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Abstract

In this paper we propose an integrated framework for the analysis of earnings inequality and mobility, which enables the analysis of the distributional dimension of inequality reduction from mobility, an assessment of the economic drivers of mobility and a sense of which drivers are equalising and dis-equalising. In particular we are able to capture the extent to which life-cycle characteristics, key life events, job related characteristics, and changes in working time affect overall mobility and inequality. The framework also offers a bounded approach to isolating the underlying inequality reduction resulting from mobility from measurement error which can otherwise lead to a substantial upward bias. Using data from the Australian HILDA survey we find evidence of a sizable degree of earnings mobility in Australia over the years 2001/2 to 2008/9. The raw inequality reduction resulting from economic mobility was 0.148 Gini points from an initial estimate of 0.368, however, the bounded range based on two alternative versions of two stage estimation lies between 0.072 and 0.102 or between ¼ and 1/3 of original inequality. We show how the inequality reduction from mobility is primarily driven in the bottom part of the initial distribution, with the upper tail being particularly prone to measurement issues. A sizeable part of the identified mobility is simply driven by age-earnings growth that sees more rapid wage increases for younger workers and wage progression among women in notably stronger in reducing inequality because they start lower in distribution. Yet this rather smooth picture of earnings rising with age is shown to be substantially driven by a series of less frequent step changes associated with job-to-job moves, promotions and taking on more responsibility. There are also shocks which run against this equalising process, most notably job loss, which has substantial negative effects on earnings and disproportionately falls on lower waged workers.

JEL classification: D31, J01, J60

Keywords: Earnings, mobility, distributional analysis, measurement error

1. Introduction

In this paper we integrate a number of recent developments in the literature around economic mobility and offer a framework that allows the exploration of the extent to which mobility reduces economic inequality combined with assessment of directional and distributional mobility, the separation of measurement error from true mobility, and, an in depth examination of the job and life changes people experience that drive observed mobility patterns.

Prior to the availability of longitudinal household surveys, much of the literature examining inequality compared the distribution of income or earnings at various points in time of different cross sections of society. With the arrival of longstanding nationally representative longitudinal household surveys for most developed countries attention turned to also examining the mobility of incomes and/or earnings over time. Such that in a comparison of two periods, any mobility will mean that whilst there are still people who are the poorest or most affluent, but they aren't necessarily the same people.

Following Shorrocks (1978) seminal paper 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). However many of the measures developed give an assessment of aggregate mobility without providing the analyst with any additional information about the local underlying process such as where in the distribution mobility occurs and especially the individual contribution to overall mobility, or the economic processes that drive individual earnings. 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. Another key feature of the recent literature on economic mobility concerns measurement error (see for example Zimmerman 1992) which can lead to significant upward biases in estimated measures of mobility.

Here we seek to integrate some existing approaches so as to offer an aggregate picture of mobility taking account of potential measurement error and facilitate discussion of the disaggregate localised and individual process involved.

The starting point of our analysis is Jenkins and Van Kerm (2006), who show how mobility can affect inequality by the degree to which changes in incomes are progressive (that is income growth is faster for the poorest) and also by the degree of re-ranking that occurs in the distribution. Such that progressive (or pro-poor) income growth tends to reduce overall inequality unless more than offset by substantial individual re-ranking. 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. As discussed in Van Kerm (2006) this summary measure can then be linked to Van Kerm's (2009a) mobility profiles providing a "distributional sense" of mobility as the degree to which earnings growth is inequality reducing. Here we offer the first direct application of this link for the regular Gini measure of inequality.

Our next major contribution is to isolate true mobility from measurement error, which can lead to substantial upward bias in estimates of mobility. This is undertaken in two different ways which allow us to identify bounds on the effect of measurement error on observed mobility. By using an alternative earnings measure to rank people in the initial period distribution, under classical measurement error assumptions, we are then able to purge our mobility estimates of measurement error. We show that this approach will offer an upper bound of true mobility to the extent that non-classical measurement error means that there is a correlation between the errors in the two measures. This approach can be thought of as a variant of a two stage estimation approach. As is the second, lower bound, approach where we engage in two stage estimation of the dependent variable. This will not only purge observed earnings changes of measurement error but is likely to understate true mobility to the extent to which not all movements are able to be predicted.

We adopt the unusual step of applying the two stage approach to the dependent variable, as it then then allows us to also explore the economic predictors of inequality reducing mobility. This allows the research on mobility and inequality carried out by Jenkins and Van Kerm (2006) and Van Kerm (2009a) to be linked with the large labour market literature on earnings changes over time in an integrated framework. In particular we are able to explore the extent to which earnings movements growth is explained by life-cycle characteristics, key life events, job related changes and changes in working time. This enables us to see how economic variables increase or decrease inequality and hence to capture to some "directional mobility". We show intuitively how the impact on inequality of an economic shock is a function of the associated wage change and where those people experiencing the shock are in the original distribution. For instance, job loss increases inequality as it results in lower wages and hits lower paid workers more frequently.

