Individual Earnings Mobility and the Persistence of Earnings Inequalities in Australia

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September 2014

Abstract

This paper assesses earnings mobility among workers in Australia between 2001/2 and 2008/9 using HILDA household panel data. We examine the pattern of individuals' earnings growth and explore the importance of mobility as an equaliser of longer-term earnings. We find that progressive earnings growth decreased overall inequality even after considering the re-ranking that occurred in the distribution. This was partly driven by age-earnings growth and partly by step changes associated with job-to-job moves, promotions and taking on more responsibility. Shocks also acted against this equalising process, most notably job loss, which had substantial negative effects on earnings and disproportionately fell on lower waged workers.

Keywords : Earnings, mobility, inequality, measurement error
JEL Classification: D31, J01, J60

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Acknowledgements: We would to thank Stephen Jenkins, Phillipe Van Kerm and two anonymous referees for useful comments on earlier versions of this paper and comments received at the ESPE conference and seminars at the Melbourne Institute, Department of Economics and Law, University of Rome "La Sapienza" and CMPO Bristol.

1. Introduction

Rising earnings inequality in Australia over the last twenty five years, although flattening somewhat in the last decade, continues to be of concern (Grenville, et al. 2013; OECD, 2011). When assessing inequality patterns it is important to not only assess the extent of inequality at a point-in-time but also the degree of mobility in a society, as the lowest paid or poorest individuals in one year are not necessarily the lowest paid in the next as individuals move both up and down the earnings distribution over time. Thus researchers have assessed the importance of mobility as an equaliser of longer-term incomes (Fields, 2010; Shorrocks, 1978). Social evaluations of mobility, therefore, depend on how changes in income or earnings are distributed relative to people's original positions in the overall distribution (Van Kern 2006). In addition, various subgroups of the population may find it more or less difficult to progress up the earnings distribution, either because of their initial characteristics or because they face adverse shocks. For policy purposes it is critical to understand the factors that underlie any observed mobility to get a sense of how it may be influenced.

In this paper we utilise the Household, Income and Labour Dynamics in Australia (HILDA) survey to examine earnings mobility among workers in Australia between 2001/2 and 2008/9. Specifically, by examining the pattern of individuals' earnings growth and isolating where in the initial earnings distribution earnings growth occurred, we explore the importance of mobility as an equaliser of longer-term earnings. We do this within a framework that also allows us to explore the major drivers behind observed earnings movements. This includes life-cycle movements in earnings, which tend to equalise earnings as younger workers start among the lowest paid but receive rapid earnings growth. The evolution of individuals' earnings is also heavily influenced by job changes: promotions, moving positions to secure higher pay and job loss all effect patterns of earnings growth in various ways. For instance, job losses hit lower-paid workers more frequently than higher paid workers and result in earnings losses. In addition earnings whilst in the same job can vary for reasons such as bonuses, overtime worked and unpaid absences from work which reduce monthly earnings.

Our study adds to the very limited evidence base on income mobility in Australia, which is much less established than in the international literature, and is the first, to our knowledge, that examines how individuals' earnings evolved between 2001/2 and 2008/9, the second decade of Australia's long economic boom. We also fill a considerable gap in the international literature on mobility. Although, following Shorrocks (1978) seminal paper on income mobility, there have been a large number of studies and measures developed of different concepts of mobility (see Fields 2010, Solon, 1992, Schluter & Trede, 2003 and Jenkins & Van Kerm 2006, among others), the measures developed largely provide an assessment of aggregate mobility. They do not however provide the analyst with information about the local underlying process that generates this mobility. Therefore analysts are left with little understanding of who it is in the population that has actually experienced mobility and why. This is important as even if there is substantial mobility in aggregate, various subgroups of the population may find it more difficult to progress up the earnings distribution either because of their initial characteristics or because they face adverse shocks. We address this gap by providing a much more nuanced assessment of the process underlying earnings mobility.

The starting point of our analysis is to assess the degree to which changes in earnings are progressive (that is earnings growth is faster for the lowest paid). We do this by calculating the standard Gini measure of inequality using individuals' initial (2001/2) rank position but their earnings in the later period (2008/9) as proposed by Jenkins & Van Kerm (2006). This can alternatively be thought of as the persistence of the original pattern of inequality over time. This measure of the inequality reducing effect of the earnings mobility observed in the data is then linked to Van Kerm's (2009a) mobility profiles, which provides a "distributional sense" of the inequality reduction from earnings mobility (Van Kerm, 2006). This provides a graphical picture of where in the original distribution the inequality reduction emanates from (i.e. the contributions of rapid rises in the earnings of the low paid or falls among high earners). The crucial advance in this approach compared to other mobility measures is that the summary measure is assessed as the sum of individual movements integrated with respect to each person's rank in the original period. Here we offer the first direct application of this link.

Second, we investigate the economic drivers of mobility. Here we explore the extent to which earnings growth patterns are explained by the life-cycle evolution of earnings, key life events, job related changes and changes in working time by approximating the mobility profile with a linear regression model. We are then able to examine "directional mobility" by isolating the factors which equalise longer-term earnings (by inducing reversion to the mean) from those which exacerbate it. Importantly, our approach shows the impact of any economic shock as a function of the associated wage change and where those people experiencing the shock were in the original distribution.

Finally, we use a number of approaches to address measurement error in our estimates, which can lead to significant upward biases in estimated measures of mobility. We find, after accounting for measurement error, that two-thirds to three-quarters of earnings inequality in the original distribution is still apparent after eight years. Around forty percent of the reduction in inequality reflects life-cycle movements in earnings as individual's age in the workforce or other major life-cycle events, like motherhood. Job changes, promotions and job loss account for another quarter over and above how job changes drive the life-cycle events. Changes in hours of work and weeks worked in a year only explain a little over and above movements associated with other job changes. On the other hand, many major factors behind movements in earnings do not materially affect our assessment of inequality or act to increase inequalities. Examples of the latter include , job loss, which is more common for lower-paid workers, and rising returns to education among young well-educated men, as they are earning above average earnings when quite young.

The remainder of the paper is structured as follows. The next section provides an overview of the existing literature on mobility, emphasising limitations of existing approaches that we seek to resolve. Section 3 then describes the approach taken, first integrating the theoretical framework of the Gini decomposition (Jenkins and Van Kerm, 2006) with mobility profiles (Van Kerm, 2009a), and finally showing how these mobility profiles can be approximated within a linear regression framework thus allowing us to investigate the determinants of mobility and measurement error. Section 4 describes data and variables used. The final two sections discuss the results and draw general conclusions.

2. Background

As discussed in Fields (2007) there are a wide range of mobility measures available each capturing a slightly different concept of mobility. One major group looks at overall measures of inequality reduction as a result of mobility (see Shorrocks, 1978; Fields 2010; Solon, 1992; and Jenkins & Van Kerm 2006, among others). Jenkins & Van Kerm (2006) offers an approach that is of particular interest, showing that when assessing the change in inequality between two periods with the widely used Gini measure that there are two offsetting forces contributing to the change. The first, which they call pro-poor growth, is the progressivity of income growth, or the degree to which incomes grow fastest for those who were initially the poorest. This is offset by the degree of re-ranking that occurs in the distribution as incomes have evolved. Thus even when aggregate inequality is equivalent at two points in time, the poorest or lowest paid are not always the same people. Some of the originally poor (low paid) have progressed up the distributional hierarchy to some degree and been replaced by others who have fallen in the distribution. A similar story in reverse is likely to occur for the richest. In an empirical application of this method Jenkins & Van Kerm (2008) explore the differences in pro-poor income growth in the UK between two sub-periods: the period 1992-1996 under a Conservative government, and the period 1999-2003, under Labour. The analysis of the mobility profiles reveals that growth was pro-poor in both periods, but to a larger extent during the Labour government.[1]

While providing a global assessment of the importance of mobility as an equaliser of longer-term incomes (Fields, 2010; Shorrocks, 1978), the global indices cited above don't provide the analyst with any information about where mobility occurs in the distribution. This is important as 'most social evaluations of mobility depend on how income changes are distributed relative to people's positions in the base period income distribution' (Van Kerm 2006, p. 4). To address this, a recent research literature has emerged that has been focused on providing a "distributional picture" of mobility. The local approximation method (Schluter & Trede, 2003) allows measures of mobility to be expressed as a weighted local distributional change. This approach gives the reader the possibility to get a distributional sense of mobility and to identify which parts of the overall distribution contribute most to the global mobility measure. Gregg & Vittori (2008) offer an application for a set of European countries. One of the main limitations of this approach is that, since it is based on kernel estimates, it does not allow analysts to capture mobility at the individual level.

