Life Course Centre Working Paper Series

lifecoursecentre

ARC Centre of Excellence for Children and Families over the Life Course

Intergenerational Earnings Elasticity Revisited: How Does Australia Fare in Income Mobility?

Yangtao Huang
Institute for Social Science Research, The University of Queensland

Francisco Perales
Institute for Social Science Research, The University of Queensland

Mark Western
Institute for Social Science Research, The University of Queensland

A more recent version of this paper was published as Huang Y, Perales F and Western M. (2015) A Land of the 'Fair Go'?: Intergenerational Earnings Elasticity in Australia. Australian Journal of Social Issues, 51(3), 361-381

No. 2015-14
July 2015

The University of Queensland Australia

The University of Melbourne

The University of Western Australia

The University of Sydney

Australian Government
Australian Research Council

NON-TECHNICAL SUMMARY

Strengthening and maintaining the land of a "fair go" has been a policy aim in Australia for decades. A fair society may feature a certain amount of economic inequality, provided that there is equality of opportunity. Equal opportunity means that people's life chances rely more on individual effort and hard work than on parental socioeconomic status and family background. Intergenerational income mobility is an important measure of linkages between parental socioeconomic status and adult children's outcomes. It is a measure of the extent to which parental income determines grown-up children's economic performance. It is quantified by intergenerational earnings elasticity, also known as intergenerational earnings persistence, a measure of how offsprings' earnings are related to parents' earnings. A larger earnings elasticity indicates less income mobility. While an extensive body of literature has estimated intergenerational earnings elasticities in developed and developing countries, and cross-national comparative studies have flourished in recent years, there is surprisingly little research on earnings elasticity in Australia. Existing evidence is based predominantly on cross-sectional data, which obscures underlying dynamics. Trend analyses rely on different datasets for different time points, which faces issues of inconsistent income measures. Therefore, new and more robust estimates of earnings elasticity for Australia using recent longitudinal data and panel regression models are warranted.

We use the Household, Income and Labour Dynamics in Australia Survey and the Longitudinal Labour Force Survey to examine the patterns and dynamics of father-son earnings elasticity in contemporary Australia. We contribute to the literature in the following ways. Methodologically, we implement two stage regression models that take advantage of longitudinal and other characteristics of the data. Substantive improvements are made by comparing different approaches to see how sensitive elasticity estimates are to analytic choices. First, detailed occupation categories enable us to estimate earnings elasticity based on the level at which occupations are disaggregated. Second, we examine changing patterns in earnings elasticity by considering linear and curvilinear trends over time. Third, comprehensive earnings measures allow us to assess the effect of earnings volatility on elasticity estimates.

We find that intergenerational earnings persistence in contemporary Australia lies between 11% and 30%, situating Australia internationally as a country with moderately high income mobility. The overall trend of earnings elasticity since 2001 is upward, although there is a declining tendency after 2011. More data are required before we can conclude that the decline after 2011 signals a new trend. Elasticity estimates are larger using two-digit level occupations and two-sample approach than the estimates using one-digit occupations and one-sample approach, respectively, and using different earnings measures results in substantially different elasticity estimates. We read these findings as indicating that elasticities are sensitive to the use of methods and data.

ABOUT THE AUTHORS

Yangtao Huang is PhD Candidate in the Institute for Social Science Research at The University of Queensland. His research interests include intergenerational mobility of socioeconomic status, gender inequality, social networks and subjective wellbeing. Email: y.huang3@uq.edu.au

Francisco Perales is Research Fellow in Family Dynamics in the Institute for Social Science Research at The University of Queensland. His recent research has been on social disadvantage, gender inequalities, life course transitions, subjective wellbeing, and the use of household panel surveys within sociology. His recent research has been published in outlets such as *Journal of Marriage and Family*, *Social Forces*, *Social Science Research*, and *PLoS One*. Email: f.perales@uq.edu.au

Mark Western is the Director of the Institute for Social Science Research at the The University of Queensland, a Fellow of the Academy of Social Science in Australia, and a sociologist. Mark is currently involved in a number of projects including studies of social, economic and educational inequality, research into social networks, and developments in survey research methods. His empirical research primarily relies on analyses of Australian and international cross-sectional and longitudinal surveys, but he is increasingly also working with aggregate and administrative data. Email: m.western@uq.edu.au

ACKNOWLEDGEMENTS: We would like to thank Arturo Martinez for helpful comments on earlier versions of this paper. This research was supported by the Australian Research Council Centre of Excellence for Children and Families over the Life Course (project number CE140100027). The views expressed herein are those of the authors and are not necessarily those of the Australian Research Council. This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute.

lifecoursecentre

(ARC Centre of Excellence for Children and Families over the Life Course)
Institute for Social Science Research, The University of Queensland
St Lucia, Qld 4072, Telephone: +61 7 334 **67477**
Email: lcc@uq.edu.au, Web: www.lifecoursecentre.org.au

Abstract

This paper contributes to the existing income mobility literature by adopting a two-stage panel regression model, investigating linear and curvilinear trends over time, and assessing the effects of using different levels of occupational disaggregation, different sample compositions, and different earnings measures on the magnitude of father-son earnings elasticity in Australia. We find that the overall intergenerational earnings elasticity in Australia between 2001 and 2013 ranges from 0.11 to 0.30, with evidence of an upward trend. Elasticity estimates are larger using two-digit level occupations and two-sample approach than the estimates using one-digit occupations and one-sample approach, respectively, and earnings volatility has substantial effects on elasticities. We read these findings as indicating that Australia has a moderately high level of income mobility by international standards, and that findings are sensitive to the use of methods and data.

Keywords: parental background; intergenerational transmission; earnings elasticity; occupation; trends; panel data; Australia

JEL classification codes: J62, C23

1 Introduction

Strengthening and maintaining the land of a "fair go" has been a policy aim in Australia for decades. A fair society, as many Australians believe, may feature a certain amount of economic inequality, provided that there is equality of opportunity (Andrews & Leigh, 2009). Equal opportunity means that people's life chances rely more on individual effort and hard work than on circumstances over which they have no control, such as parental status and family background. Theoretically, if parental socioeconomic status has little influence on individuals' life outcomes, we should observe high levels of intergenerational mobility. In reality, evidence from many western countries tells the opposite story: children from high income families are more likely to become top earners than children from low income families (Corak, 2013a). The fact that parental earnings capacity is a strong predictor of adult children's economic performance has therefore been found in an extensive body of literature, and substantial attention has been paid to how intergenerational earnings elasticity is defined, estimated and compared.

Intergenerational earnings elasticity is a measure of the extent to which parental earnings determine children's earnings outcomes. As an index of intergenerational income mobility, earnings elasticity benchmarks adult children's earnings with their parents' earnings after controlling for demographic characteristics. Hence, a larger earnings elasticity indicates less income mobility.

While a burgeoning literature has estimated the intergenerational earnings elasticity in developed and developing countries and cross-national comparative studies have flourished in recent years, there is surprisingly little research on earnings elasticity in Australia. This gap needs to be addressed because Australia's institutional and historical arrangements make it an important case study. First, for most of the 20th century, Australia had an internationally distinctive set of labour market institutions built around centralised pay setting by industrial tribunals that promoted both high real wages and substantial uniformity of pay and working conditions across occupations and industries (Castles, 1985). These institutions began to be unwound by successive governments in the 1990s, but they potentially lay a path-dependent foundation for earnings inequality and mobility that makes Australia a noteworthy case. Second, Australia has a relatively egalitarian culture (Thompson, 1994), characterised by public attitudes leaning towards egalitarianism, a relatively flat social structure that is not marked by pronounced symbolic or behavioural class distinctions, and strong anti-discrimination legislation. Third, existing evidence shows that generally, intergenerational mobility is inversely associated with inequality (OECD, 2011). Countries with higher mobility (i.e. lower earnings elasticity) exhibit less economic inequality (typically measured by the Gini index). Nevertheless, plotted on the Great Gatsby Curve (Corak, 2013b), which locates countries according to economic inequality and mobility, Australia presents a distinctive case with both a high level of mobility and a moderate level of inequality. New, robust evidence on intergenerational earnings elasticity in Australia would enrich international comparisons.