The focus on Australia is in part because of some attractive data features but also because the Australian literature on either income or earnings mobility is much less well established. Therefore in addition to making a key contribution to the international literature by offering an integrated framework to examine earnings mobility, we also fill a major gap in the empirical understanding of earnings mobility and resulting impacts on inequality in Australia.

The reminder of the paper is structured as follows. The next section provides a general overview of the existing literature on mobility. Section 3 then describes the approach taken integrating the theoretical framework of the *S-Gini* decomposition (Jenkins and Van Kerm, 2006), mobility profiles (Van Kerm, 2009a), and finally, how to approximate the mobility profiles within a linear regression method 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. Literature Overview

As discussed in Fields (2007) there are a wide range of mobility measures 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 and Van Kerm 2006, among others). Jenkins and Van Kerm (2006) offer a decomposition of the change in Gini inequality across two periods, into the progressivity of income growth, that is the degree to which incomes grow fastest for those who were initially the poorest, which they call pro-poor growth. This is offset in terms of cross-sectional inequality in the second period through a re-ranking of individuals position in the distribution as incomes have evolved. This approach has the attractive feature of expressing inequality reduction as a result of mobility in Gini units, which is the most common expression of inequality, therefore offering the potential for the approach to be linked with other literature examining Gini measured inequality and mobility. Jenkins and 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]

The global indices cited above give an assessment of mobility without providing the analyst with any additional information about the local underlying process. Yet, recent research has been focused on providing a "distributional picture" of mobility. The local approximation method (Schluter and Trede, 2003) allows measures of mobility as an equaliser of longer-term incomes (Fields, 2010, Shorrocks, 1978) 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 parts of the overall distribution that contribute more to the global mobility measure. Gregg & Vittori (2008) offer a recent application with a comparison 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.

[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.

Van Kerm (2009a) shows how a broad range of mobility measures can be instead expressed as population averages statistics that are defined at the individual level, making it possible to capture the mobility experienced by each person. With this method, the distance measure representing mobility is expressed as individual distance rather than distributional difference of kernel densities. Hence it is applied in the "different and largely simplified context of "distance-based" measures" (Van Kerm, 2003, p. 2). The mobility profiles approach developed by Van Kerm, (2009a) is used to analyse individuals' income growth in Europe (ECHP, 1996-2001). The analysis shows that income growth among the poorest is higher in Ireland, Spain or Denmark than in most other countries, and that the expected income losses of the richest are much smaller in Portugal than in countries such as Greece or Denmark.

To date, mobility profiles have been used to visually show differences in income growth across countries (Van Kerm 2009a), periods, and population sub-groups (Jenkins and Van Kerm, 2008) [2]. Nevertheless, as discussed by Van Kerm (2006), mobility profiles can also be adopted to explore progressive growth hence providing a clear link with the Jenkins and Van Kerm (2006) decomposition. Here we offer the first direct application of this link. We then go on to show that individual earnings growth patterns over the distribution, shown visually in the mobility profiles literature, can be summarised by regression approaches that allow a good approximation of the aggregate Gini reduction as a result of pro-poor income growth (see Section 3).

There is also a parallel literature on individual earnings dynamics and the modelling of the covariance structure of earnings.[3] 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 the number of years of schooling completed and a quadratic function of years since leaving school, following the human capital theory developed by Mincer (1974).[4] This

[2]Both Jenkins and 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.

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

[4]"An individual's "earnings profile" reflects his lifetime acquisition of human capital, and the

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 Thornton et al. 1997, and Manning, 2000). Earnings tend to increase in the early career and then plateau in the middle age (Manning, 2000). Gosling et al. (2000) analyse the male wages distribution in the UK and the evolution of wages distribution is modelled with three components: (1) a function of age and education, (2) a cyclical time effect, and (3) a cohort effect. The interaction of age with education reflects changes in wages over the life-cycle with returns to experience positive for all workers, 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. Obtaining further education, promotional opportunities and job loss or demotion will all affect individuals' earnings in different ways. Here we bring together this literature on earnings dynamics with the literature on income mobility to more formally examine directional mobility of earnings.