To address this limitation Van Kerm (2009a) shows how a broad range of mobility measures can be expressed as population averages of statistics derived from individual level mobility profiles and hence can be applied in the "different and largely simplified context of "distance-based" measures" (Van Kerm, 2003, p.2). To date, mobility profiles have been a graphical tool to show differences in income growth across countries (Van Kerm 2009a), periods, and population sub-groups (Jenkins & Van Kerm, 2008)[2]. In addition, they can also be adopted to explore progressive growth hence providing a clear link with the Jenkins & Van Kerm (2006) decomposition (Van Kerm, 2006). Our paper offers

[1]In the first period, progressivity is below re-ranking hence inequality increases. In the second period, the small decline in inequality is due to progressivity prevailing on re-ranking (associated also with a decline in re-ranking). Income inequality increases from 0.290 to 0.294 during the Conservative period, while it declines from 0.288 to 0.270 during the Labour period.

[2]Both Jenkins & Van Kerm (2008) and Van Kerm (2009) define individual mobility as changes in logs income from one year to another (average growth rate). This is explained more technically in the next section.

the first direct application of this link.[3]

There is also a parallel literature on individual earnings dynamics and the modelling of the covariance structure of earnings.[4] Pioneering contributions were provided by Lillard and Willis (1978), MaCurdy (1982) and Abowd and Card (1989). This literature focuses on how the covariance structure should be modelled and how the structure varies over the life cycle and with other individual characteristics. The evolution of earnings over time is specified as a combination of a permanent and transitory component. Hence a persons' earnings profile over time can be thought of as a combination of continuous incremental changes in returns to pre-existing characteristics over the life course, such as education, and the incidence of and returns to newly arrived characteristics. These new characteristics may well be a discrete event such as a shift in hours resulting from becoming part-time after child birth, or job loss or a promotion.

Numerous labour market studies have modelled hourly wages as a function of years of schooling completed and a quadratic function of years since leaving school, following the human capital theory developed by Mincer (1974).[5] This function describes the relationship between age and earnings of an individual and is commonly used to describe the growth of earnings over the life-cycle (see for instance Manning, 2000 and Thornton et al. 1997). Gosling et al. (2000) analyse the male wages distribution in the UK and its evolution as people age, highlighting how wages rise with age until a plateau in the mid part of a working life, but less so and for a shorter period for the less educated. In addition, there are a large range of individual life or job events that are likely to influence wage growth between periods such gaining further education, promotional opportunities or job loss. Here we bring together this literature on earnings dynamics with the literature on income mobility to

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[3] In doing so, we build on Vittori (2011) who explored the degree of progressive earnings growth across some European countries over the period 1994-2001.

[4] See Atkinson et al. (1992) for an overview of the literature.

[5] "An individual's "earnings profile" reflects his lifetime acquisition of human capital, and the aggregate distribution of earnings is viewed as a distribution of individual earnings profiles" (Mincer, 1974, p.2).

more formally examine directional mobility of earnings.

Also, measurement error is a major concern in studies of mobility. If the error is non-permanent, where a person always under or over reports by the same magnitude, then differences in reporting errors across periods will look like mobility. We attempt to account for measurement error using two different approaches both based on the commonly used two-stage estimation approach.

The literature described above has largely come out of the US and Europe: the Australian literature on mobility (income or earnings) is much less well established. At the time of writing, there was only two studies formally examining mobility: Leigh (2009), examining income mobility, and Rodhe et al (2010) examining earnings mobility. These studies focus on comparing aggregate patterns of mobility across countries rather than on an in-depth examination of individual level mobility. Therefore in addition to making a contribution to the international literature on mobility we also fill a major gap in the empirical understanding of earnings mobility and resulting impacts on inequality in Australia.

3. Approach

When examining differences in inequality across time periods, the most common inequality measure used is the single parameter Gini or S-Gini (Donaldson & Weymark, 1980, 1983; Yitzhaki, 1983). Letting $p = F(y)$ be the individual rank, expressed as the proportion of people with income less than y, and $f(y)$ as the probability density function of income y with mean μ. The *S-Gini* is then a weighted mean of each individual's relative income:

$$G(\upsilon) = 1 - \int w(p;\upsilon)\frac{y}{\mu} f(y)dy, \quad \upsilon > 1 \tag{1}$$

where the weighting function $w(p, \upsilon) = \upsilon(1-p)^{\upsilon-1}$ or social weight, depends on the individual rank p and on the inequality aversion parameter υ, set at 2 for the conventional Gini index.

Jenkins & Van Kerm (2006) show that a change in the Gini index can be written as a change in individuals' relative income as well as a change in the individuals' position (rank):

$$\begin{aligned} \Delta Gini &= Gini_1 - Gini_0 \\ &= R(\upsilon) - P(\upsilon) \end{aligned} \tag{2}$$

Where,

$$P(\upsilon) = \int \int w(p_0;\upsilon) \left[\frac{y_1}{\mu_1} - \frac{y_0}{\mu_0} \right] f(y_0, y_1) dy_0 y_1 \tag{3}$$

$$R(\upsilon) = \int \int w(p_0;\upsilon) - w(p_1;\upsilon) \frac{y_1}{\mu_1} f(y_0, y_1) dy_0 y_1 \tag{4}$$

Hence, the overall change in inequality can be separated into the contribution of two components, each representing one particular aspect of the change. $P(\upsilon)$, from equation (3), reflects the change in inequality attributable solely to changes in individual relative incomes, with the rank fixed at the base year. This is a measure of mobility as progressivity of income growth (or earnings in our study), which Jenkins & Van Kerm (2006) describe as pro-poor growth. This captures the extent to which mobility acts as an equaliser of longer-term incomes or, alternatively, of the persistence of the original pattern of inequality over time. This is the main focus in the rest of this paper and is what we mean when we refer to mobility being inequality reducing.

By contrast, $R(\upsilon)$ is a measure of the extent of re-ordering, reflecting changes in the rank order of individuals from income changes, while fixing relative incomes to those observed in the second year. This captures the re-sorting in the population reflecting that those who are the poorest or richest (lowest or highest paid) in the later period were not necessarily those that were initially the poorest or richest.

In our context this allows us to show the extent to which earnings growth is progressive, i.e. fastest among those who were the original lowest paid individuals, from equation (3), whilst noting, as we are using a balanced panel, that they will have been replaced as the lowest paid by some of those who were originally further up the distribution. For our purposes only the first part of the decomposition is used for further analysis as this part tells about the persistence in earnings inequality or how earnings movements equalise the assessment of inequality over the longer term

The limitation with this decomposition is that whilst it offers an informative summary measure of inequality reducing impact of mobility in Gini units; it does not provide any sense of where in the distribution economic mobility is occurring or as to who the individuals are who benefit or lost out as a result of the observed mobility patterns. We can however offer a pictorial representation of the individual process behind the overall mobility measure by adapting the mobility profiles developed by Van Kerm (2006) to our framework. As Van Kerm points out, a mobility profile is generated by plotting the overall expected individual mobility conditional on a person's position (rank) in the base period distribution:

$$m(p) = m(Y_0, Y_1 \mid Y_0 = y_0(p_0)) \tag{5}$$

A summary measure of mobility can then be obtained by integrating the regression function in (5) with respect to the individual rank p_0.

Van Kerm (2006) shows that in the special case where the distance measure adopted is the change in relative earnings from one year to another and if the mobility profile is weighted according to the Gini social weight, $w(p_0;\upsilon) = \upsilon(1-p_0)^{\upsilon-1}$, the integral of equation (5) will be exactly equivalent to the measure in (3). This equivalence enables us to capture each individuals' contribution to the overall degree of progressive earnings or income growth

Approximating the mobility profile

The mobility profile expressed in equation (5) captures the underlying individual process behind the aggregate picture of mobility. As equation (5) is a conditional expectation it can be estimated using regression based techniques, either using non-linear non-parametric regression methods, as in Van

Kerm (2006) and (2009a), or by using linear methods as shown in equation (6) below.[6] This then creates a regression based approximation of the inequality reducing process. As before, we consider the change in earnings relative to the mean from year 0 to year 1 and we regress it on the initial rank at time 0 $p_{i,0}$:

$$\Delta y_{i,t} = \beta p_{i,0} + \varepsilon_{i,1} \tag{6}$$

The estimated coefficient $\hat{\beta}$ captures the degree to which each individual's initial rank is associated with earnings changes, so the overall degree of progressive earnings growth.[7] Where mobility is equalising earnings over the longer-term, $\hat{\beta}$ will be negative, such that individuals who initially start with a low rank see faster earnings growth. Where earnings movements are unrelated to the initial distribution $\hat{\beta}$ will be zero.

