A land of the “fair go”? Intergenerational earnings elasticity in Australia

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Abstract

This paper contributes to the existing income mobility literature by adopting a two-stage panel regression model, investigating elasticity trends over time, and assessing the effects of using different levels of occupational disaggregation 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 than three- and four-digit levels. Earnings volatility has substantial effects on elasticities. We read these findings as indicating that elasticity estimates are sensitive to the use of different methods and data.

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

JEL classification codes: J62, C23

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1 Introduction

Strengthening and maintaining the land of the “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 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 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. 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 labor market institutions built around centralized 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 laid a path-dependent foundation for earnings inequality and mobility that makes Australia a noteworthy case. Second, Australia has a relatively egalitarian culture (Thompson, 1994), characterized by public attitudes leaning towards egalitarianism, a relatively flat social structure that is not marked by pronounced symbolic or behavioral class distinctions, and strong anti-discrimination legislation. Third, existing cross-national evidence shows that 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.

Using panel data from the Household, Income and Labor Dynamics in Australia (HILDA) Survey, 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) introducing and applying a two-stage panel regression model to estimating elasticities, (ii) establishing elasticity trends over time, (iii) examining how occupational disaggregation and different earnings measures affect elasticity estimates, and (iv) using more recent data than previous Australian studies.

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 than three- and four-digit levels. Using different earnings measures results in substantially different elasticity estimates. We read these findings as indicating that elasticity estimates are sensitive to the use of methods and data. This point has two important implications: (i) analyses of earnings elasticity should explore the extent to which results are robust to analytic choices, and (ii) comparative analyses should recognize that differences in approach across comparison units may contribute to observed 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 labor 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). We present a summary of up-to-date measures of income mobility in OECD countries since the late 1980s 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 increase in offspring's earnings associated with a one-percent increase in parental earnings. Estimation takes place via ordinary least squares (OLS) regression or instrumental variable (IV) regression methods. Early contributors 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; Corak & Heisz, 1999; 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 (Dustmann, 2008; Hammarstedt & Palme, 2012; Leigh, 2007; Vogel, 2006) 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 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, a two-stage panel regression model is proposed and applied to estimating elasticities. 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

Our analyses are performed on the Household, Income and Labor 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 labor force participation of respondents is collected, with a multiplicity of income measures readily available to the researcher. These include weekly as well as annual wages and salary from different sources. Here, we will use three income types: hourly earnings from the main job; weekly earnings from the main job; 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

[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 Labor Dynamics in Australia Survey* (2001-2004).

across waves (Summerfield et al., 2014), to minimize biases associated with changes in these self-reported earnings, we use the derived gross weekly and annual earnings variables. We adjust these earnings using annual Consumer Price Index rates, 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. Fathers' actual ages should be included in computing their earnings, because (i) it increases the precision in the computation of their earnings, and (ii) it allows for more variation in the imputed earnings between fathers, which is closer to the variation in earnings distribution of the father's population. In contrast, substituting a uniform age (e.g., 40) for fathers across the sample may over-compute fathers' earnings whose actual ages were below 40 when respondents were 14, and under-compute fathers' earnings for fathers whose actual ages were above 40 when respondents were 14. Fathers' ages, therefore, are important to be taken into account in the computation and be controlled in estimating earnings elasticities.

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 unconfidentialized 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, as it allows for precise matching in occupational codes before the computation and avoids over- or under-predicting fathers' earnings using a higher or lower occupational level.

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.

3.2 Methodological approaches

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

$$\ln Y_i^c = \alpha + \beta \ln Y_i^p + \varepsilon_i \qquad (1)$$

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, using young fathers' or young sons' earnings results in downward-biased elasticity estimates (D'Addio, 2007; Grawe, 2006; Piraino, 2007).

The longitudinal data analysis in this study mitigates the first type of measurement error. We propose a two-stage panel regression model with the computation of fathers' earnings at stage one and the estimation of elasticities at stage two. Since fathers' earnings when their sons were 14 are a time-constant construct, we employ a between-effects model that uses the over-time averages in sons' earnings, ages and occupations before computing fathers' earnings. This helps to smooth the transitory fluctuations in sons' earnings over multiple years (the mean duration for our analytical sample to stay in the panel is over seven years). The model is outlined below.