Using panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey and the Longitudinal Labour Force Survey (LLFS), we examine the patterns and dynamics of father-son earnings elasticity in contemporary Australia. Since fathers' earnings are not observable in the HILDA Survey, we apply a two-stage panel regression model which first computes fathers' earnings based on sons' reports of fathers' occupations at stage one, and then estimates the earnings elasticity at stage two. We add to the existing literature by (i) using more recent data than those in previous studies, (ii) establishing trends in earnings elasticity in Australia over time, and (iii) examining how occupational disaggregation, different sample compositions, and different earnings measures affect elasticity estimates.

Key findings show that father-son earnings elasticity in Australia between 2001 and 2013 ranges from 0.11 to 0.30, and has increased over the observation window. Elasticity estimates are larger using two-digit level occupations and two-sample approach than the estimates using one-digit occupations and one-sample approach, respectively, and using different earnings measures results in substantially different elasticity estimates. We read these findings as indicating that Australia has a moderately high level of income mobility by international standards, and that findings are sensitive to the use of methods and data. This point has two important implications: single analyses of earnings elasticity should explore the extent to which results are robust to analytic choices, and comparative analyses should recognise that differences in approach across comparative settings may contribute to finding comparative similarities or differences.

The structure of this paper is as follows. In section two, we review the existing literature and outline our contributions. In section three, we detail the data sources, sample selection, statistical models, common methodological issues and how we address these issues. We proceed by explaining our findings in section four. Section five concludes.

2 Literature review

Research on intergenerational socioeconomic status can be traced back to the 1920s (Sorokin, 1927) with modern work on occupational mobility from the 1950s (Glass, 1954) and socioeconomic status from the 1960s (Blau & Duncan, 1967). In the last three decades, economic research on income mobility (typically measured using earnings elasticity) has gained in popularity (Blanden, Haveman, Smeeding, & Wilson, 2014; Torche, 2015). The measure of income used to estimate earnings elasticity differs across studies, primarily due to data availability. Ideally, researchers would use labour income (i.e. earnings from employment), as this is argued to best capture the effect of parental economic capacity on offspring's outcomes (Björklund & Jäntti, 2012). Earnings elasticity has been widely accepted and estimated on different parent-children linkages, among which father-son earnings elasticity is the most commonly investigated. Correspondingly, a variety of estimation methods are employed to accommodate differences in the available data.

International comparisons provide almost unanimous evidence that intergenerational earnings elasticity is highest in developed countries such as the US, UK, Italy and developing countries like Brazil, China and South Africa, and lowest in Nordic countries (Blanden, 2013; Causa & Johansson, 2010; Corak, 2006; D'Addio, 2007; Gong, Leigh, & Meng, 2012; Grawe, 2004; Jäntti et al., 2006; Mocetti, 2007; Ng, 2007; Piraino, 2007; Solon, 2002). Most countries have earnings elasticities that fall within the Nordic-US spectrum, such as France (Lefranc & Trannoy, 2005), Germany (Couch & Dunn, 1997), Canada (Corak, 2013a), Australia (Leigh, 2007), Japan (Lefranc, Ojima, & Yoshida, 2008; Ueda, 2009) and South Korea (Ueda, 2013). A summary of estimates for OECD countries since the late 1980s can be found in Table A1 in the Appendices.

Most studies use cross-sectional data to estimate earnings elasticity, understood as the regression coefficient on parent's earnings in an equation modelling offspring's earnings. This shows the percentage difference in offspring's earnings, for a one percent difference in parental earnings. Estimation takes place via ordinary least squares (OLS) or instrumental variable (IV) methods. Early contributors have found that OLS results are downwardly biased, in which case IV estimation is a good remedy, provided that a valid instrument is identified (Björklund & Jäntti, 1997; Solon, 1992; Zimmerman, 1992). More recently, other methods have also been applied, including quantile regression (Bratberg, Nilsen, & Vaage, 2007), tobit regression (Mazumder, 2005), two-sample two-stage least squares (TS2SLS) models (Gong, Leigh, & Meng, 2012; Mocetti, 2007; Nicoletti & Ermisch, 2007; Piraino, 2007), simulation extrapolation method (Ueda, 2013) and non-parametric analyses (Bhattacharya & Mazumder, 2011; Ueda, 2013).

Daughters' permanent earnings are less predictable than sons', because women's employment circumstances remain more heterogeneous than men's (Steiber & Haas, 2012), with high rates of part-time work and long-term economic inactivity. Father-daughter earnings elasticities are also complicated by occupational sex segregation, while mother-daughter elasticities are complicated by women's discontinuous employment histories. As a result, most attention in the literature has been devoted to father-son earnings elasticities – although with good-quality data and careful sample selection, under certain assumptions, father-daughter elasticities can be robustly estimated (see Bratberg, Nilsen, & Vaage, 2007; Chadwick & Solon, 2002; Couch & Dunn, 1997; Grawe, 2004; Hansen, 2010; Hertz, 2007; Lee & Solon, 2009; Lefranc & Trannoy, 2005; Mazumder, 2005; Pekkala & Lucas, 2007). Comparisons by ethnicity (Bhattacharya & Mazumder, 2011; Hertz, 2006; Kearney, 2006; Mazumder, 2014) and migrant status (Hammarstedt & Palme, 2012; Leigh, 2007) have also been undertaken.

Research on intergenerational earnings elasticity in Australia, compared to other OECD countries, is scarce, and the available evidence is "limited and inconclusive" (Argy, 2006: 14). The most recent study of earnings elasticity in Australia was conducted by Leigh (2007), who estimated father-son single-year earnings elasticities using hourly wages and four different survey datasets.[1] He found that earnings elasticity in Australia is likely to be 0.2-0.3 (compared to 0.4-0.6 in the United States), with no significant changes between 1965 and 2004.

Leigh's (2007) work provides the best Australian evidence to date, but is not without limitations. First, his conclusions are based on analyses of different datasets with different income measures: annual income measured in six bands in the 1965 survey, weekly income measured in 16 bands in the 1973 survey, and a continuous income measure in the 1987 and 2004 surveys. Second, Leigh uses cross-sectional methods that capture earnings elasticities in a point-in-time fashion, which obscures underlying dynamics. At the time of writing these data were the best available. However, as Corak (2011: 75) points out, the study of intergenerational earnings elasticity "ideally requires data from a longitudinal study of a large, nationally representative sample of individuals and families". Finally, the most recent data

[1] The data in Leigh (2007) come from the following four surveys: *Social Stratification in Australia* (1965), *Social Mobility in Australia Project* (1973), *National Social Science Survey* (1987-1988), and *Household, Income and Labour Dynamics in Australia Survey* (2001-2004).

Leigh used are now over ten years old. Therefore, while Leigh pioneered the research of intergenerational earnings elasticity in Australia, work that extends his analyses by leveraging recent longitudinal data and panel regression models is warranted.

We contribute to the existing literature on earnings elasticity in Australia in the following ways. Methodologically, we employ a two-stage panel regression model as our main model, supplemented by an improved two-sample two-stage estimation in which interval regression is used at stage one and a random-effects model at stage two. Substantive improvements are made by comparing different approaches to see how sensitive elasticity estimates are to analytic choices. First, detailed occupation categories enable us to estimate the earnings elasticity based on the level at which occupations are disaggregated. Second, we examine changing patterns in earnings elasticity by considering linear and curvilinear trends over time. Third, comprehensive earnings measures allow us to assess the effect of earnings volatility on elasticity estimates.

3 Data and methods

3.1 Data

3.1.1 The Household, Income and Labour Dynamics in Australia Survey

Our main analyses are performed on the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Survey is a nationally representative panel survey initiated in 2001 with 13,969 respondents from 7,682 households. Data were collected primarily via face-to-face interviews and self-complete questionnaires with in-scope respondents residing in private dwellings aged 15 years and over (Watson & Wooden, 2002). Since then, interviews with participants have been conducted annually. The HILDA Survey has relatively high wave-on-wave response rates ranging from 86.8% in wave two to 96.4% in wave 13 (Summerfield et al., 2014).