The advantage in adopting a linear approximation method is that it makes it fairly straightforward to assess the economic drivers of mobility in terms of both their size and direction. First we predict the overall change in earnings attributable to individual predictors q_i without capturing any direction of movement in the sense that they are inequality reducing or enhancing:

$$\Delta y_{i,1} = \theta q_i + \eta_i \tag{7}$$

For simplicity we now refer to the predicted individual earnings growth from (7) $\bar{\Delta} y_{i,1}$ as Δy_q. This tells us what factors are driving earnings changes from one period to the next.

If we estimate equation (7) with a linear OLS model we can explore the extent to which the observed predicted mobility Δy_q is moving people away or towards the mean by regressing it on the initial rank

[6] In selecting a specific weight one is required to make an explicit ethical judgment on the importance given to individuals of any given rank. Once we move from the overall measure (3) to a local analysis of the individual process and its drivers, we abstract from any judgment and hence avoid the inclusion of any weight. Let us note that although we do not adopt an explicit pro-poor weighting a downward sloping mobility profile would still signal faster earnings growth of low earnings people and hence inequality reducing pro-poor growth.

[7] In the results section we denote $\hat{\beta}$ with "b0" and we refer to it as the degree of mean reversion or progressive earnings growth.

and can retrieve the contribution made by each regressor term in equation (7).

$$\bar{\Delta} y_q = \beta_q p_0 \quad (8)$$[8]

This exercise can be applied to each predictor in equation (7) or to specific groups of covariates, allowing us to identify what factors have been "progressive" and "regressive", hence introducing an assessment of directional mobility. Secondly, by building up the regressions we can observe the extent to which the apparently continuous process of the age-earnings profile is made up of a series of discrete events such as job to job moves, promotions and job loss. Finally, we can compare the predictors of earnings changes and the extent to which they are inequality reducing. It is likely that earnings changes for those in the middle of the distribution will reduce inequality less than if the movements occurred in the tails of the distribution, thus rather different drivers may be explaining inequality reduction relative to the drivers of earnings growth more broadly.

Measurement error

A key concern in recent literature on economic mobility concerns measurement error which can lead to significant upward biases in estimated measures of mobility (see for example Zimmerman, 1992). In our application we are exploring the relationship between a person's change in earnings between two periods and their initial starting point or rank (equation 6). Any reporting error in the initial period report of earnings will thus be on both sides of the estimating equation, being in both the lagged earnings on the LHS and the initial rank on the RHS. This then creates a bias to the estimated $\hat{\beta}$. This bias will make the coefficient appear more negative, as the lagged earnings on the LHS has a negative sign attached to it, which leads to an over estimation of the progressivity of changes in earnings (overstating the extent earnings mobility reduces inequality).

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[8] Given the overall $\hat{\beta}$ from equation 6 and $\hat{\beta}_q$ from equation 8, the following condition holds: $\hat{\beta} = \hat{\beta}_q + \hat{\beta}_{residuals}$ where $\hat{\beta}_{residuals}$ is obtained by regressing the η_i from equation 7 on the initial rank p_0 ; $\hat{\eta}_i = \hat{\beta}_{residuals} p_0$

To address measurement error in our analysis we adopt two approaches, both of which try to rid the model of the same reporting error being on both sides of the estimating equation. First we utilise an alternative earnings measure from the same data but reported in a different year to construct an alternative measure of the initial rank p_0 (see data description below), which to the extent it has a different error structure will break this correlation. This approach has a long history in medical studies, such as Davis (1976) in an epidemiological study. Jenkins & Van Kerm (2011) does this using an average of lead and lagged income. Approaches that utilise data from other periods through averaging or lead/lag averaging are likely to also remove some aspects of genuine, period specific, transitory income variation, remove those with missing data in the lagged (lead) period, and in the case of studies of earnings, also lose cases zero earnings in the lagged (lead) period.[9] Moreover, if reporting errors from the two alternative measures of initial earnings are correlated, despite being reported in different years, some over estimation of mobility may still be present.

Our second approach to account for measurement error is to use an explicit two-stage approach using the predicted earnings changes from equation 7. Dearden et al. (1997) proposed and operationalised this approach with respect to intergenerational mobility and Fields (2003) uses it in a mobility setting akin to our own. The two-stage approach argues that if any error is unrelated to observable characteristics of the individual, then earnings proxies and indeed changes in earnings proxies can be used to identify earnings free from error reporting. This approach should eliminate measurement error from our estimation but any true earnings mobility not captured by our proxy measure is lost.

4. Data and definitions

The HILDA survey

The data used for this study comprise the first nine waves of the Household Income and Labour

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[9] See also, Gottschalk & Danziger (1997) and Jenkins & Van Kerm (2006) amongst others.

Dynamics in Australia (HILDA) Survey (Release 9.0), providing information collected annually over the period 2001 to 2009. Described in detail in Goode & Watson (2006), the HILDA Survey began in 2001 with 13,969 respondents in 7,682 households. Of these, 9,245 respondents were interviewed in wave 9, although the total number of respondents in Wave 9 was 13,301 due to new entrants to the sample between Waves 1 and 9 (for example, because an individual has joined a household containing a sample member or because a child of a sample member has turned 15 years of age).

Non-response rates are similar to those experienced by comparable household panel studies internationally, such as the British Household Panel Study (BHPS) and the German Socio-Economic Panel (GSOEP), but there are nonetheless some concerns about the ongoing representativeness of the sample. Rates of sample attrition are, for example, highest among persons who are young, living alone, born overseas and from a non-English-speaking background and who, at Wave 1, were living in Sydney. However, analysis by Watson & Wooden (2004) suggests that the impact of any resultant bias is likely to be relatively small. Also our results are not sensitive to the use of panel weights to account for attrition.

Measures of earnings

In this analysis we are interested in individuals gross annual earnings. Fieldwork for the HILDA survey occurs between the periods of September and February each year, with respondents interviewed at annual intervals. At each interview respondents are asked to record their total annual gross earnings from the previous financial year (i.e. the period between July 1st and June 30th immediately prior to the interview). Therefore in wave 1 they will be asked to report their annual earnings for the 2000/2001 financial year, in wave 2 the 2001/2 financial year, and so on. Respondents are also asked to report their current gross earnings, which are recorded in the release data file as a weekly estimate.

This gives us two estimates of earnings from which to base our analysis on, one that directly records individual annual earnings from the previous financial year –our main variable of interest– and also one based on current earnings. To ensure that the two variables cover a similar period we match the annual (financial year) earnings estimate from wave = t+1 with the current weekly earnings estimate and all other characteristics from wave = t. Hence the two estimates are derived from two separate waves of HILDA, which is likely to reduce any correlation in reporting errors. We can then impute an equivalent annualised earnings estimate from the current weekly earnings estimate by multiplying it by the number of weeks each person was in employment in the corresponding year. The difference between the two estimates will include any measurement error which is not common to the two estimates plus any within year transitory earnings. Finally, as we are interested in real changes in earnings, we adjust all of our earnings estimates for inflation, and reflect earnings in base year (2001) prices.

Sample restrictions

As we are focused on earnings mobility we restrict the sample to those persons 18-64 years in the initial survey. In practice because of the use of seven years of panel data all participants over 57 will be lost to the study. Also, in the interests of not overstating mobility in earnings, we only look at respondents with positive, reported financial year earnings, therefore omitting persons with zero or imputed earnings values.[10]

Table 1 describes the sample selection process. In the first column the sample numbers from wave 2 are presented, with details of the impact of each stage of the selection process presented as we move down the rows of the table. As we are using both a measure of annual earnings from wave 2 and the corresponding earnings measure from wave 1, we must first restrict the sample to individuals observed in both waves 1 and wave 2 (thus new entrants at wave 2 are not included), resulting in 9,478 persons aged 18-64 years. Of these, 7,728 were recorded as having been employed at some stage

[10] We do however undertake sensitivity analysis to these exclusions, finding that the final year wage distribution of entrants (i.e. those with zero or imputed earnings in the base year but positive earnings in the final year) is similar to the base year wage distribution of exiters (i.e. those with positive earnings in the base year and zero or imputed earnings in the final year) with entrants and exiters overrepresented in the lower end of the wage distribution.

throughout the year. However, only 6,974 had positive annual earnings recorded, 405 of which actually had missing earnings information and had their earnings imputed by the HILDA researchers. Following the same selection process for persons also responding in waves 8 and 9 we end up with 3,872 respondents aged 18-57 in the initial period with recorded positive annual earnings. A number of other minor restrictions are made to ensure that our resulting sample also has non-missing current earnings in wave 1 and that observations where there are inconsistencies in their employment and earnings information are omitted. Our resulting sample is therefore made up of 3,733 individuals.[11]

Summary information on our earnings estimates in the two periods examined is presented in Table 2. The first two columns examine summary statistics of respondents' reports of their gross financial year (annual) earnings for the base and final year, while the final column presents corresponding statistics based on the proxy earnings estimate for the corresponding base year (2001/2). Also reported in this final column is the correlation between the two alternative earnings estimates for the base year. The favourable business cycle conditions in Australia over this period led to a 25 per cent increase in real gross earnings over the period. The proxy estimate of annual earnings based on current earnings understates average earnings in each period slightly, which is expected as the annualised estimate does not account for wage increases that may have occurred within the financial year due to annual increments (which tend to occur at the end of calendar years rather than financial years) and/or promotion. The two earnings measures are also highly correlated with a correlation coefficient of 0.75.