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

Where $\boldsymbol{\theta}' = (\theta_1, \dots, \theta_N)$, and $\boldsymbol{X}_{\boldsymbol{i}}^{s\prime} = (x_i^{(1)}, \dots, x_i^{(N)})$. Y_i^s denotes the earnings of son i, $\boldsymbol{X}_{\boldsymbol{i}}$ is a set of occupation dummies, each of which is denoted as $x_i^{(j)}, j = 1, \dots, N$; $\bar{A}_i^s$ represents the average of the i^{th} son's ages, and N is the total number of occupation categories, which depends on the level of aggregation used. The coefficients obtained from model (2) are then used to compute fathers' earnings (denoted as Y_i^f) by substituting sons' retrospective reporting of fathers' occupations and ages in the following equation:

$$Y_i^f = e^{\alpha + \boldsymbol{\theta}'\boldsymbol{X}_i^f + \delta_1 A_i^f + \delta_2 {A_i^f}^2} \tag{3}$$

The theoretical model of earnings elasticity in (1) can be improved by adding both sons' and fathers' ages as control variables (Piraino, 2007). We follow this updated method, centering ages of both generations at 40, and fitting a random-effects model:

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

The random-effects model takes account of the longitudinal dependence (repeated measures for individuals) in the data, whereas the cross-sectional regression model does not. The random-effects estimator is a weighted average of within and between estimators with weights being a function of the variances of subject-specific (i.e. time constant) and individual by time-varying errors (i.e. 'usual' errors).

We subsequently examine trends in elasticity by interacting fathers' logarithmic earnings with different powers of the time variable t (i.e., wave), and adding the interaction term in model (4). These are generalized to the function below:

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

Where $f^{(n)}(t)$ and $g^{(n)}(t)$ are functions of time t with power $n, n = 1, 2, 3$. To be specific, denote $\boldsymbol{\varphi}'^{(n)} = (\varphi_0, \dots, \varphi_n)$ as the coefficient vector for the interaction terms with power n, and $\boldsymbol{\omega}'^{(n)} = (\omega_1, \dots, \omega_n)$ 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 ${\boldsymbol{T}_{\boldsymbol{f}}'}^{(n)} = (1, t, \dots, t^n)$ and ${\boldsymbol{T}_{\boldsymbol{g}}'}^{(n)} = (t, \dots, t^n)$. In this way, we depict the linear, quadratic and cubic trends of earnings elasticity. These trends capture changes in elasticity for our analytical sample over the observed years. Model diagnostics then help decide which trend fits the data best.

In relation to the life-cycle bias discussed previously, the age distributions of fathers and sons in our data ameliorate this 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 centered 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 Analytical sample and variables

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 minimize 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 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 labor force for education or retirement reasons. We similarly exclude fathers outside the same age range when their sons were 14.[2] For comparison purposes, we restrict both fathers' and sons' ages to prime working ages at stage two. Table 1 reports descriptive statistics for the main analytical variables in the HILDA Survey.

Table 1 Descriptive statistics for main analytical variables in the model

Variable	Sons			Fathers					
				1-digit			2-digit		
	Mean	s.d.	N	Mean	s.d.	N	Mean	s.d.	N
Log hourly earnings in the main job	3.41	0.52	30175	3.36	0.20	30175	3.29	0.31	30175
Log weekly earnings in the main job	7.14	0.62	30211	7.10	0.28	30211	7.04	0.35	30211
Log annual earnings	11.08	0.72	32675	11.00	0.30	32675	10.94	0.39	32675
Age	42.44	10.32	30175	44.63	6.14	30175	44.63	6.14	30175
Wave	7.56	3.79	30175						

Notes: Sons' earnings adjusted for inflation using the Consumer Price Index. Father's predicted earnings differ based on the levels of occupational disaggregation that we use in stage one of the model. The age and wave statistics reported are from the analyses using main-job hourly earnings.
Source: Authors' calculations from the HILDA Survey (2001-2013).

4 Results

4.1 Intergenerational earnings elasticity by levels of occupational disaggregation

We begin by fitting our stage-one model, as in equations (2)-(4) in section 3. Table 2 displays the elasticity results by levels of occupational disaggregation and by different age restrictions in model (4). The father-son earnings elasticity in Australia between 2001 and 2013 ranges from 0.11 to 0.30. Comparing elasticities across occupational digits, the point estimates are larger at two digits than three and four digits. Lower elasticities associated with more detailed occupation categories would be expected if earnings vary by occupational categories and fathers' and sons' occupational

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

categories are more likely to differ when occupations are disaggregated. Elasticities within occupational digits exhibit a same pattern: the point estimates are higher when age is restricted to prime working age (30-55) than when using a broader age restriction (25-64), although differences in these point estimates are relatively small.