Detailed information on the labour force participation of respondents is collected, with a multiplicity of income measures readily available. These include weekly as well as annual wages and salary from different sources and for both the main job and all jobs. Here, we will use five income types: hourly earnings from the main job; hourly earnings from all jobs; weekly earnings from the main job; weekly earnings from all jobs; and annual earnings. Weekly and annual earnings are directly reported by respondents, whereas hourly earnings are derived from weekly earnings divided by usual weekly hours of work. For confidentiality reasons, the HILDA Survey top-coded reported earnings before creating derived gross income variables. Further changes in these derived variables include estimated gross income (by translating after-tax income) and imputed gross income (by a three-step imputation process, see Hayes & Watson, 2009). Since the imputed values change across waves (Summerfield et al., 2014), to minimise biases associated with changes in these self-reported earnings, we use the derived gross weekly and annual earnings variables. We adjust these earnings by using annual rates of the Consumer Price Index, taking year 2013 as the base year.

The person questionnaire of the HILDA Survey contains modules on "family background" and "history and status of parents". The former is administered annually whereas the latter is administered in waves eight and 12. These modules contain rich retrospective information on the employment circumstances of the respondent's father and mother when the respondent was 14 years old, including employment status and occupational titles at different levels of disaggregation.

Information on father's age when the respondent was 14 was derived from responses to survey questions asking about father's year of birth and current age (if alive). These questions, however, were only included in waves eight and 12. Since respondents in the HILDA Survey are at least 15 years of age, father's age when they were 14 constitutes time-constant information. As a result, such information can be extrapolated to other survey waves.

Occupational data are coded to the 2006 Australian and New Zealand Standard Classification of Occupations (ANZSCO). The 2006 ANZSCO is structured into five hierarchical levels: major groups (one-digit level, n=8), sub-major groups (two-digit level, n=43), minor groups (three-digit level, n=97), occupational units (four-digit level, n=358), and individual occupations (n=998) (ABS, 2006). In its general release, the HILDA Survey contains one- and two-digit level occupations, whereas in its unconfidentialised release, occupations are disaggregated up to the four-digit level. Using the same level of occupational disaggregation for fathers and sons improves the computation of fathers' earnings.

It is worth pointing out the trade-off between occupational precision and small sample sizes in some occupation categories at highly-disaggregated levels. Using detailed occupational levels in estimating earnings elasticity reduces within-occupation heterogeneity that exists at more aggregated levels. However, a highly-disaggregated occupational level such as the four-digit level yields sample sizes for some occupation categories that are too small for robust analysis.

Therefore, elasticity estimates from an occupational level that attain a balance —the two-digit level— are our preferred estimates.

3.1.2 The Longitudinal Labour Force Survey (2008-2010)

We use the Longitudinal Labour Force Survey (LLFS) as an auxiliary dataset to conduct a two-sample two-stage regression in sensitivity analyses. The LLFS provides labour related data derived from the monthly Labour Force Survey (LFS) between January 2008 and December 2010. Respondents in the LFS are selected for a period of 8 consecutive months, and their responses have been linked across time to form the longitudinal data structure (ABS, 2012). The LLFS contains information from over 150,000 households, resulting in over 1.8 million records (ABS, 2012).

3.2 Methodological approaches

Becker and Tomes (1979, 1986) first introduced the theoretical model by which the intergenerational earnings elasticity is estimated:

$$\ln Y_i^c = \alpha + \beta \ln Y_i^p + \varepsilon_i \tag{1}$$

where Y_i^c and Y_i^p denote adult children's and parental lifetime earnings, respectively, and β reflects the extent to which intergenerational earnings persist. In practice, lifetime earnings for both generations cannot be captured within most longitudinal surveys, requiring a measure of short-run earnings as proxies for long-run earnings (Lee & Solon, 2009). However, the use of such a *proxy* should be exercised with particular caution due to measurement errors from a variety of sources. First, the number of periods these proxies use influences the precision of the results. Single-year estimation, as in the early literature, produces downward-biased elasticities due to response errors and transitory fluctuations (Corak, 2006; D'Addio, 2007; Mazumder, 2001). Second, elasticities vary depending on the age at which earnings are measured (life-cycle bias). For instance, the computation of young fathers' earnings, or the estimation using earnings of sons who are at an early stage of their careers, may result in the elasticity estimates biased downwards (D'Addio, 2007; Grawe, 2006; Piraino, 2007).

The longitudinal data analysis in this study mitigates the first measurement error. We apply a two-stage panel regression model with the computation of fathers' earnings at stage one and the estimation of earnings elasticity at stage two. Since fathers' earnings when their sons were 14 are a time-constant construct, we employ a between-effect model that uses the over-time averages in sons' earnings, ages and occupations before computing fathers' earnings, as outlined below:

$$\overline{\ln Y_{it}^{s}} = \alpha + \boldsymbol{\theta}'\overline{\boldsymbol{X}}_{\boldsymbol{it}}^{\boldsymbol{s}} + \delta_1 \bar{A}_{it}^{s} + \delta_2 \bar{A}_{it}^{s\,2} + u_i + \bar{e}_{it} \tag{2}$$

Where $\boldsymbol{\theta}' := (\theta_1, \dots, \theta_N)$, and $\boldsymbol{X}_{\boldsymbol{it}}' := (x_{it}^{(1)}, \dots, x_{it}^{(N)})$. Y_{it}^{s} denotes the earnings of son i at time t, $\boldsymbol{X}_{\boldsymbol{it}}$ is a list of occupation dummies, each of which is denoted as $x_{it}^{(j)}, j = 1, \dots, N$; A_{it}^{s} represents the i^{th} son's age at time t, and N is the total number of occupation categories, which depends on the level of aggregation used. We assume $u_i \sim i.i.d(0, \sigma_u^2)$, $e_{it} \sim i.i.d(0, \sigma_e^2)$, and $cov(u_i, e_{it}) = 0$. The coefficients obtained from model (2) are then used to compute fathers' earnings (denoted as Y_{it}^{f}) by substituting sons' retrospective reporting of fathers' occupations and ages in the following equation:

$$Y_{it}^{f} = e^{\alpha + \boldsymbol{\theta}'\boldsymbol{X}_{it}^{f} + \delta_1 A_{it}^{f} + \delta_2 A_{it}^{f\,2}} \tag{3}$$

The theoretical model (1) of earnings elasticity is improved in recent studies by adding both sons' and fathers' ages as control variables (Leigh, 2007; Piraino, 2007). We follow this updated method, centring age at 40, and fitting a random-effects model:

$$\ln Y_{it}^{s} = \tilde{\alpha} + \beta \ln Y_{it}^{f} + \lambda_1 (A_{it}^{s} - 40) + \lambda_2 (A_{it}^{s} - 40)^2 + \lambda_3 \left(A_{it}^{f} - 40\right) + \lambda_4 \left(A_{it}^{f} - 40\right)^2 + \gamma t + \tilde{u}_i + \tilde{e}_{it} \tag{4}$$

The random-effects model takes account of longitudinal dependence (repeated measures for individuals) in the data, whereas the cross-sectional regression model does not. We subsequently examine curvilinear trends in elasticity by interacting fathers' logarithmic earnings with different powers of the time variable, and adding the interaction term in model (4). These are generalised to the function below:

$$\ln Y_{it}^{s} = \check{\alpha} + f^{(n)}(t) \cdot \ln Y_{it}^{f} + \check{\lambda}_1 (A_{it}^{s} - 40) + \check{\lambda}_2 (A_{it}^{s} - 40)^2 + \check{\lambda}_3 \left(A_{it}^{f} - 40\right) + \check{\lambda}_4 \left(A_{it}^{f} - 40\right)^2 + g^{(n)}(t) + \check{u}_i + \check{e}_{it} \tag{5}$$