The predictors of changes in earnings

As discussed above changes in earnings can arise due to changes in returns to given characteristics as

[11] In the interests of keeping as broad a representation of earners in the sample as possible we keep observations where respondents are not working at the time of their wave 1 interview but have positive annual earnings. Furthermore as we use the proxy annual earnings measure only to construct a person's rank in the initial distribution we re-rank people with zero proxy earnings based on their weeks worked in the corresponding financial year. The correlation between the two rank measures improves when we adopt this.

people age in the labour market or they can arise due to changes in the characteristics or other events which have an economic return. Hence in predicting the evolution of individual earnings as outlined in equation 7 we include both initial levels and changes of most variables in our regressions. The variables that we examine can be grouped into four major categories. In the first we examine respondents base year (2001) life cycle characteristics typically examined in the human capital literature when estimating age-earnings profiles. These include gender; 4 age groups (18 to 29 years, 30 to 39 years, 40 to 49 years and 50 years plus); and 3 education levels (didn't complete secondary school, completed secondary school and completed a post-secondary qualification). We separate these variables by gender as we expect age and education to affect men and women differently, and education to affect those of different age groups unequally as well. Hence we have 24 different terms for education by age by gender. As having a child typically affects the labour supply (and later earnings) of women, we also include indicator terms to reflect the presence of a dependent child under 15, which we interact with gender. We hereafter refer to these sets of characteristics as 'life-cycle factors'.

The second set of characteristics examined represents various 'life events'. These include whether over the period examined: the respondent had a child (interacted by gender); attained a further educational qualification; experienced a serious illness or injury; or was incarcerated/in detention over the period. The third set of characteristics examined relates to a range of job characteristics that the literature has found affect earnings. These can be grouped into a set of initial job characteristics[12] (tenure with employer, sector of employment (public, private or other), firm size (whether 20 or more employees at workplace), whether in casual employment; whether have supervisory responsibilities in their job); factors associated with career advancement (whether had a job promotion, an increase in

[12] Initial job characteristics reflect the job of each respondent at the wave 1 interview. An indicator for those not working at this interview is included in the model. Also included are indicators for observations with missing information for each of the initial job characteristics variables.

occupation status, an increase in supervisory responsibility, became a fixed term/permanent employee, had work related training, or had a job change without an intervening spell of joblessness at any stage over the period examined): a job loss or demotion (a spell of joblessness, was fired or made redundant, time spent jobless over the period examined, experienced a decrease in occupation status, a decrease in supervisory responsibility, or became a casual employee): or other indicators of job change associated with potential changes in earnings (moves between sectors, or to a larger or smaller firm).

Our final group of variables consists of measures of 'working time'. Here we include measures of both hours worked per week (weekly hours worked at initial interview and indicator variables for whether weekly working hours increased or decreased between the initial and final period) and total time worked per year (proportion of the initial financial year in employment and indicator variables for whether the proportion of the financial year employed increased or decreased between periods). By examining the impact of each of these 4 sets of variables in stepwise fashion, we can therefore see how much of the changing returns to the life course come through life cycle factors, life events, job promotions or job displacements, or changes in time spent working. Summary descriptive statistics of these variables are provided in Appendix Table A1.

5. Results

We start by exploring the evolution of the earnings distribution between the periods 2001/02 and 2008/09 in Table 3, decomposing the changes in inequality into the progressivity of earnings growth ('pro-poor' in the terminology of Jenkins & Van Kerm, 2006 but as we consider earnings rather than income, this phrase is somewhat misleading) and the extent of re-ranking that occurred. In contrast to earlier studies such as Athanasopoulos & Vahid (2003), Briggs, Buchanan & Watson (2006) and Keating (2003) showing growing earnings inequality in the decades immediately preceding the 21st century in Australia, the Gini estimates of 0.368 in 2001/2 and 0.331 in 2008/9 and associated bootstrapped standard errors suggest a small, but statistically significant, decrease in cross-sectional earnings inequality between 2001/02 and 2008/09.[13][14]

Decomposing this change in inequality as per equation 2, we disentangle the extent to which progressive earnings growth reduces inequality and the positional re-ranking that occurs between the first and second period as a result of these earnings changes (equations 3 and 4 respectively). This shows how people's earnings change over time and the lowest earners at a point in time were not necessarily the lowest earners some years before. In other words, earnings of the lowest paid tend to rise faster than the average, meaning they are no longer the lowest paid. However others experience shocks that push them down the earnings distribution becoming the new lowest paid in the second period. The progressive earnings growth term, then, measures how mobility equalises longer-term earnings measures and thus captures the persistence of the original pattern of earnings inequality as people move away from their starting point.

Table 3 shows that progressive earnings growth ("P-component") reduced the Gini coefficient of inequality by 0.148 units, or 40 per cent of initial inequality, between the two periods. Earnings inequality seven years later is thus sharply lower than in the initial period when assessed according to peoples initial position (i.e. if we do not re-rank according to who is now the lowest and highest paid). This, at face value, suggests that the extent to which the lowest or highest paid remain the lowest or highest paid appears quite modest.

Individuals' relative earnings changes, or earnings share movements, between 2001/2 and 2008/9 are plotted in Figure 1. These are the mobility profiles of Van Kerm (2009a) corresponding to equation 5. Actual changes (dots) are compared with a non-linear semi-parametric estimate of the

[13] Weighting these estimates for sample attrition makes little difference to the overall estimates.
[14] In contrast, the Australian Bureau of Statistics Survey of Income and Housing (SIH) finds that cross-sectional earnings inequality over this decade continued to rise marginally, however as Wilkins (2014) notes: 'while the SIH show that the wage distribution among employed persons became more unequal, the absence of a similar increase in inequality in the HILDA data, combined with the fact that much of the increase occurred when methods and concepts were changing, including the move to measuring salary sacrificed income, means we cannot be certain of the veracity of this trend. Looking to other ABS earnings data collected over the early to mid-2000s cannot resolve this uncertainty, because all ABS surveys conducted over this period experienced the same changes in wage measurement.'

profile, using local polynomial regression, and a linear approximation of the profile denoted in equation 6. The earnings change is defined relative to the mean in this approach to allow a direct link to Gini based inequality, rather than the more typical log change. Looking first at the plots of actual earnings changes, most movements in earnings are bound by gains or losses equivalent to a one mean change but there are a small number where the change is twice the mean. At very high initial earnings there are more large earnings gains and losses.[15] The non-linear approximation essentially captures this pattern, while the linear approximation captures the overall regression to the mean, but fails to capture the steeper slopes at the tails of the distribution.[16]

Measurement Error

Figure 2 presents the non-linear estimates of the mobility profiles (equation 5), alongside our two approaches to dealing with measurement error. Thus we present the regression based approximation mobility profiles of changes in annual earnings on the rank with no correction for measurement error, annual earnings change where the rank is based on the alternative annual earnings measure and predicted annual earnings growth on the original rank.[17] The profile obtained derived from the weekly earnings measure matches the original profile quite closely over most of the distribution but differs substantially in the tails, where measurement error would be expected to be greatest. Both new profiles suggest far less true mobility at the very top decile once accounting for measurement error. A concern is that both approaches to dealing with measurement error systematically underestimate earnings changes at the top end. When using the predictors of earnings changes, this may reflect that there are few good predictors of earnings movements among high earners. For the other profile the concern is

[15] Of the 51 individuals who experienced an earnings change equivalent to at least twice the mean, 38 were in the top earnings decile in the base year.
[16] Approximations of the progressive earnings growth component generated by these profiles are very close to that observed in the data for both linear and non-linear approximations and indeed across the approaches to reducing measurement error discussed below. These can be provided by the authors on request. The non-linear estimate is obtained using locally weighted regression (LOESS), (Cleveland, 1979).
[17] Results from the earnings growth regressions forming the basis of the second approach to take out measurement error are presented fully in Table 7 and will be discussed when exploring the predictors of mobility later.

that our weekly earnings measure systematically underestimates some part of high earnings such as bonus payments related to firm performance. We, however, find no evidence of this when we compare the earnings distributions using the two measures.[18] Therefore we are confident that a significant part of the mobility observed at this top decile is due to reporting error.