Measurement error is a major concern in studies of mobility. In addition to the two components of earnings growth discussed above reported earnings is likely to contain a third transitory element owing to measurement error. Whilst the error might be small relative to total earnings it is likely to be much larger relative to the change or evolving element. 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. There are three main approaches to tackling measurement error problems in mobility studies. The first is to trim outliers at the top and bottom of the distribution of reported income/earnings where errors are likely to be proportionately larger. A second approach taken, which is perhaps the most commonly used, is to average across data periods at the beginning and end period considered. The problem with this approach is that it only reduces the impact of measurement error rather than eliminating it and averaging removes some genuine transitory movement in income between periods. The third is to undertake a two-stage approach, first predicting the incomes or earnings of individuals with observable characteristics and then using these predicted values to undertake analysis (Fields, 2003, Dearden et al. 1997). A slight variation on this approach is to replace the income/earnings measure with an alternative measure from another period. Jenkins and Van Kerm (2011) do this using an average of lead and lagged income, but again as averaging across years is applied this will also remove some year specific genuine transitory income/earnings variation. We seek to apply two variants of this third approach to give an upper and lower bound to the contribution of measurement error with the regression base pro-poor mobility approach developed.

The literature described above has largely come out of the US and Europe. We use Australian data here in part because of some attractive data features but also because

aggregate distribution of earnings is viewed as a distribution of individual earnings profiles" (Mincer, 1974, p.2).

the Australian literature on either income or earnings mobility is much less well established. At the time of writing, there were only two studies formally examining mobility; Leigh (2009), who examines income mobility, and Rodhe et al (2010) who examine earnings mobility. These studies are however quite limited in their approaches, with a 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 key 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. Methodology: From the S-Gini decomposition to a regression approach

3.1 The S-Gini decomposition

The Gini index is one of the most recognized and adopted inequality measures and it can be expressed in several ways. One of these allows one to easily draw an interesting link between mobility and inequality: the single parameter Gini or S-Gini (Donaldson and Weymark, 1980, 1983; Yitzhaki, 1983). Let $p = F(y)$ 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 domain $\left[z_-, z_+\right]$ and mean μ. The S-Gini is a weighed mean of each individual's relative income:

$$G(\nu) = 1 - \int_{-z}^{+z} w(p;\upsilon)\frac{y}{\mu} f(y)dy \tag{1}$$

where the weighting function $w(p;\upsilon)$ or social weight, depends on the individual rank p and on the inequality aversion parameter. For υ equal to 2, the conventional form of the Gini index is obtained.

Let us now consider a change in the S-Gini for a fixed population of individuals from year 0 to year 1 and denote with $f(y_o, y_1)$ the joint probability density function of income y_0 in year 0 and y_1 in year 1. In a comparison of two periods, any mobility will mean that the individual person will have a different value of income and whilst there are still people who are the poorest or most affluent, they aren't necessarily the same people. Hence, as shown by Jenkins and Van Kerm (2006), the 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):

$$\Delta G(\upsilon) \equiv G_1(\upsilon) - G_0(\upsilon)$$

$$= -\int_{-z}^{+z}\int_{-z}^{+z} w(p_1;\upsilon)\frac{y_1}{\mu_1} - w(p,\upsilon)\frac{y_0}{\mu_0} f(y_{0,}y_1)dy_0 y_1 \tag{2}$$

which we can rewrite as:

$$\Delta G(\upsilon) = \int_{-z}^{+z} w(p_0,\upsilon)\frac{y_0}{\mu_0} f(y_0)dy_0 - \int_{-z}^{+z} w(p_1;\upsilon)\frac{y_1}{\mu_1} f(y_1)dy_1 \tag{3}$$

Hence, the overall change can be separated into the contribution of two components, each representing one particular aspect of the change:

$$P(\upsilon) = \int_{-z}^{+z}\int_{-z}^{+z} w(p_0;\upsilon)\left[\frac{y_1}{\mu_1} - \frac{y_0}{\mu_0}\right] f(y_0,y_1)dy_0 y_1 \tag{4}$$

and

$$R(\upsilon) = \int_{-z}^{+z}\int_{-z}^{+z} w(p_0;\upsilon) - w(p_0;\upsilon)\frac{y_1}{\mu_1} f(y_0,y_1)dy_0 y_1 \tag{5}$$

$P(\upsilon)$ reflects the change in inequality attributable solely to changes in individual relative incomes, with the rank fixed at the base year (p_0). This is a measure of mobility as progressivity of income growth, which Jenkins and Van Kerm (2006) describe as pro-poor growth. By contrast, $R(\upsilon)$ is a re-ranking index, reflecting only changes in the initial rank, while fixing the relative income at the second year (y / μ_1). It follows that the overall change in equation 2 can be rewritten as:

$$\Delta G(\upsilon) = R(\upsilon) - P(\upsilon). \tag{6}$$

Thus progressive income growth leads to reductions in inequality as a result of economic mobility, whether inequality is actually lower in the second period depends also on whether this is more than offset by re-ranking in the distribution as those who were the poorest or most affluent in the initial period are replaced by others.