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

Results	Occupational disaggregation							
	One digit		Two digits		Three digits		Four digits	
	Age 25-64	Age 30-55	Age 25-64	Age 30-55	Age 25-64	Age 30-55	Age 25-64	Age 30-55
Elasticities	0.232	0.301	0.259	0.282	0.235	0.255	0.112	0.129
	(0.034)	(0.040)	(0.022)	(0.026)	(0.019)	(0.023)	(0.013)	(0.015)
R^2 (overall)	*0.044*	*0.038*	*0.060*	*0.051*	*0.061*	*0.053*	*0.050*	*0.044*
rho	*0.694*	*0.709*	*0.690*	*0.705*	*0.689*	*0.705*	*0.693*	*0.708*
N (observations)	*30175*	*21101*	*30175*	*21101*	*30175*	*21101*	*30175*	*21101*
N (individuals)	*4960*	*3603*	*4960*	*3603*	*4960*	*3603*	*4960*	*3603*

Notes: Standard errors in parentheses. 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 the estimation model are overall mean elasticities across 13 years. In this section we extend the estimation model by incorporating the interaction terms of fathers' logarithmic earnings with survey wave, namely models (5)-(7), to delineate trends in earnings elasticity over time. For simplicity, we present the trends using a larger sample with the age restriction of 25-64.[3] We first include the product of fathers' earnings and wave, assuming the trend is linear. The linear assumption is the simplest way to capture overall changes in elasticity. The changes can be derived from the marginal effects of fathers' earnings, namely, $f^{(n)}(t)$ in model (6). Test results show that the linear trends are significant. There is an 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 is less mobility in the long run. This decline in income mobility is consistent with previous findings for the US (Aaronson & Mazumder, 2008), the UK (Nicoletti & Ermisch, 2007), Norway (Hansen, 2010) and Finland (Pekkala & Lucas, 2007).

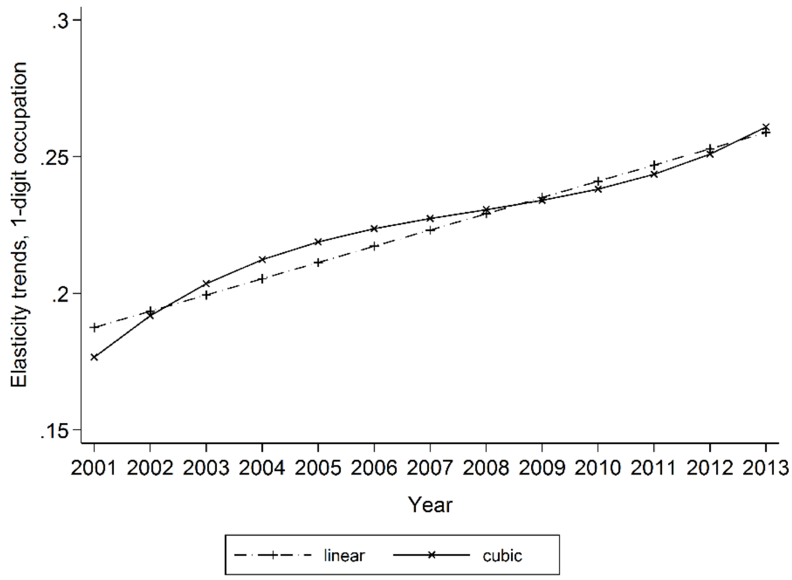
A linear trend assumes that earnings elasticity changes by a constant amount over time. This may not be empirically accurate. To address this issue, we fit models including higher-order polynomials of survey wave. We test the significance of the added polynomials in ascending order, with results revealing that the cubic model better depicts how earnings elasticity is changing over time.[4] We plot results from the cubic model together with the linear trends in Figures 1 and 2.

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 suggests a maximum in 2011 and a decline thereafter. Since this curve corresponds to our preferred level of occupational disaggregation, it constitutes our preferred estimate and is therefore used in our subsequent analyses.

[3] The elasticity trends for the subsample with prime working ages are similar.