The extent of mobility occurring in the bottom quintile differs to a degree across the two approaches suggesting that the predicted earnings approach may not be fully capturing true mobility in this part of the distribution. Although it may also be possible that reporting errors are more persistent here and the alternative rank measure overstates mobility. The mobility profile that relies on using the alternative earnings measure to construct the rank shows quite a flat profile between the 40 and 80th percentiles, suggesting very limited reversion to the mean in this part of the distribution.

Figure 3 shows the mobility profiles weighted by the standard weighting function used to construct the standard Gini coefficient (equation 5 weighted by the Gini social weight with υ=2). By integrating the area under these curves we are then able to derive the approximations of the extent of earnings inequality reduction through mobility (equation 3 with υ=2), presented in Table 4. Here we see that by using the alternative measure of earnings to rank people the resulting estimate of progressivity of earnings growth is 5 to 7 Gini points lower taking account of measurement error than our original estimate. Measurement error will also lead to an overstatement of inequality and we can also construct an estimate of the initial level of inequality using this alternative rank measure. This suggests a moderately lower level of initial inequality (a Gini of 0.311) and hence the inequality reduction as a result of progressive earnings changes is about one quarter (0.072 Gini points reduction from a base of 0.31) to one third (0.1/0.31) over seven years compared to the 40 per cent reduction observed without addressing measurement error. Still this suggests that cross-sectional earnings inequality is substantially reduced over a longer time horizon.

[18] These can be provided by the authors on request.

Explaining directional mobility

Tables 5 and 6 present the results of decomposing the slope term as per equation 8 (seen as the predicted earnings slope in Figure 3). This enables us to see how each of the broad sets of characteristics contributes to the inequality reduction associated with the progressiveness of earnings growth. The estimated beta slope presented in row 1/column 1 of Table 5 corresponds to the slope of the linear approximation of the mobility profile shown in Figure 1, whilst in Table 6 the alternative rank based on current reported weekly earnings is used to address measurement error. From Table 6 we can see that the estimate of beta is reduced by just under a third when the alternative rank is used, in line with the discussion of measurement error above. The results of decomposing the beta slope to examine the contribution of the 4 sets of factors examined: life cycle, life events, job characteristics and working time are presented in each of the corresponding columns. In row (2) we examine the contribution that life-cycle effects have in isolation, with the contribution of each additional set of factors examined in a step-wise fashion as you move down each row of the table.

A comparison of the original slope coefficients (row 1 in each table) with those in row 2 suggests that the evolution of earnings across age, education and gender groups explains around a quarter of progressive earnings mobility when measurement error is not considered and about one third when the alternative rank measure is used to reduce the effect of measurement error. Hence a sizable part of the inequality reduction from earnings mobility reflects age and experience and can be thought of as the difference between current earnings and life-time earnings inequality. The contribution of life cycle mobility itself does not differ whether we control for measurement error through the proxy earnings measure. This remains true as we include more regressors, this strongly suggests that the deviation between the original and proxy earnings measure is unrelated to the observed characteristics in the data, reinforcing the sense that this is reporting error.

Adding life events in row 3 improves the total share explained to a modest degree and reduces the life cycle effect by a small amount. On the other hand, respondents' initial job characteristics (e.g. tenure) and observed job changes such as promotions explain a substantial amount of mobility. Job related changes are also quite correlated with life cycle characteristics, as the life cycle contribution is reduced substantially when job related changes are included. This shows that the young and especially the more educated young workers seeing faster earnings growth through experiencing more opportunities for job promotion, gaining supervisory responsibilities and career advancement. Working time factors (changes in hours and share of the year employed) predict a large share of the progressivity of earnings growth (a bit over half of the total predicted as shown in row 5 of each table). However, this is really telling us that the bulk of the observed earnings mobility related to the life-cycle and changes in job characteristics flow through changes in hours per week and weeks worked.

Whilst the summary results presented in Tables 5 and 6 offer an overall picture of progressive earnings mobility they don't show what individual factors predict overall earnings movements. A large portion of earnings changes may in fact be regressive with initial higher earners seeing faster growth in their earnings. Table 7 therefore presents the full regression results that formed the basis for the summary data used in Tables 5 and 6 and Figures 2 and 3. Column 1 reports the detailed regression results for predicting earnings changes excluding working time variables (hours worked per week and proportion of year worked) and column 3 includes them. This is to show how all other factors considered interact with these work intensity movements. Columns 2 and 4 show the respective contributions to the overall progressivity of earnings growth and thus we can directly observe the contribution each regressor makes to inequality reduction and indeed which are pushing the other way. Here it matters little as to whether we look at the contributions when regressing annual earnings on either rank measure, thus we only present the results using the original rank measure.[19]

The first section of the table covers the life cycle age-earnings profiles by education group

[19] Results using the alternative rank measure can be obtained from the authors on request.

where the findings are consistent with the literature on age-earnings profiles (for instance see Gosling et al. 2000 and Manning, 2000). Column 1 shows the average earnings growth for each age-education group. It is clear that the young show very rapid earnings growth when they have completed upper secondary education or higher education. This is most marked for men but is still substantial for women. On the other hand those aged over 50 generally experienced lower earnings growth, at least for men. Women who already have children also experienced significant earnings growth over the period. The fully interacted model means that many terms are not individually significant, however.

Column 2 shows the contribution each component of earnings growth to inequality reduction. Thus groups with faster earnings growth will lead to reduced inequality if they start low in initial distribution but will increase inequality if they start already well paid. Earnings growth experienced by the young is thus quite progressive, as these people start lower in the distribution. The exception here is young males with a post-secondary qualification (degree) whose earnings growth is rapid but regressive as they are already in the top half of the distribution in the initial period. Introducing hours and weeks worked changes the earnings growth coefficients and the degree of progressivity very little. Among the next age group earnings growth is still fairly rapid but for males it is now regressive as these are an already well-paid group. In fact, earnings growth for men is slightly regressive overall. For women, earnings growth is very strongly progressive as young and prime age women get quite rapid wage growth and start very much in the lower half of the distribution. This is also true for women in their 40s. Women with children in the initial base year tend to see progressive earnings growth. Note here that this is women who already have children and so part-time working etc is already priced in to lower wages in the first period. Hence higher wage growth reflects a catch up from lower initial wages which essentially comes about through an increase in hours and weeks worked, no doubt due to working more as children age. Earnings growth among the over 50s is generally slow but has no strong progressivity pattern.

Life events that occur over this time period, such as increased educational qualifications, having a child and going to jail, have sizable wage consequences, positive for the former and negative for the latter two, but their overall contribution to progressivity is low as the events are either spread across the distribution or, in the instance of going to jail, quite rare. Increased educational qualifications had the strongest effect with associated earnings growth slightly concentrated amongst those initially in the lower part of the distribution. Of note is the very large wage penalty for women having (further) children between the two periods but this is not strongly progressive as those having children are not particularly low paid. But this large penalty lies behind the later progressive earnings recovery in women's wages discussed above.

The effect of job characteristics are then presented in four subcategories: characteristics of initial job, career advancement, job loss or demotion and other indicators of job change. We include a number of initial job characteristics that predict earnings growth (initial firm size, public sector and a casual job) but again they do not contribute much to the degree of progressivity once working time is accounted for. Following Altonji & Shakotko (2005) we find slower wage growth in longer tenured jobs. In addition we find that this slower wage growth is progressive as those in longer tenured jobs are initially higher paid. Plausibly job characteristics associated with job promotion such as increases in occupation level, increases in supervisory responsibility, job to job moves (i.e. changing jobs with no intervening unemployment), transition from casual employment to ongoing positions and self-reports of promotion are all significantly associated with higher earnings growth over this period. Not all of these characteristics are however progressive. Earnings growth associated with increases in occupation level and in supervisory responsibility did appear to affect those initially in the bottom half of the distribution more than their counterparts. However earnings growth associated with self-reports of job promotion was regressive, as was training as both of these events occurred more often among those already higher earnings.

Likewise, and as expected from the related literature (Arulampalam et al. 2001; Farber et al. 1993 and Jacobson et al. 1993), characteristics associated with job displacement or job demotion are associated with earnings penalties. What we add to this literature is the effect that job displacement has on mobility, as we find that the earnings penalties associated with job displacement are largely concentrated at the lower end of the distribution, and therefore have a substantial regressive effect. Likewise the earnings penalties associated with becoming a casual employee in the final period are experienced by those who were in the lower half of the earnings distribution in the base year. These penalties hit those initially low paid more frequently and hence produce regressive wage mobility. On the other hand, changes in working time arrangements over the period examined were substantial drivers of earnings changes and indeed progressive, with those initially working less and therefore earning less more likely to experience earnings growth than those initially working full-time throughout the year.