3.2 Mobility profiles

The limitation with the decomposition expressed in equation 6 is that it whilst it provides an informative summary measure, it does not provide any sense of where in the distribution economic mobility is occurring or as to individual mobility patterns. Van Kerm (2009a) shows how a broad range of mobility measures can be expressed as population averages of statistics derived from the individual distance measure and hence can be applied in the "different and largely simplified context of "distance-based" measures" (Van Kerm, 2003, p.2). Let Y_0 and Y_1 with joint distribution $F(y_0, y_1) = Pr[Y_0 <= y_0, Y_1 <= y_1]$ describe the distribution of incomes at two time periods (base and final year) as a realisation of (y_0, y_1), and let $d(y_0, y_1; F)$ be a distance function. A wide range of mobility measures can be expressed in the following way (Van Kerm, 2006):

$$M(Y_0, Y_1) = \int_{z_-}^{z_+}\int_{z_-}^{z_+} d(y_0, y_1; F)dF(y_0, y_1) \tag{7}$$

where individual changes in income from the base year $_0$ to the final year$_1$ are summarized into a global scalar. Mobility depends on the information contained in the original and final year distribution, and on the specific choice of the distance function.

Starting from this general form, a mobility profile can be obtained by rewriting equation 7 in terms of the base year individuals' rank. Let F_{Y_0} and F_{Y_1} be the marginal distribution function of Y_0 and Y_1 and $F_{Y_0|y_1}$ and $F_{Y_1|y_0}$ the respective conditional distributions.[5]

$$\begin{aligned} M(Y_0,Y_1) &= \int_{-z}^{+z}\int_{-z}^{+z} d(y_0,y_1;F)dF_{Y_1|y_0}(y_1)dF_{Y_0}(y_0) \\ &= \int_{-z}^{+z} m(Y_0,Y_1|Y_0=y_0)dF_{Y_0}(y_0) \\ &= \int_0^1 m(Y_0,Y_1|Y_0=y_0(p))dp \end{aligned} \tag{8}$$

The mobility profile is generated by plotting the expected mobility $m(p)=m(Y_0,Y_1 \mid Y_0=y_0(p))$ over the individuals' ranks p in the base year, hence conditional on where individuals started in the base year distribution. The area underneath the curve, obtained by integrating the regression function with respect to the individual rank p, is a measure of mobility. Mobility profiles "provide evocative pictures of the underlying mobility structure" and are "appealing tools for depicting the structure of income mobility" (Van Kerm, 2009a). The mobility profile in equation 8 can then be weighed according to an ethical weight $w(p)$, determining the importance given to the individual's rank p, when assessing overall mobility.

$$M^w(Y_0,Y_1)=\int_0^1 w(p)m(p)dp \tag{9}$$

A natural choice for the weighting function, is the one contained in the $S-Gini$ index (eq.1), where $p=F(y)$ is the normalized rank of the base period distribution. In the classical expression of the Gini, as earlier discussed, $\upsilon=2$. According to the distance function adopted, the measure $M(Y_0,Y_1)$ will capture a different aspect of mobility, as discussed in Fields and Ok (1996, 1999b).[6] For instance, if the distance measure adopted is the change in log income from year y_0 to y_1, $d(y_0,y_1;F)=\log(y_1)-\log(y_0)$., mobility will reflect the growth of a person's income.

The mobility profile approach can also be adopted to explore the degree of

[5]Mobility profiles differ from growth incidence curves (see for instance Ravallion and Chen, 2003). The growth incidence curve refers to incomes of two different individuals (cross sectional perspective), while mobility profile track the income changes of each individual as summarised by the individual income growth function which depends on the joint bivariate distribution of income (longitudinal perspective). Indeed the growth incidence curve approach abstracts from the fact that the composition of some income groups may change over time (Jenkins and Van Kerm, 2011).
[6]Examples of distance measures can be found in Fields and Ok (1999a).

progressive income (pro-poor) growth expressed in equation 4. As noted by Van Kerm (2006), the progressivity term is in fact a special case of equation 9 where the distance measure adopted is a measure of mobility as "income share movement" (Fields, 2007) and the weighting function is the Gini with aversion parameter 2.[7]

$$d(y_0, y_1; F) = (\frac{y_1}{\mu_{y1}} - \frac{y_0}{\mu_{y0}}) \tag{10}$$

We exploit this special case and integrate the advances made by Jenkins and Van Kerm (2006) with Van Kerm (2006, 2009a) to provide an insightful framework to exploring earnings mobility.