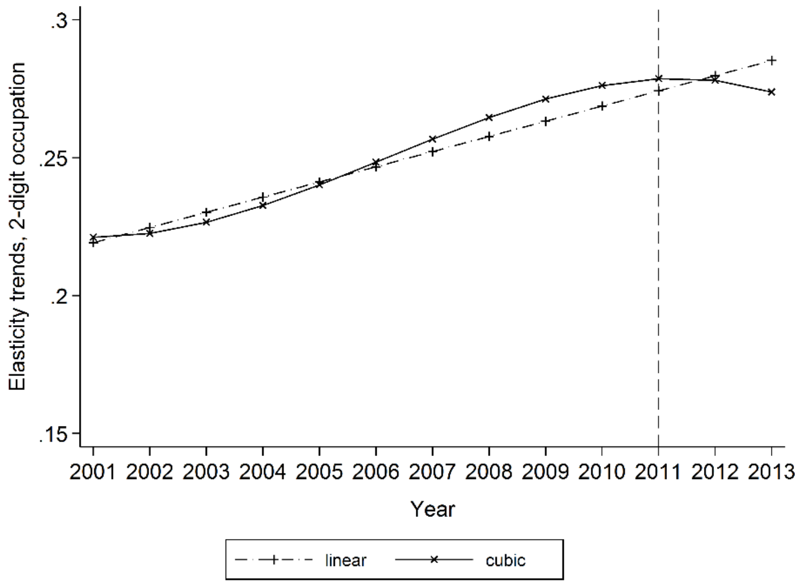
[4] We also considered using quartic trends, but the fourth-order survey wave polynomials were not statistically significant.

Figure 1 Trends in father-son earnings elasticity in Australia using 1-digit occupations



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).

Figure 2 Trends in father-son earnings elasticity in Australia using 2-digit occupations

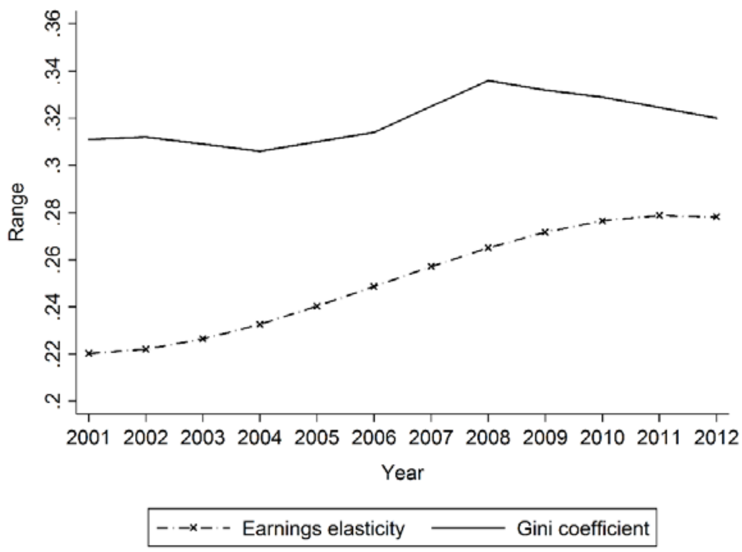


Notes: Elasticities estimated using hourly earnings in the main job. All elasticities are statistically significant at the 0.1% level.
Source: Authors' calculations from the HILDA Survey (2001-2013).

While we have established that there is an upward trend in earnings elasticity in Australia, the reasons behind this trend remain unexplored. Although a detailed examination is beyond the scope of this paper, one potential explanation is a contemporaneous increase in earnings inequality. This is because, as discussed before, earnings inequality and mobility have been found to be highly associated (Corak, 2013a). Such relationship has been established comparing countries. We argue that it should hold within a country over time. As a tentative test, we further examined the association between inequality and mobility in Australia using our preferred elasticity estimates (i.e. estimates from the cubic model using 2-digit occupations) and Gini coefficients.[5] Figure 3 shows trends in earnings elasticity and Gini coefficients. The elasticities range from 0.22 to 0.28 between 2001 and 2012, whereas the Gini coefficients range from 0.3 to 0.34 over the same period. Both trends display a smooth "S" shape: the Gini coefficient reaches its local maximum in 2008, and declines afterwards; similarly, the elasticity moves downwardly after 2011.

We also assessed the strength of this association while accounting for the artifactual correlation resulting from mutual dependence on time by detrending the data. We apply both parametric and non-parametric methods to detrend the data. For the parametric method, we model the two time series separately using linear regressions, and peruse their respective residuals. Test statistics confirm normality and homoscedasticity in these residuals. The correlation coefficient between the two residual variables is 0.87 and is statistically significant at the 1% level. For the non-parametric method, we take the first difference of each of the time series. Tests of autocorrelation show that these first differences are not autocorrelated. The correlation coefficient between the first differences of the earnings elasticity and those of the Gini coefficient is 0.71 and is statistically significant at the 5% level. These findings provide evidence from Australia that earnings inequality is positively associated with earnings immobility, and that future research on country-specific elasticity trends needs also to take into account the dynamics of earnings inequality.