Where $f^{(n)}(t)$ and $g^{(n)}(t)$ are functions of time t with power n, $n = 1, 2, 3$. To be specific, denote $\boldsymbol{\varphi}'^{(n)} := (\varphi_0, \ldots, \varphi_n)$ as the coefficient vector for the interaction terms with power n, and $\boldsymbol{\omega}'^{(n)} := (\omega_1, \ldots, \omega_n)$ as the coefficient vector for time t with power n. $f^{(n)}(t)$ and $g^{(n)}(t)$ can then be written as:

$$f^{(n)}(t) = \sum_{k=0}^{n} \varphi_k \cdot t^k = \boldsymbol{\varphi}'^{(n)} \boldsymbol{T}_{\boldsymbol{f}}^{(n)} \tag{6}$$

$$g^{(n)}(t) = \sum_{l=1}^{n} w_l \cdot t^l = \boldsymbol{\omega}'^{(n)} \boldsymbol{T}_{\boldsymbol{g}}^{(n)} \tag{7}$$

Where $\boldsymbol{T}'_{\boldsymbol{f}}{}^{(n)} := (1, t, \ldots, t^n)$ and $\boldsymbol{T}'_{\boldsymbol{g}}{}^{(n)} := (t, \ldots, t^n)$. In this way, we depict the linear, quadratic and cubic trends of earnings elasticity. Model diagnostics then help decide which trend fits the data best.

To perform the two-sample two-stage estimation, LLFS data are used at stage one. Earnings in the LLFS, however, are main-job weekly earnings in *banded* form: with a width of \$100, earnings are grouped into 21 intervals, from \$1 - \$99 per week through to more than \$1999 per week. We thus use interval regression to estimate the relationship between respondents' logarithmic earnings, ages and occupations. The coefficients are then substituted in equation (3), with which fathers' earnings are independently computed. The elasticities are thereafter estimated by repeating model (4). Furthermore, we perform an analogous interval regression analysis using the HILDA Survey data at stage one by grouping sons' observed main-job weekly earnings into the same categories as those in the LLFS, and repeat the aforementioned steps. The results are then compared to explore the differences between the one-sample and two-sample approaches.

In relation to the life-cycle bias discussed previously, the age distributions of fathers and sons in our data ameliorate the downward bias in estimating earnings elasticity. As documented in previous research, the bias is small and not significant if current earnings as proxies for lifetime earnings are measured between the early thirties and the middle forties (Böhlmark & Lindquist, 2006; Haider & Solon, 2006). In operation, age is centred at 40 and restricted to a certain range for estimation (Gong, Leigh, & Meng, 2012; Lee & Solon, 2009). Both sons' and fathers' ages in our data exhibit normal distributions with mean and median age ranging from 42 to 45, ensuring precise estimation with reduced life-cycle bias.

3.3 Sample selection

Our HILDA Survey sample consists of male respondents (hereafter referred to as sons) who are employed with positive earnings and non-missing data on the analytical variables and who took part in at least one survey wave. In this way we create an unbalanced panel to avoid the loss of information associated with a balanced panel. We correct implausible values of fathers' ages when their sons were 14 by excluding fathers whose ages were below 12 or above 70 when their sons were born. To minimise volatility associated with early or late career effects when computing fathers' earnings, we run model (2) with sons in prime working ages (i.e. ages between 30 and 55). Ninety-four percent of fathers' ages when sons were 14 in our main model fall within this range. When estimating earnings elasticity at stage two, we exclude sons younger than 25 or older than 64, as they are more likely to be out of the labour force for education or retirement reasons. We similarly exclude fathers outside the same age range when their sons were 14.[2] Likewise, the LLFS sample comprises male respondents aged 25-64 who were in employment and provided positive earnings.

3.4 Descriptive statistics

Table 1 reports means and standard deviations for the main analytical variables in our two datasets. The distribution for ages of respondents in our LLFS sample resembles that of sons in the HILDA Survey (see table A2 in the appendices), and both datasets use 2006 ANZSCO to classify occupations. Like the HILDA Survey general releases, the LLFS contains occupations at the one- and two-digit level. These resemblances help map and bridge the two

[2] We also tested the effects of restricting both fathers' and sons' ages at stage one on elasticity estimates, and the results are very close to those by restricting ages at stage two. These results are available upon request.

samples, largely minimising unobserved heterogeneity due to the introduction of a new sample while enabling two-sample two-stage estimation.

Table 1 Descriptive statistics for main analytical variables in the model from two Australian samples

Variable	Sons			Fathers					
				1-digit			2-digit		
	Mean	s.d.	N	Mean	s.d.	N	Mean	s.d.	N
HILDA									
Log hourly earnings in the main job	3.41	0.52	32363	3.36	0.20	38382	3.28	0.32	38382
Log hourly earnings in all jobs	3.40	0.52	32082	3.35	0.19	38382	3.27	0.33	38382
Log weekly earnings in the main job	7.13	0.62	32400	7.11	0.28	38382	7.04	0.34	38382
Log weekly earnings in all jobs	7.15	0.61	32109	7.13	0.28	38382	7.05	0.34	38382
Log annual earnings	11.06	0.73	35000	11.01	0.30	38382	10.93	0.39	38382
Age	42.43	10.46	41043	44.76	6.27	41043	44.76	6.27	41043
Wave	7.63	3.76	41043						
LLFS									
Age	42.42	10.67	26349						
Earning groups									
[$1, $100)	0.0055								
[$100, $200)	0.010								
[$200, $300)	0.014								
[$300, $400)	0.018								
[$400, $500)	0.019								
[$500, $600)	0.032								
[$600, $700)	0.058								
[$700, $800)	0.075								
[$800, $900)	0.082								
[$900, $1000)	0.080								
[$1000, $1100)	0.087								
[$1100, $1200)	0.065								
[$1200, $1300)	0.072								
[$1300, $1400)	0.048								
[$1400, $1500)	0.040								
[$1500, $1600)	0.049								
[$1600, $1700)	0.033								
[$1700, $1800)	0.029								
[$1800, $1900)	0.022								
[$1900, $2000)	0.020								
[$2000, +∞)	0.14								

Notes: Sons' earnings adjusted for inflation using the Consumer Price Index. Father's predicted earnings differ based on the levels of occupations we use at stage one in our main model. The ages for both the HILDA Survey and the LLFS samples are restricted to 25-64.
Source: Authors' calculations from the HILDA Survey (2001-2013) and the LLFS (2008-2010).

4 Results

4.1 Intergenerational earnings elasticity by levels of occupational disaggregation

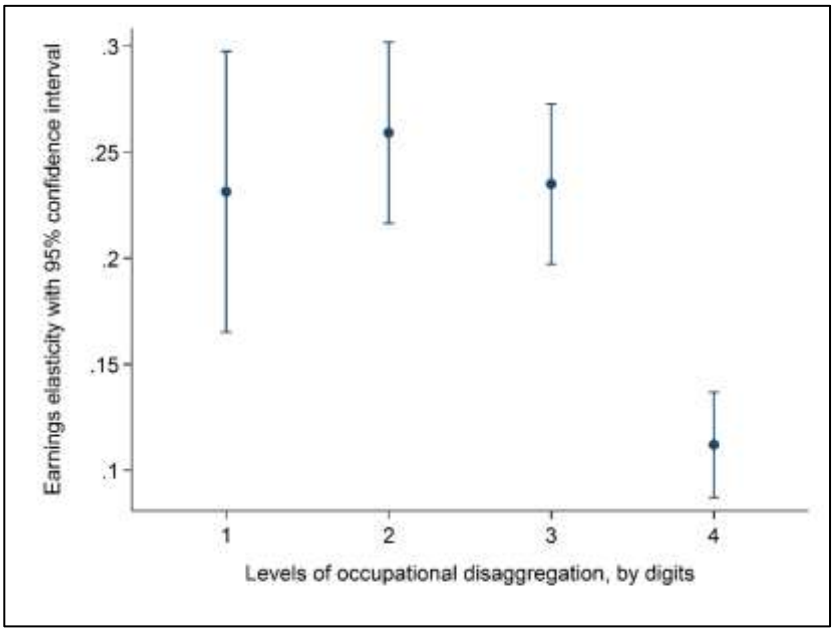
We start by fitting our main model, as in models (2)-(4) in section 3. Table 2 displays the elasticity results by levels of occupational disaggregation. The father-son earnings elasticity in Australia between 2001 and 2013 ranges from 0.11 to 0.30. This is consistent with Leigh's (2007) estimates for early cohorts. The point estimates are larger at two and three occupational digits than one and four (see Figure 1). More detailed occupation categories do not uniformly produce lower elasticities, as might be expected if earnings vary by occupational categories and fathers' and sons' occupational categories are more likely to differ when occupations are disaggregated. Occupations at the two-digit level yield the highest elasticity, whereas those at the four-digit level yield the lowest.