The mobility profile M_P, now expresses the individual change in relative income conditional on the initial rank:

$$M_P = \int_0^1 (\frac{y_1}{\mu_{y1}} - \frac{y_0}{\mu_{y0}})dp \tag{11}$$

This can be weighted adopting the social weight in equation 2:

$$M_P^{\upsilon} = \int_0^1 \upsilon(1-p)^{\upsilon-1}(\frac{y_1}{\mu_{y1}} - \frac{y_0}{\mu_{y0}})dp \tag{12}$$

By setting $\upsilon = 2$, M_P^2 is equivalent to the measure of pro-poor growth $P(\upsilon)$ expressed in equation 4:

$$M_P^2 = \int_0^1 2(1-p)(\frac{y_1}{\mu_{y0}} - \frac{y_0}{\mu_{y0}})dp \tag{13}$$

So $P(\upsilon)$ corresponds graphically to the area underneath the curve (mobility profile M_P), multiplied by the social weight $2(1-p)$. By drawing a mobility profile, as expressed in equation 11, we are able to capture the underlying individual process behind the global degree of mobility as pro-poor growth, and hence of the part of mobility that tends to reduce inequality over time.

3.3 Regression approximation

As the mobility profile presented in equation 11 is a conditional expectation it can be estimated using regression based techniques. In Van Kerm, 2006 & 2009a non-linear non-parametric regression methods are applied. However the relationship can also be estimated using linear methods as presented in equation 14 below. Considering for simplicity a change in income from year 0 to year 1:

$$\Delta y_{i,1} = \beta_{\Pr oPoor} p_{i,0} + \varepsilon_{i,1} \tag{14}$$

The estimated coefficient $\hat{\beta}_{\Pr oPoor}$ captures the degree to which initial ranks can

[7] "Share movement takes place if and only if an individual's income rises or falls relative to the mean" (Fields, 2007, p.3). In particular, the measure in equation 15, is defined by Fields as the mean absolute value of share changes.

predict income changes, so the overall degree of pro-poor growth.[8] With inequality reducing mobility $\beta_{\Pr oPoor}$ will be negative, such that individuals who initially start with a low rank see faster income growth. Where there is no inequality reducing mobility the measure will tend to zero. The estimation represents a regression based approximation of the mobility profile approach and the less parametric the approach taken the closer the approximation and the more informative it is about the distributional mobility pattern. We explore local polynomial based regression estimation and linear OLS and show the size and distribution of any divergence that is generated by this approximation. Once again by integrating the predicted income change and applying the social weighting we can get an estimate of the Gini change due to the pro-poor component as with equation (13). This allows an obvious comparison with the true Gini change to test the accuracy of the approximation. This regression based approximation opens two further steps to our analysis discussed below.

3.4 Measurement Error

In addition to actual income growth, reported income movements are likely to contain a transitory element owing to measurement error. 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. This is illustrated in the following.

Let us define with y_0^* and y_1^* true income at year $t = 0,1$. If income is reported with error:

$$y_0 = y_0 * + v_0 \tag{15}$$

$$y_1 = y_1 * + v_1 \tag{16}$$

the reported base year rank is given by:

$$p_0 = p_0 * + \eta_0 \tag{17}$$

Rewriting equation (14) using the same notation:

$$y_1 - y_0 = \beta p_{i,0} + \varepsilon_{i,1} \tag{18}$$

the extent of pro-poor mobility estimated for true incomes/earnings is given by:

$$\beta^* = \frac{cov(y_1^* - y_0^*, p_0^*)}{var(p_0^*)} \tag{19}$$

while the estimated pro-poor mobility based on reported incomes is given by the following:

$$\beta = \frac{cov(y_1 - y_0, p_0)}{var(p_0)} \tag{20}$$

which equates to

[8] By contrast if the coefficient is positive, it indicates divergence in earnings. To avoid confusion, we refer to $\beta_{ProPoor}$ as the degree of mean reversion or pro-poor growth.

$$\beta = \frac{cov(y_1^* - y_0^* + v_1 - v_0, p_0^* + \eta_0)}{var(p_0)} \tag{21}$$

when the measurement error terms are made explicit. In this case, the denominator is a rank, therefore the variance of the true rank and the observed rank will be the same $var(p_0) = var(p_0^*)$ and hence the normal attenuation bias from higher variance of the variable with error does not apply. Expanding out the co-variances gives

$$\beta = \frac{cov(y_1^* - y_0^*, p_0^*)}{var(p_0)} + \frac{cov(y_1^* - y_0^*, \eta_0)}{var(p_0)} - \frac{cov(v_0, p_0^*)}{var(p_0)} - \frac{cov(v_0, \eta_0)}{var(p_0)} + \\ + \frac{cov(v_1, p_0^*)}{var(p_0)} + \frac{cov(v_1, \eta_0)}{var(p_0)} \tag{22}$$