Figure 3 Trends in father-son earnings elasticity and Gini coefficient in Australia over time



Notes: Elasticities estimated using two-digit occupations and 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); ABS (2013); Whiteford (2013).

4.3 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

[5] The Gini coefficients for 2001, 2003-2004, 2006, 2008, 2010 and 2012 come from ABS (2013), while those for 2002, 2005, 2007 and 2009 come from Whiteford (2013). These Gini coefficients were calculated using equivalised disposable household income from ABS Surveys of Income and Housing.

hours, these earnings are thus more volatile and their use would yield lower elasticities. Occupations have also been found to better proxy individual hourly earnings than for annual earnings, because within-occupation inequality accounts for more variation in annual work hours than in hourly earnings, which makes occupations less precise in proxying annual earnings than hourly earnings (Leigh, 2007). 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 3 supports our prior argument: using weekly and annual earnings rather than hourly earnings noticeably reduces the estimated elasticities.[6] Specifically, in results for both one- and two-digit occupations with age restriction of 25-64, using main-job weekly earnings reduces elasticities by about 33%. Using annual earnings lowers the elasticities by 34% and 21% at the one- and two-digit level occupational disaggregation, respectively. Elasticities display a similarly large decrease from using hourly earnings to using weekly and annual earnings among fathers and sons with prime working ages. These results suggest that earnings volatility has substantial effects on elasticities. Since occupation is a better proxy for hourly wage than for annual earnings (Leigh, 2007), elasticities estimated using hourly earnings are preferable to elasticities estimated using other earnings measures.

Table 3 Father-son earnings elasticity using different earnings measures

Occupational disaggregation	Earnings measures					
	Hourly earnings from the main job		Weekly earnings from the main job		Annual earnings	
	Age 25-64	Age 30-55	Age 25-64	Age 30-55	Age 25-64	Age 30-55
One digit						
Elasticities	0.232	0.301	0.155	0.200	0.154	0.179
	(0.034)	(0.040)	(0.030)	(0.035)	(0.033)	(0.038)
R^2 (overall)	*0.044*	*0.038*	*0.044*	*0.028*	*0.034*	*0.021*
rho	*0.694*	*0.709*	*0.754*	*0.775*	*0.678*	*0.677*
N (observations)	*30175*	*21101*	*30211*	*21125*	*32675*	*22857*
N (individuals)	*4960*	*3603*	*4962*	*3604*	*5017*	*3674*
Two digits						
Elasticities	0.259	0.282	0.175	0.234	0.205	0.235
	(0.022)	(0.026)	(0.025)	(0.029)	(0.025)	(0.029)
R^2 (overall)	*0.060*	*0.051*	*0.052*	*0.037*	*0.043*	*0.030*
rho	*0.690*	*0.705*	*0.754*	*0.773*	*0.676*	*0.674*
N (observations)	*30175*	*21101*	*30211*	*21125*	*32675*	*22857*
N (individuals)	*4960*	*3603*	*4962*	*3604*	*5017*	*3674*

Notes: Standard errors in parentheses. 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 objectives in this paper were to (i) introduce and apply a two-stage panel regression model to estimating earnings elasticity, and (ii) provide up-to-date elasticity estimates in Australia. In doing so, we gave methodological considerations on how elasticities are affected by levels of occupational disaggregation, examined the elasticity trends over time, and assessed the effect of different earnings measures on the magnitude of elasticities.

We find that intergenerational earnings persistence in contemporary Australia lies between 11% and 30%. 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

[6] 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 similar to those presented here and are available upon request.

2011 signals the emergence of a new trend. This upward trend in elasticity in Australia is accompanied by a moderate level of inequality. A statistically significant correlation between earnings elasticity and Gini coefficients supports the empirical argument that economic mobility is inversely associated with economic inequality. This suggests that changing patterns of earnings elasticity in a given country need to be evaluated against the dynamics of inequality.

Elasticity estimates are larger using two-digit level occupations than those using three- and four-digit levels, and using different earnings measures results in substantially different elasticity estimates. These results indicate 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 be exercised with caution because of differences in data and methods across studies (D'Addio, 2007; Jerrim, Choi & Rodríguez, 2013; Solon, 2002).