6. Conclusion

This paper adds to recent advances in the literature on economic mobility by offering an integrated framework that directly links earnings mobility to conventional inequality measures, assesses the extent to which measurement error leads to an overstatement of true mobility, provides an account of where in the distribution mobility and indeed measurement error are located, and finally, assesses the contribution of the major drivers of observed earnings mobility. The framework developed is very flexible and could easily be applied to other settings such as income and intergenerational mobility with minor adjustments.

The particular application is to examine individual earnings growth and mobility in Australia between 2001/2 and 2008/9. Using data from the Australian HILDA survey we find that the earnings growth that occurred over the period was strongly progressive and, taken on face value, suggests that a large portion (40 per cent) of the initial inequality is transitory. Measurement error in the data, however, considerably exaggerates the picture in the raw data. Yet even after accounting for measurement error progressive earnings growth, that is faster annual earnings growth among the lower paid and slower growth among initial high earners, acted to decrease original inequality by a quarter to a third over seven years.

Examining the pattern of earnings growth across the earnings distribution we find evidence of relatively large amounts of upwards earnings mobility in the bottom 40 per cent of the distribution, little movement in the mid to upper section of the distribution and only modest downwards earnings mobility in the very top of the distribution (the top 10%) after measurement error is considered. Thus persistence in low pay is considerably less than persistence in high pay.

About one third of all progressive earnings growth, after measurement error adjustment, can be attributed to the stage of the life cycle people start at. High earnings growth amongst young people is typically very progressive. Continued rapid earnings growth among prime-age men, especially the well-educated, is however regressive as they are already well paid. Relatively rapid earnings growth of young and prime aged women lies behind a large part of observed progressivity of earnings mobility. Other life event changes such as having a baby for women, gaining an educational qualification, suffering an illness or going to prison have a powerful effect on earnings but, only explain a modest amount of observed progressive mobility. This is because they either occur to a similar extent over the full distribution or are rare. The exception is gaining higher educational qualifications, which is progressive.

The major drivers of progressive earnings changes over the period examined, and indeed the progressive elements of life-cycle mobility, are related to job change factors such as promotion, changing jobs (without intervening unemployment), increases in occupational status and responsibility. However, while job characteristics associated with job promotion are all significantly associated with earnings growth over this period, they are not always associated with progressive earnings growth. For instance, earnings growth associated with self reports of job promotion and job-related training were regressive as the principal beneficiaries were generally already well paid. Importantly, we also find that the earnings penalties associated with job displacement or job demotion were regressive, as those losing work were more often drawn from the lower paid. This is the first time that the relationship between the widely noted cost of job loss and overall earnings mobility has been shown linking distributional mobility and directional mobility. Finally, changes in working time arrangements over the period examined were generally progressive with those initially working less and therefore earning less more likely to experience earnings growth than those initially working full-time. Movements in hours worked drive a substantial part of the observed mobility associated with job changes. Hence the rather smooth picture of age-earnings profiles showing steadily rising wages in peoples 20s and 30s followed by a period slowing growth and then a plateau is substantially made up by a series of events in people's lives such as promotions, redundancies, having children and moves between full and part-time work, which are irregular, discrete and not always in same direction.

Finally we note that the findings of this paper are likely to reflect the relatively unique conditions of the period examined, the second decade of a long boom with strong employment and earnings growth. With no comparable longitudinal data on individuals prior to 2001 we can't infer what patterns of mobility were like in previous periods. However we will make the point that in contrast to the second decade of the boom, there was a much clearer increase in earnings inequality in the 1990s (Greenville et al. 2013) thus the patterns of earnings growth were likely to be very different to those experienced by individuals in the 2000s.

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Figure 1: Mobility profiles as earnings share movements between 2001/2 and 2008/9

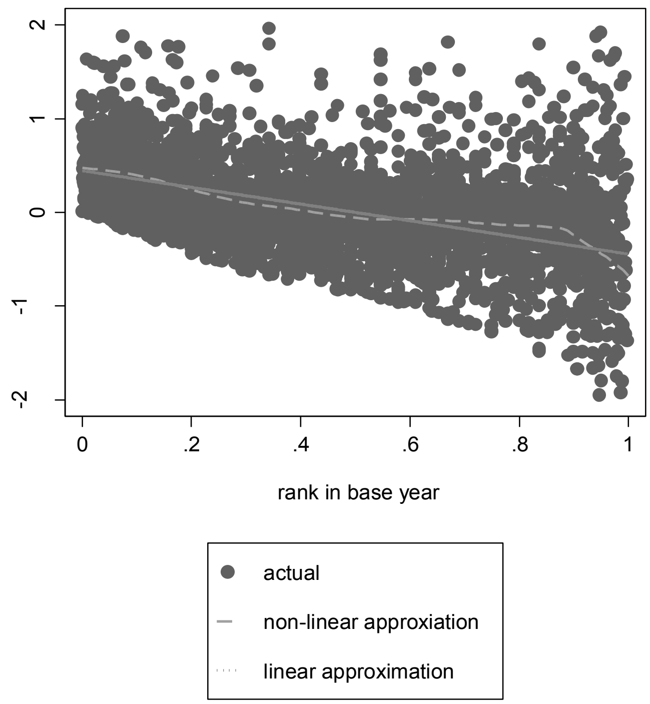

Figure 2: Mobility profiles

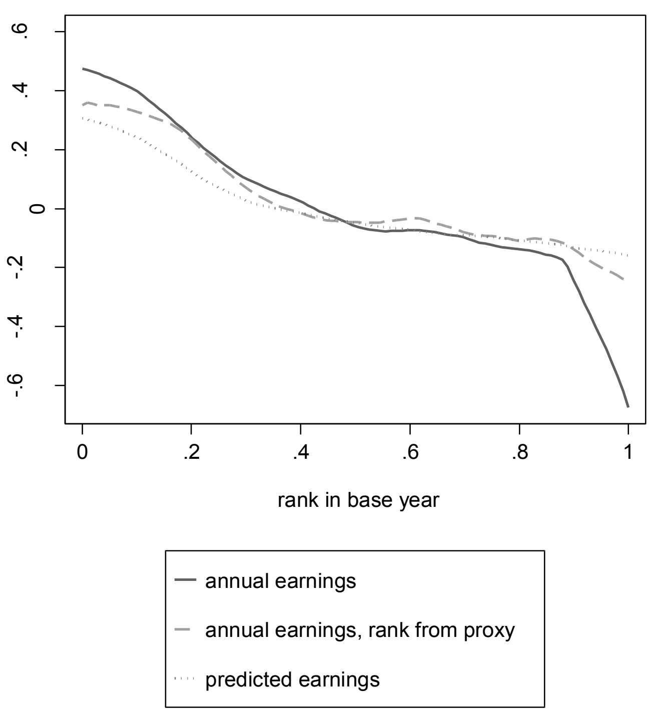

Figure 3. Weighted mobility profiles (inequality aversion parameter $\upsilon = 2$)

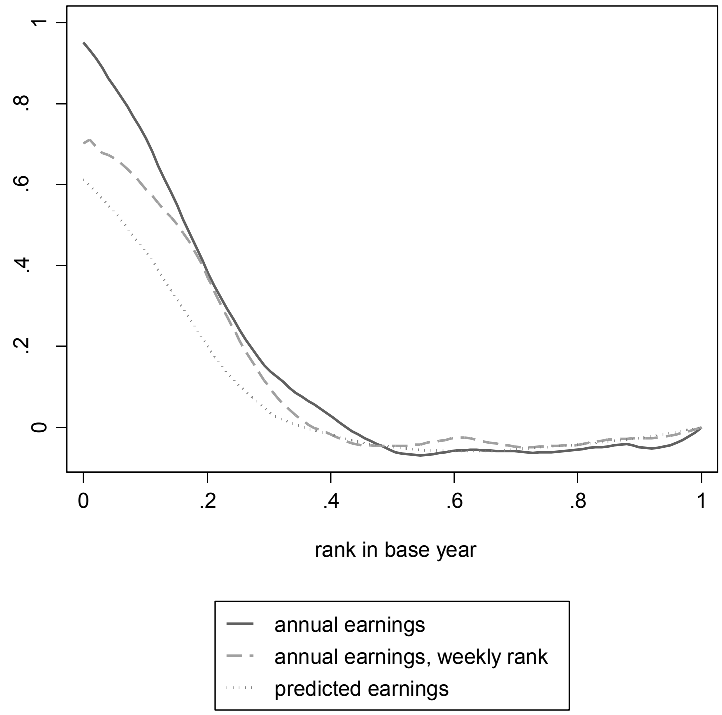

Table 1. Details of sample restrictions and result on sample size

	Wave 2	Wave 2 & 9
Responding persons 18-64 years[1]	9,478	6,588
Employed	7,728	4,826
With positive annual earnings	6,974	4,133
- minus those with earnings imputed	-405	-261
With reported positive annual earnings	6,569	3,872
- minus those with missing current earnings in wave 1 and inconsistent earnings and employment status information[2]		
Resulting sample		3,733