Table 2 Father-son earnings elasticity in Australia, by levels of occupational disaggregation

Results	Occupational disaggregation			
	One digit	Two digits	Three digits	Four digits
Elasticity	0.231	0.259	0.235	0.112
R^2 (overall)	*0.043*	*0.060*	*0.061*	*0.050*
rho	*0.694*	*0.690*	*0.689*	*0.693*
N (observations)	*30175*	*30175*	*30175*	*30175*
N (individuals)	*4960*	*4960*	*4960*	*4960*

Notes: Elasticities estimated using hourly earnings in the main job. All elasticities are statistically significant at the 0.1% level.
Source: Author's calculations from the HILDA Survey (2001-2013).

Figure 1 Father-son earnings elasticity with 95% confidence intervals, by levels of occupational disaggregation

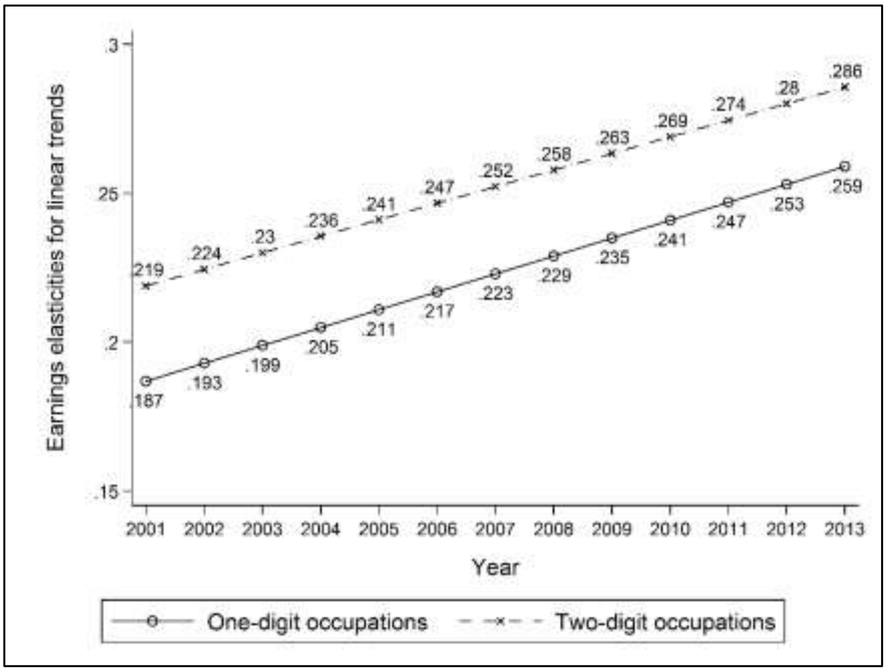


Notes: Elasticities estimated using hourly earnings in the main job. All elasticities are statistically significant at the 0.1% level.
Source: Author's calculations from the HILDA Survey (2001-2013).

4.2 Trends in intergenerational earnings elasticity over time

The results obtained from our main model are overall mean elasticities across 13 years. In this section we extend our main model by incorporating the interaction terms of fathers' logarithmic earnings with survey year, namely models (5)-(7), to delineate trends in earnings elasticity over time. We first include the product of fathers' earnings and year, assuming the trend is linear. The linear assumption is the simplest way to capture overall changes in the elasticity. The changes can be derived from the marginal effects of fathers' earnings, namely, $f^{(n)}(t)$ in model (6). Figure 2 presents the linear trends, annotated with elasticities in each year. There is a clear upward tendency in father-son earnings elasticity at the one- and two-digit level of occupational disaggregation, suggesting that earnings persistence in Australia is strengthening and there appears to be less mobility in the long run.

Figure 2 Linear trends of father-son earnings elasticity in Australia



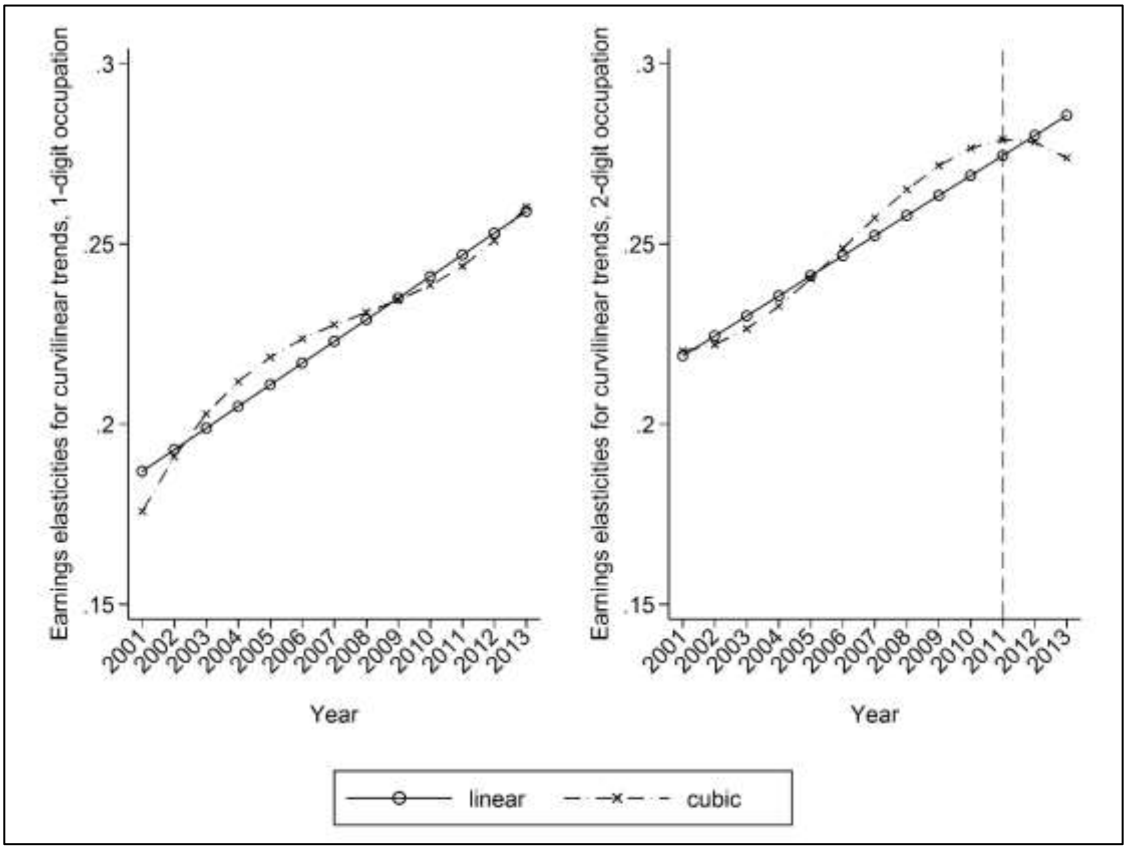
Notes: Elasticities estimated using hourly earnings in the main job. All elasticities are statistically significant at the 0.1% level.
Source: Author's calculations from the HILDA Survey (2001-2013).