The limitations of this study are three-fold. First, fathers' earnings are imputed, 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 availability (Andrews & Leigh, 2009; Björklund & Jäntti 1997; Leigh, 2007; Piraino, 2007), retrospective reports of parental characteristics are prone to measurement error and recall bias (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 is based on a deterministic instead of a stochastic model which results in the same imputed earnings for all individuals in the same age-occupation categories. In this respect, our imputed fathers' earnings may not perfectly represent their earnings when the respondents were 14 years of age.

It has been documented that imputing parental earnings using information from sons may lead to downward bias on elasticity estimates (Leigh, 2007). The obvious solution to this bias is to observe father's earnings. While father's lifetime earnings cannot be captured in survey data (as discussed above), averaging father's and son's earnings over multiple years helps to reduce this bias (Mazumder, 2005), if earnings of both generations are contained in long panel surveys. This could not be achieved using Australian panels, since the HILDA Survey has so far run just over a decade. Second, administrative data provide rich information on earnings, but in the Australian context these data remain difficult to access (Productivity Commission, 2013). A third way to observe "father's" earnings is to use a separate dataset containing an older sample of pseudo fathers, with a similar age distribution to that in the main dataset. The regression coefficients on these pseudo fathers can then be perused to impute father's earnings based on son's retrospective reports of parental characteristics in the main dataset (Bjorklund & Jantti, 1997; Piraino, 2007; Solon, 2002). However, suitable datasets for Australia are scarce. Given that none of these courses of action is currently possible in Australia, the elasticity estimates we report constitute a conservative lower bound of the true levels of earnings elasticity in contemporary Australia. Future research should consider the aforementioned possibilities to improve current estimates of earnings elasticity in Australia.[7]

[7] An alternative strategy to adjust for the downward bias involves calculating an "adjustment ratio". This is a ratio of the magnitude of elasticities estimated using observed father data (benchmark estimates) to the magnitude of elasticities estimated using imputed father data. This course of action requires long-running panel data and has sometimes been done using the US Panel Study of Income Dynamics. An example can be found in Leigh (2007), which obtained a ratio of 1.23 with a benchmark US estimate of 0.4. This suggested that the downward bias using imputed father's data is around 19% (0.23/1.23). Applying this ratio to our estimates would move them to be in the range of 0.14 (1.23×0.11) to 0.37 (1.23×0.30). However, these results are to be interpreted with care for three reasons. First, there is a lack of theoretical and mathematical justification for the ratio adjustment, and no simulation studies have tested its appropriateness. Second, the benchmark elasticity estimate in the US depends heavily on the data and methodology used to calculate the elasticity. This is a non-trivial matter, as there are strong divergences across US studies: for example, Solon's (1992) estimate was 0.4, whereas Mazumder's (2005) estimate was 0.6. Therefore, the choice of the benchmark US estimate is arbitrary. Third, using a ratio calculated from US or any other data to adjust the Australian estimates relies on the assumption that the bias in the Australian estimate is identical to the bias in the benchmark estimate, regardless of the characteristics of the data sources used. Such assumption, however, is not rigorously tested.

A second limitation of this study is that our analyses are performed on unweighted data and this may have implications on the observed time trends in the presence of panel attrition. Correcting for this would nevertheless cause significant selection bias, chiefly because the longitudinal weights adjusting for attrition in the HILDA Survey can only be used with a strongly balanced panel. Restricting our analytical sample to respondents who participated in all 13 waves in the survey reduces the sample size from 30,175 to 18,174 person-year observations and excludes 57% of sample members. Hence, using the longitudinal weights in estimation arguably introduces more selectivity than it corrects for. Respondents who attrited from the HILDA Survey are more likely to be immigrants, from an ethnic minority, unemployed, or working in low-skilled occupations (Summerfield et al., 2014), so these groups are underrepresented in our unweighted sample - and progressively more as time unfolds. Studies have found much less upward mobility among ethnic minorities (Bhattacharya & Mazumder, 2011; Hertz, 2006), and elasticities are larger for immigrants than for natives (Dustmann, 2005; Hammarstedt & Palme, 2012; Vogel, 2006). Correcting for the attrition of these groups would hence likely increase the observed earnings elasticities, and the elasticity trends would have been steeper had our panel data had zero attrition.

A third and final limitation of this study is that 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.

This study has provided estimates of intergenerational earnings elasticity in Australia using different techniques. In doing so, it helps show the range of elasticities consistent with different approaches, and enables more reliable estimates for Australia to be used in future research. 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.

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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 summarize 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).