1. Persons must have responded in both waves 1 and 2 as we are combining information from the 2 interviews. Also note that the age restriction applies to the age of respondents at the wave 1 interview as this reflects the age of respondents at the time of their annual earnings
2. To be precise we drop those with:
    a. Missing information on contemporaneous current earnings
    b. positive 2001/2 annual earnings but reporting zero contemporaneous current earnings and no time working over the financial year, and
    c. positive 2001/2 annual earnings but reporting zero contemporaneous current earnings and worked for full year and currently employed

Table 2. Summary statistics

	Reported gross annual earnings ($)		Proxy gross annual earnings[1] ($)
	2001/02 (w2)	2008/09 (w9)	2001/02 (w1)
Mean	40,144	49,777	36,582
Standard deviation	32,195	34,635	27,467
N	3,733	3,733	3,733
Correlation between earnings measures for 2001/02			0.75

1. Estimated by multiplying reported current weekly earnings from the interview of the previous wave multiplied by time worked over the corresponding financial year.

Table 3. Inequality decomposition of earnings in 2001/2 and 2008/9[1]

	Gross annual earnings
Initial S-Gini	0.368
	(0.006)
Final S-Gini	0.345
	(0.005)
Absolute change	-0.023
	(0.006)
R-component	0.126
	(0.005)
P-component	0.148
	(0.008)
Relative change (%)	-6.2
R-component (%)	34.1
P-component (%)	40.3
N	3,733

1. Inequality aversion parameter $\upsilon = 2$
2. Bootstrap standard errors with 999 replications are shown in parentheses

Table 4. Aggregate Progressiveness of earnings growth

	Gross annual earnings
Observed P	0.148
(2SLS estimate)	0.072
(proxy rank estimate)	0.103
N	3,733

Table 5. Explaining Progressive Earnings movement in gross earnings, no measurement error correction (n=3733)

	b0	Predicted by life-cycle factors	Life events	Job Characteristics	Time working	All characteristics	Unexplained	Adj R-Squared
(1)	-0.891***							0.128
	(0.054)							
(2)		-0.216***				-0.216***	-0.674***	0.096
		(0.011)				(0.011)	(0.054)	
(3)		-0.199***	-0.047***			-0.246***	-0.645***	0.096
		(0.011)	(0.007)			(0.013)	(0.053)	
(4)		-0.133***	-0.022***	-0.217***		-0.371***	-0.519***	0.130
		(0.008)	(0.004)	(0.011)		(0.016)	(0.052)	
(5)		-0.079***	-0.017***	-0.042***	-0.306***	-0.444***	-0.446***	0.156
		(0.007)	(0.003)	(0.008)	(0.010)	(0.017)	(0.052)	

Table 6. Explaining Progressive Earnings movement in gross earnings, defining ranks using annualized estimate of weekly earnings (n=3733)

	b0	Predicted by life-cycle factors	Life events	Job Characteristics	Time working	All characteristics	Unexplained	Adj R-Squared
(1)	-0.612***							0. 065
	(0.044)							
(2)		-0.207***				-0.207***	-0.405***	0.089
		(0.011)				(0.011)	(0.042)	
(3)		-0.190***	-0.050***			-0.240***	-0.371***	0.094
		(0.011)	(0.006)			(0.012)	(0.042)	
(4)		-0.126***	-0.025***	-0.238***		-0.389***	-0.223***	0.144
		(0.008)	(0.004)	(0.011)		(0.016)	(0.041)	
(5)		-0.074***	-0.019***	-0.029***	-0.351***	-0.473***	-0.139***	0.180
		(0.007)	(0.003)	(0.008)	(0.009)	(0.017)	(0.040)	

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 7. Linear prediction of change in relative earnings growth between 2001/2 and 2008/9

	Coeff (se's) (1)	Contribution to β_p (2)	Coeff (se's) (3)	Contribution to β_p (4)
Life cycle		***-0.133******		***-0.079******
Males		*0.001****		*0.004****
Male, 18-29 yrs, no secondary	0.087	-0.004***	0.059	-0.002***
	(0.127)	(0.001)	(0.126)	(0.001)
Male, 18-29 yrs, secondary	0.464***	-0.047***	0.407***	-0.042***
	(0.074)	(0.006)	(0.075)	(0.005)
Male, 18-29 yrs, post-secondary	0.340***	0.013**	0.312***	0.012***
	(0.072)	(0.004)	(0.071)	(0.004)
Male, 30-39 yrs, no secondary	0.149**	0.000	0.120*	0.000
	(0.065)	(0.001)	(0.066)	(0.001)
Male, 30-39 yrs, secondary	0.213***	0.005***	0.171**	0.004***
	(0.078)	(0.001)	(0.077)	(0.001)
Male, 30-39 yrs, post-secondary	0.212***	0.049***	0.194***	0.045***
	(0.065)	(0.004)	(0.064)	(0.003)
Male, 40-49 yrs, no secondary	0.053	0.001	0.035	0.000
	(0.062)	(0.000)	(0.062)	(0.000)
Male, 40-49 yrs, post-secondary	0.010	0.003***	0.000	0.000***
	(0.073)	(0.000)	(0.074)	(0.000)
Male, 50 yrs plus, no secondary	-0.066	-0.001**	-0.034	-0.000**
	(0.086)	(0.000)	(0.086)	(0.000)
Male, 50 yrs plus, secondary	-0.158	-0.001	-0.122	-0.001
	(0.254)	(0.001)	(0.241)	(0.001)
Male, 50 yrs plus, post-secondary	-0.163	-0.015***	-0.135	-0.013***
	(0.119)	(0.002)	(0.118)	(0.002)
Females		*-0.136****		*-0.083****
Female, 18-29 yrs, no secondary	0.146*	-0.008***	0.086	-0.005***
	(0.075)	(0.001)	(0.074)	(0.001)
Female, 18-29 yrs, secondary	0.341***	-0.045***	0.250***	-0.033***
	(0.067)	(0.004)	(0.068)	(0.003)
Female, 18-29 yrs, post-secondary	0.255***	-0.011***	0.214***	-0.009***
	(0.069)	(0.003)	(0.068)	(0.003)
Female, 30-39 yrs, no secondary	0.155**	-0.015***	0.093	-0.009***
	(0.077)	(0.002)	(0.077)	(0.001)
Female, 30-39 yrs, secondary	0.096	-0.005***	0.025	-0.001***
	(0.073)	(0.001)	(0.071)	(0.000)
Female, 30-39 yrs, post-secondary	0.137**	-0.008***	0.090	-0.005***
	(0.066)	(0.002)	(0.066)	(0.001)
Female, 40-49 yrs, no secondary	0.035	-0.003***	-0.014	0.001***
	(0.070)	(0.000)	(0.070)	(0.000)
Female, 40-49 yrs, secondary	0.157**	-0.005***	0.111	-0.003***
	(0.071)	(0.001)	(0.070)	(0.001)
Female, 40-49 yrs, post-secondary	0.106	-0.001	0.067	-0.000
	(0.069)	(0.002)	(0.069)	(0.001)
Female, 50 yrs plus, no secondary	0.052	-0.002***	0.026	-0.001***
	(0.063)	(0.000)	(0.064)	(0.000)
Female, 50 yrs plus, secondary	0.123	-0.000	0.111	-0.000
	(0.087)	(0.000)	(0.087)	(0.000)
Female, 50 yrs plus, post-secondary	-0.068	-0.001**	-0.080	-0.002**
	(0.069)	(0.001)	(0.068)	(0.001)
Male with kids	-0.003	-0.001***	-0.006	-0.002***
	(0.047)	(0.000)	(0.047)	(0.000)
Female with kids	0.071***	-0.031***	0.030	-0.013***
	(0.026)	(0.002)	(0.026)	(0.001)
Life events between periods		***-0.022******		***-0.017******
Gained education qualifications	0.096***	-0.023***	0.077**	-0.018***
	(0.034)	(0.002)	(0.032)	(0.001)
Had children (Males)	0.002	0.000***	0.011	0.001***
	(0.054)	(0.000)	(0.052)	(0.000)
Had children (Females)	-0.326***	0.001	-0.248***	0.001
	(0.039)	(0.004)	(0.037)	(0.003)
Suffered from major illness	-0.043	-0.001	-0.034	-0.001
	(0.035)	(0.001)	(0.035)	(0.001)
Went to jail	-0.149	0.000*	-0.160	0.001*
	(0.132)	(0.000)	(0.187)	(0.000)
Job characteristics		***-0.217******		***-0.042******
Initial job characteristics		*-0.157****		*-0.008****
2 to 4 years with employer	0.017	0.000	0.029	0.000
	(0.032)	(0.000)	(0.030)	(0.001)
5 to 9 years with employer	-0.022	-0.003***	-0.010	-0.001***