A linear trend assumes that earnings elasticity is changing by a constant amount over time. This may not be empirically accurate. To address this issue, we fit models including higher-order polynomials of the year variable and plot them with the linear trends for comparison purposes. We also test the significance of the added polynomials in ascending order. The test results show that the linear and cubic trends are statistically significant, indicating that the cubic model better depicts how earnings elasticity is changing over time.[3] We plot the linear and cubic trends in Figure 3.

The cubic trends display a similar overall increase in father-son earnings elasticity for both one- and two-digit level occupations. However, the shapes of the two cubic curves are different: earnings elasticity using two-digit occupations suggest a maximum in 2011 and a decline thereafter.

[3] We also considered using quartic trends, but the fourth-order survey year polynomials were not statistically significant.

Figure 3 Curvilinear trends of father-son earnings elasticity in Australia



Notes: Elasticities estimated using hourly earnings in the main job. All elasticities are statistically significant at the 0.1% level.
Source: Authors' calculations from the HILDA Survey (2001-2013).

4.3 Two-sample two-stage estimation of intergenerational earnings elasticity

So far we base our estimations solely on HILDA Survey sample. While the one-sample approach is the conventional method, the application of two-sample two-stage least squares is becoming more common (Gong, Leigh, & Meng, 2012). In a similar vein, we implement a two-sample two-stage estimation in our analysis, utilising an ancillary LLFS sample at stage one and the HILDA Survey sample at stage two. Because earnings in the labour force survey are interval-coded, we use interval regression to compute fathers' earnings. For comparison, we also present the HILDA Survey results based on interval regression. Furthermore, we append the results using actual earnings in the HILDA Survey to illustrate the effects of grouping earnings on the elasticity estimates. Table 3 summarises these results.

The elasticities estimated using the two-sample approach are greater than those using the one-sample approach by around 0.03. This resonates with Leigh's (2007) finding that obtaining fathers' earnings from an earlier sample increased elasticities. Interestingly, grouping earnings in the same sample has an effect of increasing elasticity by an even larger magnitude, suggesting that interval-coded earnings create a larger measurement error in proxying lifetime earnings, which in turn affects the precision of the elasticity estimates.

Table 3 Father-son earnings elasticity from two samples

Occupational disaggregation	Sample at stage one		
	LLFS	HILDA[a]	HILDA[b]
<u>One digit</u>			
Elasticity	0.222	0.190	0.155
R^2 (overall)	*0.045*	*0.044*	*0.044*
rho	*0.754*	*0.754*	*0.754*
N (observations)	*30211*	*30211*	*30211*
N (individuals)	*4962*	*4962*	*4962*
<u>Two digits</u>			
Elasticity	0.248	0.219	0.175
R^2 (overall)	*0.051*	*0.052*	*0.052*
rho	*0.754*	*0.754*	*0.754*
N (observations)	*30208*	*30211*	*30211*
N (individuals)	*4961*	*4962*	*4962*

Notes: Elasticities estimated using weekly earnings in the main job. Weekly earnings in the LLFS are interval-coded. All elasticities are statistically significant at the 0.1% level.
[a] Respondents' earnings are coded into the same intervals as those in the LLFS at stage one.
[b] Respondents' actual (i.e. unbanded) earnings are used.
Source: Authors' calculations from the HILDA Survey (2001-2013) and the LLFS (2008-2010).

4.4 Intergenerational earnings elasticity using different earnings measures

Elasticities depend also on the measure of earnings considered, in particular, the time period in which earnings are measured. We argue that, compared to hourly earnings, weekly and annual earnings are weaker in estimating elasticities, as they are affected by hours of work which are positively correlated with earnings rate. Since weekly and annual earnings are affected by working hours, these earnings are thus more volatile and their use should in theory yield lower elasticities. Drawing upon rich wage and salary information in the HILDA Survey, we test the effects of using different earnings measures on elasticity estimates.

Evidence in table 4 confirms our prior argument: using weekly and annual earnings rather than hourly earnings noticeably reduces the estimated elasticities.[4] Specifically, in results for both one- and two-digit occupations, using main-job weekly earnings reduces elasticities by 33%, whereas using all-job weekly earnings decreases elasticities by 28%. Using annual

[4] We conducted robustness checks by excluding observations in the top and bottom 1% of the distribution of usual weekly work hours. The elasticity estimates are very similar to those displayed in this paper. These estimates are available upon request.

earnings lowers the elasticities by 33% and 20% at the one- and two-digit level occupational disaggregation, respectively. These results show that earnings volatility has substantial effects on elasticities, and that hourly earnings are a better *proxy* for permanent earnings and hence preferable when estimating intergenerational earnings elasticity.

Main-job and all-job earnings produce similar elasticity estimates. This is because amongst sons who provided both positive main-job and all-job weekly earnings in our sample, 84.6% of them reported same earnings in their main jobs and all jobs, implying that other-job earnings are trivial for most respondents.[5] Consistent with our previous findings, elasticities estimated using two-digit occupations are higher than those estimated using one-digit occupations, irrespective of the earnings measure considered.

Table 4 Father-son earnings elasticity using different earnings measures

Occupational disaggregation	Earnings measures				
	Hourly earnings from the main job	Hourly earnings from all jobs	Weekly earnings from the main job	Weekly earnings from all jobs	Annual earnings
One digit					
Elasticity	0.231	0.229	0.155	0.164	0.155
R^2 (overall)	*0.043*	*0.043*	*0.044*	*0.044*	*0.033*
rho	*0.694*	*0.699*	*0.754*	*0.754*	*0.678*
N (observations)	*30175*	*29908*	*30211*	*29934*	*32675*
N (individuals)	*4960*	*4954*	*4962*	*4955*	*5017*
Two digits					
Elasticity	0.259	0.256	0.175	0.185	0.206
R^2 (overall)	*0.060*	*0.059*	*0.052*	*0.052*	*0.042*
rho	*0.690*	*0.694*	*0.754*	*0.753*	*0.676*
N (observations)	*30175*	*29908*	*30211*	*29934*	*32675*
N (individuals)	*4960*	*4954*	*4962*	*4955*	*5017*

Notes: All elasticities are statistically significant at the 0.1% level.
Source: Authors' calculations from the HILDA Survey (2001-2013).

5 Discussion and conclusion

Our main objective in this paper is to provide up-to-date estimates of intergenerational income mobility in Australia by examining the patterns and dynamics of father-son earnings elasticity. In doing so, we provided novel perspectives on how elasticities are affected by levels of occupational disaggregation, trends over time, and different samples, methods and earnings measures. Using longitudinal data, we carried out a two-stage panel regression

[5] Further analyses on a sample consisting of sons who are multiple job holders in at least one wave show that elasticity estimates are larger than those in table 4 at both the one- and two-digit level of occupational disaggregation, except for a lower elasticity estimate using all-job hourly earnings at the two-digit level occupations. Detailed analysis results are available upon request.

analysis that improves upon earlier cross-sectional analyses, and adopted a two-sample two-stage estimation strategy by incorporating a complementary labour force survey dataset.

We find that intergenerational earnings persistence in contemporary Australia lies between 11% and 30%, situating Australia as a country with moderately high income mobility in the global mobility regime. The overall trend of father-son earnings elasticity since 2001 is upward, although there is a declining tendency after 2011. More data are required before we can conclude that the decline after 2011 signals a new trend. Elasticity estimates are larger using two-digit level occupations and two-sample approach than the estimates using one-digit occupations and one-sample approach, respectively, and using different earnings measures results in substantially different elasticity estimates.

The limitations of this study are two-fold. First, fathers' earnings are computed, rather than observed, by using sons' retrospective information. While the use of imputed parental earnings is routinely undertaken in previous literature due primarily to data limitations (Andrews & Leigh, 2009; Björklund & Jäntti 1997; Leigh, 2007; Piraino, 2007), retrospective measurements of parental background could be noisy depending on the extent to which respondents are aware of their parents' statuses and how they report them (Wooden & Watson, 2000). Imputing father's earnings from regressions on sons also assumes that the destination regression regime is the same as the origin regime, and such imputation uses a deterministic instead of stochastic model which results in the same imputed earnings for same age-occupation categories. In this respect, our computed fathers' earnings may not perfectly represent their lifetime earnings. Second, we are only able to provide short-term snapshots of the changing patterns of father-son earnings elasticity with the available 13 waves of the HILDA Survey, from which to infer the long-run trend. This limitation could be addressed as new waves of the HILDA Survey are released.

