conclude that Australia is not particularly mobile in an international context. It is less mobile than the Scandinavian countries, as well as Germany, Canada and New Zealand, but is more mobile than the United States and the United Kingdom.

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Table 1 Descriptive Statistics

	Mean	SD
HILDA (2001-2012)		
son's age	39.27	8.51
son's hourly earnings (A$)	28.21	17.80
father's predicted hourly earnings (A$)	25.59	11.27
N	26,872	
PSID (2001-2007)		
son's age	38.96	8.79
son's hourly earnings (US$)	26.05	66.16
father's predicted hourly earnings		
(US$)	22.59	12.23
N	5,767	

Table 2 Elasticity Estimates

HILDA - unadjusted	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	pooled
estimated elasticity	0.171	0.222	0.192	0.174	0.230	0.305	0.249	0.185	0.236	0.235	0.261	0.272	0.227
standard error	0.032	0.039	0.031	0.048	0.034	0.049	0.036	0.044	0.043	0.038	0.037	0.043	0.020
N	2,498	2,328	2,206	2,139	2,129	2,087	2,034	1,947	2,057	2,077	2,713	2,657	26,872
PSID													
estimated elasticity	0.315		0.309		0.293		0.314						0.306
standard error	0.070		0.050		0.047		0.043						0.035
N	1,404		1,363		1,515		1,485						5,767
HILDA - adjusted													
estimated elasticity	0.265	0.343	0.296	0.269	0.355	0.472	0.385	0.285	0.365	0.363	0.404	0.421	0.350
standard error	0.057	0.072	0.058	0.080	0.066	0.093	0.070	0.074	0.078	0.071	0.073	0.082	0.050

Notes: This table shows various estimated intergenerational elasticities. The upper panel shows estimates for Australia using each wave of HILDA individually and in a pooled analysis. Father's income is imputed on the basis of reported father's occupation. Panel B shows comparable estimates for the United States. Panel C shows the HILDA results after applying an adjustment factor consistent with Corak's (2013) approach. The 95% Confidence Intervals shown are robust to heteroscedasticity and to clustering within individuals for the estimates where waves are pooled. The Confidence intervals shown in Panel C account for sampling variation in the (unadjusted) HILDA estimates and the sampling variation in the PSID estimates (The PSID estimates are used in the construction of the adjustment factor as described in the text).

Table 3 Estimated probabilities that son's earnings lie in specific intervals as a function of percentile of father's earnings