	Coeff (se's) (1)	Contribution to β_p (2)	Coeff (se's) (3)	Contribution to β_p (4)
	(0.037)	(0.000)	(0.035)	(0.000)
10 years or more	-0.058	-0.024***	-0.052	-0.022***
	(0.038)	(0.001)	(0.037)	(0.001)
Had supervisory responsibilities	-0.001	-0.001***	0.012	0.008***
	(0.024)	(0.000)	(0.024)	(0.000)
<20 employees at workplace in initial year	-0.022	0.005***	-0.036	0.009***
	(0.032)	(0.001)	(0.032)	(0.001)
Not working at initial interview	0.333***	-0.098***	-0.056	0.017***
	(0.097)	(0.006)	(0.105)	(0.001)
Public	0.021	0.007***	0.001	0.000***
	(0.030)	(0.000)	(0.029)	(0.000)
Not for profit or other	0.008	-0.000	0.015	-0.000
	(0.039)	(0.000)	(0.038)	(0.000)
In a casual job in initial year	0.061	-0.031***	-0.003	0.002***
	(0.046)	(0.001)	(0.045)	(0.000)
Career advancement		*-0.082****		*-0.056****
Promotion	0.152***	0.015***	0.149***	0.015***
	(0.027)	(0.003)	(0.026)	(0.003)
Increase in occupation level	0.032	-0.012***	0.005	-0.002***
	(0.033)	(0.001)	(0.033)	(0.000)
Became permanent/fixed term	0.142***	-0.051***	0.123***	-0.044***
	(0.048)	(0.003)	(0.048)	(0.002)
Had work-related training	0.045	0.007***	0.035	0.006***
	(0.033)	(0.001)	(0.033)	(0.001)
Increase in supervisory responsibility	0.057**	-0.011***	0.035	-0.007***
	(0.026)	(0.001)	(0.025)	(0.001)
Job change with no intervening joblessness	0.073***	-0.030***	0.057**	-0.023***
	(0.026)	(0.002)	(0.025)	(0.002)
Job loss/demotion between periods		*0.038****		*0.036****
Jobless spell	-0.092***	0.048***	-0.058**	0.030***
	(0.030)	(0.002)	(0.028)	(0.002)
Fired or made redundant	-0.155**	0.002	-0.124	0.001
	(0.076)	(0.002)	(0.076)	(0.001)
Decrease in supervisory responsibility	-0.355***	-0.020***	-0.143***	-0.018***
	(0.086)	(0.003)	(0.043)	(0.003)
Decrease in occupation level	-0.153***	-0.005	-0.113***	-0.004

	Coeff (se's) (1)	Contribution to β_p (2)	Coeff (se's) (3)	Contribution to β_p (4)
	(0.033)	(0.003)	(0.031)	(0.003)
Became a casual	-0.062	0.006***	-0.058	0.006***
	(0.044)	(0.001)	(0.043)	(0.001)
Proportion of the 7 years not working	-0.001	0.007***	-0.001	0.019***
	(0.001)	(0.000)	(0.001)	(0.001)
Other job change		*-0.016****		*-0.014****
Move to a larger firm	0.104***	-0.013***	0.112***	-0.014***
	(0.039)	(0.002)	(0.039)	(0.002)
Move to a smaller firm	-0.041	0.003***	-0.048	0.003***
	(0.031)	(0.001)	(0.031)	(0.001)
Move to private sector	0.072	0.002*	0.068	0.002*
	(0.068)	(0.001)	(0.066)	(0.001)
Move to public sector	0.091**	-0.008***	0.061	-0.005***
	(0.042)	(0.001)	(0.041)	(0.001)
Working time				***-0.306****
Initial working time				*-0.223****
Hours worked in initial period (weeks)			-0.004***	-0.145***
			(0.001)	(0.003)
Worked less than 25% of initial year			0.237***	-0.020***
			(0.087)	(0.003)
Worked 25% to 49% of initial year			0.249***	-0.035***
			(0.079)	(0.003)
Worked 50% to 74% of initial year			0.147	-0.020***
			(0.090)	(0.002)
Worked 75% to 99% of initial year			0.032	-0.003***
			(0.072)	(0.000)
Increase in working time in final year				*-0.047****
Increase in hours worked			0.069***	-0.033***
			(0.026)	(0.002)
Increase in proportion of year worked			0.033	-0.014***
			(0.074)	(0.001)
Decrease in working time				*-0.038****
Decrease in hours worked			-0.127***	-0.043***
			(0.034)	(0.003)
Decrease in proportion of year worked			-0.169***	0.005*
			(0.051)	(0.003)
Constant	-0.213***		-0.118	

	Coeff (se's) (1)	Contribution to β_p (2)	Coeff (se's) (3)	Contribution to β_p (4)
	(0.070)		(0.115)	
Observations	3,733	3,733	3,733	3,733
R-squared	0.172		0.204	

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Reference categories are: Male, 40-49 yrs, secondary; <2 yrs with employer in initial year; Private sector; Worked entire initial year

Appendix table 1. Sample means

Sample characteristics	Mean	Sample characteristics	Mean
Life cycle		10 years or more	0.236
Male, 18-29 yrs, no secondary	0.024	Had supervisory responsibilities	0.475
Male, 18-29 yrs, secondary	0.047	Didn't have supervisory responsibilities (reference)	0.524
Male, 18-29 yrs, post-secondary	0.062	<20 employees at workplace in initial year	0.358
Male, 30-39 yrs, no secondary	0.038	Not working at initial interview	0.072
Male, 30-39 yrs, secondary	0.017	Private sector (reference)	0.546
Male, 30-39 yrs, post-secondary	0.111	Public sector	0.266
Male, 40-49 yrs, no secondary	0.028	Not for profit or other	0.116
Male, 40-49 yrs, secondary (reference)	0.015	In a casual job in initial year	0.178
Male, 40-49 yrs, post-secondary	0.108	Promoted between initial and final years	0.175
Male, 50 yrs plus, no secondary	0.013	Jobless spell between initial and final years	0.434
Male, 50 yrs plus, secondary	0.005	Fired or made redundant between initial and final years	0.039
Male, 50 yrs plus, post-secondary	0.042	Job change with no intervening joblessness	0.544
Female, 18-29 yrs, no secondary	0.017	Increase in occupation level between initial and final years	0.272
Female, 18-29 yrs, secondary	0.041	Decrease in occupation level between initial and final years	0.207
Female, 18-29 yrs, post-secondary	0.063	Move to a larger firm	0.170
Female, 30-39 yrs, no secondary	0.039	Move to a smaller firm	0.121
Female, 30-39 yrs, secondary	0.027	Move to private sector	0.098
Female, 30-39 yrs, post-secondary	0.085	Move to public sector	0.076
Female, 40-49 yrs, no secondary	0.046	Increase in supervisory responsibility	0.203
Female, 40-49 yrs, secondary	0.020	Decrease in supervisory responsibility	0.166
Female, 40-49 yrs, post-secondary	0.090	Became a casual in final year	0.081
Female, 50 yrs plus, no secondary	0.025	Became permanent/fixed term in final year	0.126
Female, 50 yrs plus, secondary	0.007	Had work-related training between first and final years	0.784
Female, 50 yrs plus, post-secondary	0.031	*Working time*	
Male with kids	0.233	Hours worked at time of initial interview (weeks)	35.811
Female with kids	0.220	Worked less than 25% of initial year	0.016
Life events occurring between initial and final period		Worked 25% to 49% of initial year	0.031

Sample characteristics	Mean	Sample characteristics	Mean
Gained education qualifications	0.097	Worked 50% to 74% of initial year	0.040
Had children (Males)	0.071	Worked 75% to 99% of initial year	0.059
Had children (Females)	0.061	Worked 100% of initial year (reference)	0.853
Suffered from major illness	0.092	Increased hours worked in final year	0.455
Went to jail	0.001	Decreased hours worked in final year	0.392
Job characteristics		Increase in proportion of year worked	0.135
Time with employer in initial year (reference <2 yrs)	0.276	Decrease in proportion of year worked	0.095
2 to 4 years	0.234	Proportion of total time observed not working	5.359
5 to 9 years	0.186	N	3,733