It is worth noting that while earnings elasticity is an internationally accepted index of measuring the extent to which a society is generationally mobile or immobile, cross-country comparisons should still be exercised with much caution because of differences in the data and methods (D'Addio, 2007; Jerrim, Choi & Rodríguez, 2013; Solon, 2002). Providing various estimates for Australia using different data and techniques helps show the range of elasticities consistent with different approaches, and enables more reliable estimates for Australia to be used in subsequent international comparisons. It also promotes a better understanding of income mobility patterns in a wealthy capitalist nation with a comparative large market, a relatively large immigrant population, an efficient redistributive tax and transfer system, and a history of low wage inequality.

References

Australian Bureau of Statistics (2012). ABS offers facility for in depth analysis of the Australian labour market. Retrieved from ABS website: http://www.abs.gov.au/ausstats/abs@.nsf/lookup/6602.0Media%20Release12008-10.

Australian Bureau of Statistics (2006). Australian and New Zealand Standard Classification of Occupations, First Edition. Retrieved from ABS website: http://www.abs.gov.au/ausstats/abs@.nsf/0/64AECDFA29CFFD6CCA2571E2008355FE?opendocument.

Andrews, D., & Leigh, A. (2009). More inequality, less social mobility. *Applied Economics Letters, 16*(15), 1489-1492.

Argy, F. (2006). Equality of opportunity in Australia: Myth and reality. (Discussion Paper No. 85). Asia Pacific School of Economics and Government, Australian National University.

Becker, G. S., & Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy, 87*(6), 1153-1189. doi: 10.2307/1833328

Becker, G. S., & Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of Labor Economics, 4*(3), S1-S39. doi: 10.2307/2534952

Bhattacharya, D., & Mazumder, B. (2011). A nonparametric analysis of black–white differences in intergenerational income mobility in the United States. *Quantitative Economics, 2*(3), 335-379. doi: 10.3982/QE69

Björklund, A., & Jäntti, M. (1997). Intergenerational income mobility in Sweden compared to the United States. *The American Economic Review, 87*(5), 1009-1018. doi: 10.2307/2951338

Björklund, A., & Jäntti, M. (2012). Intergenerational income mobility and the role of family background. In B. Nolan, W. Salverda & T. M. Smeeding (Eds.), *The Oxford handbook of economic inequality* (pp. 1-21). Oxford: Oxford University Press.

Blanden, J. (2013). Cross-country rankings in intergenerational mobility: A comparison of approaches from economics and sociology. *Journal of Economic Surveys, 27*(1), 38-73. doi: 10.1111/j.1467-6419.2011.00690.x

Blanden, J., Haveman, R., Smeeding, T., & Wilson, K. (2014). Intergenerational mobility in the United States and Great Britain: A comparative study of parent–child pathways. *Review of Income and Wealth, 60*(3), 425-449. doi: 10.1111/roiw.12032

Blau, P. M., & Duncan, O. D. (1967). *The American occupational structure*. New York: John Wiley & Sons.

Böhlmark, A., & Lindquist, M. J. (2006). Life-cycle variations in the association between current and lifetime income: Replication and extension for Sweden. *Journal of Labor Economics, 24*(4), 879-896. doi: 10.1086/506489

Bratberg, E., Nilsen, Ø. A., & Vaage, K. (2007). Trends in intergenerational mobility across offspring's earnings distribution in Norway. *Industrial Relations: A Journal of Economy and Society, 46*(1), 112-129. doi: 10.1111/j.1468-232X.2007.00459.x

Castles, F. G. (1985). *The working class and welfare: reflections on the political development of the welfare state in Australia and New Zealand, 1890-1980.* Sydney: Allen & Unwin.

Causa, O., & Johansson, Å. (2010). Intergenerational social mobility in OECD countries. *OECD Journal: Economic Studies*, 1, 1-44.

Chadwick, L., & Solon, G. (2002). Intergenerational income mobility among daughters. *The American Economic Review, 92*(1), 335-344.

Corak, M. (2006). Do poor children become poor adults? Lessons from a cross country comparison of generational earnings mobility. (Discussion Paper No. 1993). IZA.

Corak, M. (2013a). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives, 27*(3), 79-102.

Corak, M. (2013b). Inequality from generation to generation: The United States in comparison. In R. S. Rycroft (Ed.), *The economics of inequality, poverty, and discrimination in the 21st century* (pp. 107-126). Santa Barbara, California: ABC-CLIO.

Corak, M., Curtis, L. J., & Phipps, S. (2011). Economic mobility, family background, and the well-being of children in the United States and Canada. In T. M. Smeeding, R. Erikson & M. Jäntti (Eds.), *Persistence, privilege, and parenting--the comparative study of intergenerational mobility* (pp. 73-108). New York: Russell Sage Foundation.

Couch, K. A., & Dunn, T. A. (1997). Intergenerational correlations in labor market status: A comparison of the United States and Germany. *The Journal of Human Resources, 32*(1), 210-232. doi: 10.2307/146246

D'Addio, A. C. (2007). Intergenerational transmission of disadvantage: mobility or immobility across generations? *OECD Social, Employment and Migration Working Papers*. OECD Publishing, Paris.

Dearden, L., Machin, S., & Reed, H. (1997). Intergenerational mobility in Britain. *The Economic Journal, 107*(440), 47-66. doi: 10.2307/2235270

Glass, D. V. (Ed.). (1954). *Social mobility in Britain*. London: Routledge & Kegan Paul.

Gong, H., Leigh, A., & Meng, X. I. N. (2012). Intergenerational income mobility in urban China. *Review of Income and Wealth, 58*(3), 481-503. doi: 10.1111/j.1475-4991.2012.00495.x

Grawe, N. D. (2004). Intergenerational mobility for whom? The experience of high-and low-earnings sons and daughters in intergenerational perspective. In M. Corak (Ed.), *Generational income mobility in North America and Europe* (pp. 58-89). Cambridge: Cambridge University Press.

Grawe, N. D. (2006). Lifecycle bias in estimates of intergenerational earnings persistence. *Labour Economics, 13*(5), 551-570. doi: http://dx.doi.org/10.1016/j.labeco.2005.04.002

Haider, S., & Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *American Economic Review, 96*(4), 1308-1320. doi: doi: 10.1257/aer.96.4.1308

Hammarstedt, M., & Palme, M. (2012). Human capital transmission and the earnings of second-generation immigrants in Sweden. *IZA Journal of Migration, 1*(1), 1-23. doi: 10.1186/2193-9039-1-4

Hansen, M. (2010). Change in intergenerational economic mobility in Norway: conventional versus joint classifications of economic origin. *The Journal of Economic Inequality, 8*(2), 133-151. doi: 10.1007/s10888-009-9109-4

Hayes, C., & Watson, N. (2009). HILDA imputation methods. (Technical Paper Series No. 2/09). Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Hertz, T. (2006). Understanding mobility in America. Center for American Progress.

Hertz, T. (2007). Trends in the intergenerational elasticity of family income in the United States. *Industrial Relations: A Journal of Economy and Society, 46*(1), 22-50. doi: 10.1111/j.1468-232X.2007.00456.x

Hugalde, A. S. (2004). Movilidad intergeneracional de ingresos y educativa en España (1980-90). (working paper n. 2004/1). Institut d'Economia de Barcelona, Centre de Recerca en Federalismo Fiscal i Economia Regional.

Jäntti, M., Bratsberg, B., Røed, K., Raaum, O., Naylor, R., Österbacka, E., … Eriksson, T. (2006). American exceptionalism in a new light: A comparison of intergenerational earnings mobility in the Nordic countries, the United Kingdom and the United States. (Discussion Paper No. 1938). IZA.