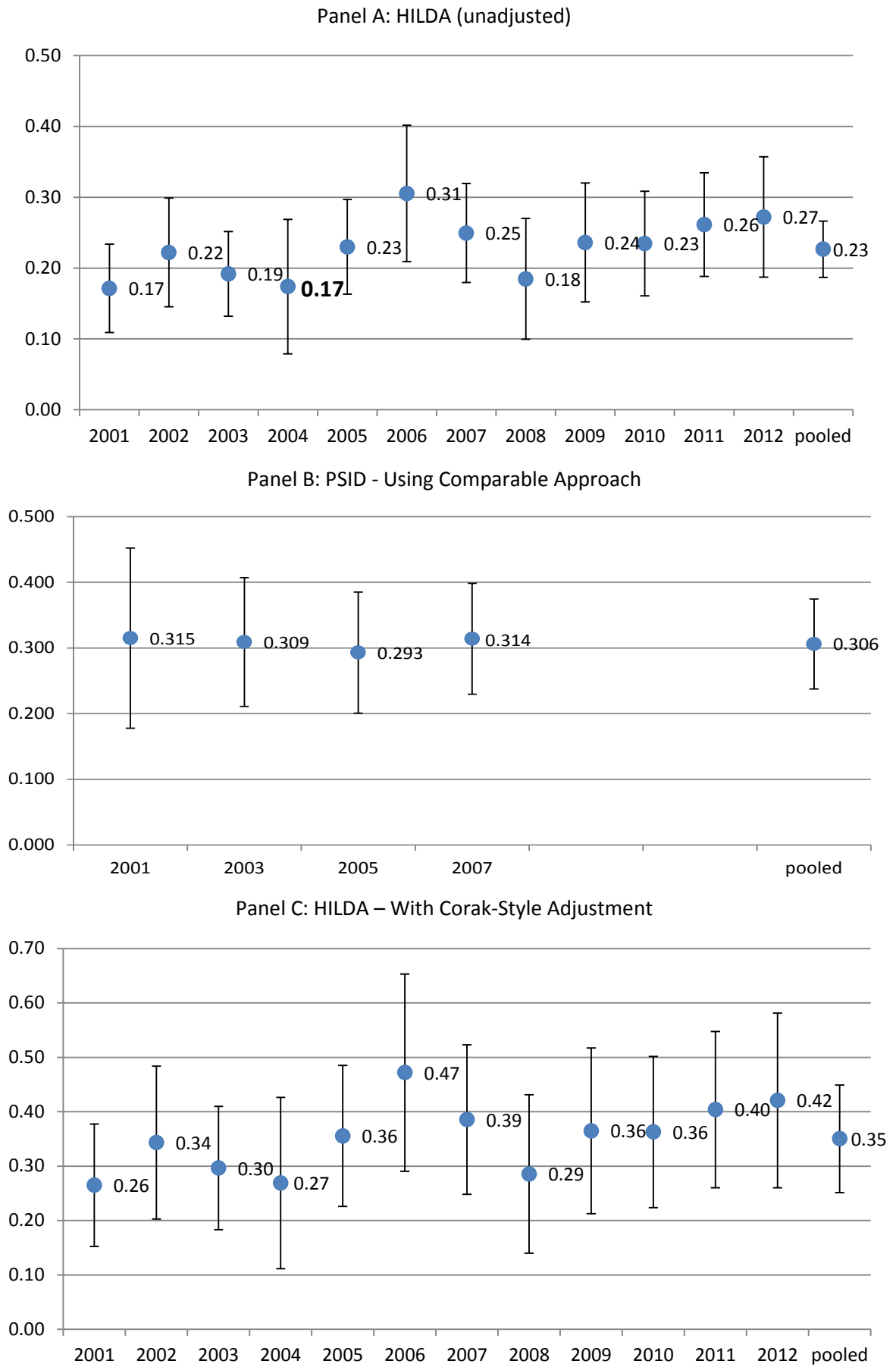|	Inter-generational elasticity (1)	Inter-generational correlation (2)	Estimated probabilities for son's earnings				
			P(lowest decile) (3)	P(lowest quintile) (4)	p(above median) (5)	p(highest quintile) (6)	p(highest decile) (7)
A: father at 5th percentile							
Using Leigh's elasticity estimate	0.25	0.167	15.3%	28.3%	39.1%	12.9%	5.7%
Using our elasticity estimate	0.35	0.233	17.8%	31.9%	34.7%	10.4%	4.3%
B: father at 20th percentile							
Using Leigh's elasticity estimate	0.25	0.167	12.3%	23.9%	44.3%	16.0%	7.5%
Using our elasticity estimate	0.35	0.233	13.2%	25.4%	42.0%	14.3%	6.4%
C: father at 50th percentile							
Using Leigh's elasticity estimate	0.25	0.167	9.7%	19.7%	50.0%	19.7%	9.7%
Using our elasticity estimate	0.35	0.233	9.4%	19.4%	50.0%	19.4%	9.4%
D: father at 80th percentile							
Using Leigh's elasticity estimate	0.25	0.167	7.5%	16.0%	55.7%	23.9%	12.3%
Using our elasticity estimate	0.35	0.233	6.4%	14.3%	58.0%	25.4%	13.2%
E: father at 95th percentile							
Using Leigh's elasticity estimate	0.25	0.167	5.7%	12.9%	61.0%	28.3%	15.3%
Using our elasticity estimate	0.35	0.233	4.3%	10.4%	65.3%	31.9%	17.8%

Notes: Columns (3) – (7) show estimated probabilities for a son's permanent earnings to lie in specific intervals of the earnings distribution, as a function of his father's ranking in the earnings distribution. The estimates draw on Solon's (1989; 1992) method, which relies on the non-trivial assumption that fathers' and sons' earnings follow a bivariate normal distribution, which for example does not allow the extent of upward mobility to differ from the extent of downward mobility. The intergenerational correlation estimates which underpin these estimates are shown in column (2). These are a function of the elasticity estimates (column 1) and changes in cross-sectional earnings inequality between generations, as shown equation (6). Our calculations draw on the time series of cross-sectional earnings inequality in Coelli and Borland (2016), as detailed in footnote (9).

Figure 1 The 'Great Gatsby Curve'

Source: Corak (2013: Figure 1) and our estimate

Figure 2 Estimates of Intergenerational Elasticity in Australia and the USA

Panel A: HILDA (unadjusted)

Panel B: PSID - Using Comparable Approach

Panel C: HILDA – With Corak-Style Adjustment

Notes: This figure shows various estimated intergenerational elasticities. Panel A shows estimates for Australia using each wave of HILDA individually and in a pooled analysis. Father's income is imputed on the basis of reported father's occupation. Panel B shows comparable estimates for the United States. Panel C shows the HILDA results after applying an adjustment factor consistent with Corak's (2013) approach. The 95% Confidence Intervals shown are robust to heteroscedasticity and to clustering within individuals for the estimates where waves are pooled. The Confidence intervals shown in Panel C account for sampling variation in the (unadjusted) HILDA estimates and the sampling variation in the PSID estimates (The PSID estimates are used in the construction of the adjustment factor as described in the text).