Under classical measurement error assumptions, the two error terms will be uncorrelated with each other, $cov(v_1, \eta_0)$=0, and the errors are uncorrelated with true measures, $cov(y_1^* - y_0^*, \eta_0)$=0, $cov(v_0, p_0^*)$=0 and $cov(v_1, p_0^*)$=0. Hence we have

$$\beta = \beta^* - \frac{cov(v_0, \eta_0)}{var(p_0)} \tag{23}$$

as the rank is constructed from the base period income variable the $cov(v_0, \eta_0)$>0 by definition. Therefore, our estimates of pro-poor mobility will have a bias which will exaggerate its magnitude in the face of error.

There are three main approaches to tackling measurement error problems in mobility studies. The first is to trim outliers at the top and bottom of the distribution of reported income where errors are likely to be proportionately larger. The second, and perhaps the most commonly used approach, is to average across data periods, typically for two periods, at the beginning and end of the period considered (see for instance, Gottschalk and Danziger (1997) and Jenkins and Van Kerm (2006) amongst others). This averaging will remove some genuine transitory movement in income between periods and only reduces the impact of measurement error rather than eliminate it. When averaged over two periods, the error components for both periods are uncorrelated and for any error draw in one of the two periods the mean expected error in the other is zero. Hence in this case measurement error is halved rather than eliminated. The third is to undertake a two-stage approach predicting the measure of income with observable characteristics (Fields et al 2003, Dearden et al. 1997). In our context this would involve predicting the rank variable on the right hand side of equation (14). A variation on this approach is to replace the RHS income measure with an alternative measure from another period. Jenkins and Van Kerm (2011) do this using an average of lead and lagged income. Unlike averaging including the current period, this will remove all classical measurement error but not non-classical error such that the errors are correlated across periods. 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.

We seek to apply two variants of this third approach to give an upper and lower bound to the contribution of measurement error with the regression based pro-poor mobility approach developed. These are discussed in detail in turn below. Note that here we are interested in individual earnings, rather than in examining a broader concept of income, henceforth y will refer to earnings.

A lower bound on measurement error

To place a lower bound on measurement error we utilise an alternative earnings measure to construct an alternative measure of p_0 (see data description below), which will have a different error structure, $p'_0 = p'^*_0 + \eta'_0$. Under classical measurement error $cov(v_1, \eta'_0) = 0$ and $cov(y^*_1 - y^*_0, \eta'_0)$=0, giving a resulting estimate of β that is unbiased by any measurement error. This is very close to a two-step estimator but here there will be no change in variance as a result of a first stage prediction equation and as the rank variable is for a common sample the variance of the original and replacement measure are the same. This approach has a long history in medical studies, such as Davis (1976) in an epidemiological study.

Studies however have suggested that measurement error in earnings is non-classical. Therefore our estimates will still have biases, the extent of which will depend on the extent to which the co-variances with the errors are greater than zero. Gottschalk and Huynh in their seminal (2010) paper explore non-classical measurement using linked self-reported and administrative data. They assume the administrative data is accurate and treat the self-report data as measured with error and then look at the reporting biases and how they influence mobility patterns. They note that $cov(v_1, p^*_0)$ and $cov(v_0, p^*_0)$, using our notation, are non-zero but of similar magnitude. They suggest that low earning people tend to overstate earnings and high earners understate and hence self-report data has mean reversion and understates measured earnings inequality. However, as these correlations are similar in magnitude but of different sign in terms of the bias that they imply for estimated mobility (see equation 22), they cancel out. They also report that people understate changes in earnings by more than they report mean reverting earnings in general. This will lead to an understatement of mobility. In our notation then this implies that $cov(y^*_1 - y^*_0, \eta_0) < 0$. Gottschalk and Huynh explore periods one year apart and suggest that this reflects an under-reporting of transitory shifts away from expected earnings. Thus people are reporting with partial adjustment to new circumstances. If this is true then when the data periods considered are farther apart, this problem will diminish, as long-term earnings changes are absorbed into a persons expected earnings. Unfortunately Gottschalk and Huynh did not consider how errors changed when data periods were further apart.