Jerrim, J., Choi, Á., & Rodríguez, R. S. (2013). Cross-national comparisons of intergenerational mobility: are the earnings measures used robust? (Working Paper). Department of Quantitative Social Science, Institute of Education.

Kearney, M. (2006). Intergenerational mobility for women and minorities in the United States, *The Future of Children, 16*(2), 37-53.

Lee, C. I., & Solon, G. (2009). Trends in intergenerational income mobility. *Review of Economics and Statistics, 91*(4), 766-772. doi: 10.1162/rest.91.4.766

Lefranc, A., Ojima, F., & Yoshida, T. (2008). The intergenerational transmission of income and education: A comparison of Japan and France. (Working Paper RSCAS 2008/25). European University Institute.

Lefranc, A., & Trannoy, A. (2005). Intergenerational earnings mobility in France: Is France more mobile than the US? *Annales d'Économie et de Statistique*(78), 57-77. doi: 10.2307/20079128

Leigh, A. (2007). Intergenerational mobility in Australia. *The B.E. Journal of Economic Analysis & Policy, 7*(2), Article 6.

Mazumder, B. (2001). Earnings mobility in the US: A new look at intergenerational inequality. (WP 2001-18). Federal Reserve Bank of Chicago.

Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data. *The Review of Economics and Statistics, 87*(2): 235-255.

Mazumder, B. (2014). Black–white differences in intergenerational economic mobility in the United States. *Economic Perspectives, 38*(1), 1-18.

Mocetti, S. (2007). Intergenerational earnings mobility in Italy. *The B.E. Journal of Economic Analysis & Policy, 7*(2), Article 5.

Ng, I. (2007). Intergenerational income mobility in Singapore. *The B.E. Journal of Economic Analysis & Policy, 7*(2), Article 3.

Nicoletti, C., & Ermisch, J. F. (2007). Intergenerational earnings mobility: Changes across cohorts in Britain. *The B.E. Journal of Economic Analysis & Policy, 7*(2), Article 9.

Organisation for Economic Co-operation and Development. (2011). An overview of growing income inequalities in OECD countries: Main findings. Retrieved from OECD website: http://www.oecd.org/els/soc/49499779.pdf.

Pekkala, S., & Lucas, R. E. B. (2007). Differences across cohorts in Finnish intergenerational income mobility. *Industrial Relations: A Journal of Economy and Society, 46*(1), 81-111. doi: 10.1111/j.1468-232X.2007.00458.x

Piraino, P. (2007). Comparable estimates of intergenerational income mobility in Italy. *The B.E. Journal of Economic Analysis & Policy, 7*(2), Article 1.

Steiber, N., & Haas, B. (2012). Advances in explaining women's employment patterns. *Socio-Economic Review, 10*(2), 343-367. doi: 10.1093/ser/mwr039

Solon, G. (1992). Intergenerational income mobility in the United States. *The American Economic Review, 82*(3), 393-408. doi: 10.2307/2117312

Solon, G. (2002). Cross-country differences in intergenerational earnings mobility. *The Journal of Economic Perspectives, 16*(3), 59-66. doi: 10.2307/3216950

Sorokin, P. (1927). *Social mobility*. New York: Harper & Brothers.

Summerfield, M., Freidin, S., Hahn, M., Li, N., Macalalad, N., Mundy, L., … Wooden, M. (2014). HILDA user manual—release 13. Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Thompson, E. (1994). *Fair enough: egalitarianism in Australia.* Kensington, N.S.W.: University of New South Wales Press, 1994.

Torche, F. (2015). Analyses of intergenerational mobility: An interdisciplinary review. *The ANNALS of the American Academy of Political and Social Science, 657*(1), 37-62. doi: 10.1177/0002716214547476

Ueda, A. (2009). Intergenerational mobility of earnings and income in Japan. *The B.E. Journal of Economic Analysis & Policy, 9*(1), Article 54.

Ueda, A. (2013). Intergenerational mobility of earnings in South Korea. *Journal of Asian Economics, 27*, 33-41. doi: http://dx.doi.org/10.1016/j.asieco.2013.05.002

Watson, N., & Wooden, M. (2002). The Household, Income and Labour Dynamics in Australia (HILDA) Survey: Wave 1 survey methodology. (Technical Paper Series No. 1/02). Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Wooden & Watson (2000). The Household, Income and Labour Dynamics in Australia (HILDA) Survey: An introduction to the proposed survey design and plan. (Discussion Paper Series No. 1/00). Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Zimmerman, D. J. (1992). Regression toward mediocrity in economic stature. *The American Economic Review, 82*(3), 409-429. doi: 10.2307/2117313

Appendices

Table A1 Intergenerational income mobility index across OECD countries

Countries	Dyad	Index[a]	Method[b]
Australia	Father-son	[0.2, 0.3]	2SLS
Canada	Father-son	[0.13, 0.26]	OLS, IV
	Father-daughter	0.22	IV
Denmark	Father-son	[0.071, 0.082]	OLS
	Father-daughter	0.034	OLS
Finland	Father-son	[0.086, 0.18]	OLS
	Father-daughter	0.08	OLS
France	Father-son	[0.36, 0.50]	IV, TS2SLS
	Father-daughter	[0.23, 032]	IV
Germany	Father-son	[0.095, 0.34]	OLS
Italy	Father-son	[0.44, 0.50]	TS2SLS
Japan	Father-son	[0.25, 0.46]	TS2SLS, IV
	Father-daughter	[0.3, 0.38]	IV
Korea	Father-son	[0.22, 0.36]	IV, SIMEX
	Father-daughter	[0.34, 0.46]	IV, SIMEX
Norway	Father-son	[0.12, 0.29]	OLS, quantile regression
	Father-daughter	[0.11, 0.22]	OLS, quantile regression
Spain	Father-son	[0.33, 0.60]	OLS, IV
Sweden	Father-son	[0.13, 0.30]	OLS, IV
	Father-daughter	0.19	OLS
United Kingdom	Father-son	[0.22, 0.59]	OLS, IV, TS2SLS
	Father-daughter	[0.33, 0.70]	OLS, IV
	Mother-son	[0.06, 0.23]	OLS, IV
	Mother-daughter	0.24	OLS, IV
United States	Father-son	[0.09, 0.61]	OLS, IV, tobit, TS2SLS
	Father-daughter	[0.28, 0.61]	OLS, IV, tobit, TS2SLS
	Mother-son	0.29	IV
	Mother-daughter	0.27	IV

Notes: We summarise up-to-date measures of parent-children income linkages, and present broad income mobility coefficients which include, but are not confined to, earnings elasticities. This is given as a range within which the estimates from studies in each country fall.

[a] The range [a, b] denotes the lowest and highest values for the income mobility index in the existing literature.

[b] OLS: ordinary least squares; IV: instrumental variable; 2SLS: two-stage least squares; TS2SLS: two-sample two-stage least squares; SIMEX: simulation extrapolation.

Source: Based on Corak (2006) and Gong, Leigh and Meng (2012), updated with new evidence from Bratberg, Nilsen and Vaage (2007), Dearden, Machin and Reed (1997), Hugalde (2004), Jäntti et al. (2006), Mazumder (2005), Nicoletti and Ermisch (2007), Piraino (2007), Ueda (2009) and Ueda (2013).

Table A2 Age distributions of sons in the HILDA Survey and male respondents in the LLFS

Summary statistics	HILDA	LLFS
Quantiles		
1%	25	25
5%	26	26
10%	28	28
25%	34	34
50%	42	42
75%	51	51
90%	57	57
95%	60	60
99%	63	63
Minimum	25	25
Maximum	64	64
Mean	42.43	42.42
Standard deviation	10.46	10.67
Variance	109.43	113.81
Skewness	0.14	0.15
Kurtosis	2.01	1.96
Observations	41043	26349

Source: Authors' calculations from the HILDA Survey (2001-2013) and the LLFS (2008-2010).