The main concern about non-classical measurement error in our analysis is that there is persistence in peoples reported errors over time, therefore $cov(v_0, \eta_0) > 0$. Gottschalk and Huynh report this as being about 0.5 of the total error. This means that our approach of using p_0' instead of p_0 will only remove half of any measurement error bias. As such, it can be considered an upper bound for true earnings mobility. Also, by examining the mobility profile using this alternative measure of people's rank in the initial distribution, we can also see where in the original distribution the error has been (partially) removed.

Upper bound on measurement error

The second approach to measurement error is to use an explicit two-stage approach. 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.

Rewriting equation 15 as,

$$y_0 = \varphi q_0 + f_0 + v_0 \tag{24}$$

where φq_0 is that part of true earnings predicted by observable characteristics q_0, f_0 that part of true earnings not captured, and v_0 the reporting error. Here we cannot distinguish between that part of true earnings not captured and reporting error. However predicted earnings will be free of error if there is no correlation between observable characteristics and reporting error.

To break the correlation between measurement error in original earnings and the rank of original earnings, we can either use the two-stage prediction approach to the LHS (the change in earnings) or RHS (the rank) variables. Fields et al (2003) uses permanent income proxies to predict the RHS. We adopt the alternative and seek to predict earnings changes. This allows us to also explore which factors are associated with mobility whilst simultaneously seeking to remove error. This approach should eliminate measurement error from our estimation but any true earnings mobility not captured will be lost and hence this approach can be seen as a lower bound of true mobility, enabling us to bound true mobility when combined with the approach described earlier.

To allow us to examine the factors predicting mobility in greater detail, we build up the predictive regression in four stages. In the first stage we follow Gosling et al. (2002) and consider how the life-cycle affects earnings changes by estimating age-earnings profiles by education group, which we denote by $LC_{i,0}$. We then add life events that have occurred between the base and final periods such as increased educational attainment, having a child, going to prison etc (LE_i). We then turn to job characteristics and changes such as firm size, responsibility levels, job loss and unemployment (J_i). Finally we explore the impact of working time by exploring changes in weeks and hours of work in the period considered (WT_i). We include both initial levels and changes of most variables in our regressions predicting the evolution of individual earnings.

Denoting with q_i the vector of individual predictors:

$$q_i = LC_{i,0} + LE_i + WT_i + J_i \tag{25}$$

We estimate:

$$\Delta y_{i,1} = \theta q_i + \omega_{i,1} \tag{26}$$

From this regression we obtain an estimate of the change $\Delta \hat{y}_{i,1} = \hat{\theta} q_i$ given by all these factors. As already discussed, the residuals $\omega_{i,1}$ will still contain some genuine mobility which we are not able to predict with q_i (f_0 in equation 24) as well as measurement error.

$$\omega_{i,1} = \text{idiosyncratic component + measurement error}$$

Denoting with Δy_q the earnings change predicted by q_i, we can then estimate the degree to which Δy_q is progressive:

$$\Delta y_q = \beta_q p_0 + \gamma \tag{27}$$

While the progressive earnings growth contained in the residuals will obviously be:

$$\omega_{i,1} = \beta_{residuals} p_0 + \psi \tag{28}$$

Such that the following conditions hold:

$$\hat{\beta}_{\Pr oPoor} = \hat{\beta}_q + \hat{\beta}_{residuals} \tag{29}$$

There are several nice features of this approach. Firstly, it allows us to capture the contribution that each group of variables makes to the overall reversion to the mean

$\beta_{Pro-poor}$ in equation (14). This exercise can be applied to each predictor in equation (26) or to specific groups of covariates, allowing us to identify what factors have been "anti-poor" and "pro-poor", hence introducing an assessment of directional mobility. For movements that reduce (increase) wages and disproportionately hit initially low (high) earners, such as job loss, will be anti-poor. 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.

4. Data and definitions

The HILDA survey

The data used for this study comprise the first nine waves of the Household Income and Labour Dynamics in Australia (HILDA) Survey (Release 9.0), providing information collected annually over the period 2001 to 2009. Described in detail in Goode and 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 or in de facto relationships, born overseas and from a non-English-speaking background and who, at Wave 1, were living in Sydney. However, analysis by Watson and 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 the weekly estimate by the amount of time 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.

As discussed in Watson and Wooden (2004a, pp.17-21) there does seem to be a tendency for the HILDA Survey to overstate wage and salary income. This however appears to be explained by an over-representation of persons working in the managerial and professional occupations in the HILDA Survey than in other nationally representative income surveys in Australia rather than due to reporting bias. There are a couple of reasons why we expect measurement error to be low for the annual earnings estimates in the HILDA data. Firstly, the fieldwork has been timed to occur in the period immediately following when most individuals/household members will have prepared their tax returns (the financial year in Australia occurs between 1 July and 30 June, with tax returns due in to the tax office by October 31st). HILDA fieldwork begins in September and ends in March of the following year, with the bulk of surveys completed in the first 3 months in field. Secondly, anecdotal accounts from interviewers obtained at post-fieldwork debriefs suggest that many respondents check their tax statements when completing the survey (although this is not systematic). However reporting bias cannot be completely discounted.

Sample restrictions

As we are focused on earnings mobility we restrict the sample to those persons 18-64 years. 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.[9]

[9] We do however undertake sensitivity analysis to these exclusions, the results of which are presenting

Table 1 describes the sample selection process and its impact on the resulting sample numbers. 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 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 wave 9 we end up with 3,872 respondents aged 18-64 years over 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.

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 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.[10]

As we are using a measure of current weekly earnings in our analysis, a decision has to be made about whether to also drop observations where respondents are not working at the time of this interview (i.e. persons with zero current earnings in wave 1). These respondents are more likely to have low annual earnings and therefore their omission could have an impact on our overall findings. In the second panel of the table we therefore produce summary measures of both earnings measures where we also omit those observations with zero current weekly earnings for the corresponding

in the appendix.

[10] The correlation coefficient between the two rank measures is 0.86.

time period. Here it is obvious that those not employed at the time of interview in each period tend to be those with low levels of annual earnings, and omitting them leads to a resulting sample of higher earners on average. Correlation across the two earnings measures is similar once those with zero weekly earnings are omitted. Therefore in the interests of keeping as broad a representation of earners in the sample as possible we keep these observations in the analysis that follows. Furthermore as we use the proxy annual earnings measure only to construct a person's rank in the initial distribution when estimating equations 13 and 14 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.

The predictors of changes in earnings

As discussed above changes in earnings can arise due to changes in returns to given characteristics as 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 when predicting the evolution of individual earnings 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[11] (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 occupation status, an

[11] 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.

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

Here we will build up the results of our analysis in a step-wise way to show how we integrate four related literatures in a way that adds new insights into earnings mobility and inequality. We start by exploring the evolution of the earnings distribution from 2001/02 to 2008/09 in Table 3, decomposing the changes in inequality into re-ranking and progressivity of earnings growth (pro-poor in terminology of Jenkins and Van Kerm, 2006 but as we consider earnings rather than income, this phrase is somewhat misleading).

In contrast to earlier studies such as Keating (2003), Athanasopoulos & Vahid (2003) and Briggs, Buchanan and Watson (2006) 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.[12] Decomposing this change in inequality as per equation 6, we disentangle the extent to which progressive earnings growth reduces inequality (or is pro-poor in Jenkins and Van Kerm's terminology) and, the positional re-ranking that occurs between the first and second period as a result of these earnings changes (equations 4 and 5 respectively). This shows how people's earnings change over time and the lowest earners at a point in time are not necessarily the lowest earners some years later. Earnings of the lowest paid tend to rise faster than

[12] Note that weighting these estimates for sample attrition makes little difference to the overall estimates as shown in Appendix Table A2.

the average, meaning they are no longer the lowest paid. However others have shocks that push them the other way and who become the newly lowest paid in the second period. The progressive earnings growth term, then, measures how earnings inequality is reduced by people moving away from their starting point.

Table 3 shows that that progressive earnings growth would have reduced the Gini coefficient of inequality by 0.148 units, or 40% of initial inequality, between the two periods. So earnings inequality seven years later is 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). Hence it suggests that the extent to which the lowest or highest paid remain the lowest or highest paid appears quite modest. The re-ranking term (R-component) shows the degree to which inequality is increased by re-sorting people according to their 2008/9 income instead of that in 2001/2. That is the extent to which they are re-ordered in the distribution by the observed earnings changes.

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). Actual changes are compared with a non-linear semi-parametric estimate of the profile, using local polynomial regression, and a linear approximation of the profile. 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 equivalent to at least twice the mean. At very high initial earnings there are more large earnings gains and losses.[13] 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. As discussed in Section 3, by integrating the area under the weighted profiles with the generalised Gini social weighting function (in this case an inequality aversion parameter of 2) we get an aggregate estimate of the progressive earnings growth component (or pro-poor term) from Equation 4. These estimates are reported in Appendix Table A4 and are very close to that observed in data for both linear and non-linear approximations and indeed across the approaches to reducing measurement error discussed below. Hence we can have confidence that the (non-)linear estimation gives a close approximation to an estimate of the extent of inequality reducing earnings mobility, expressed in Gini units.

Measurement Error

Column 2 of Table 3 shows the effect of taking the commonly used approach to

[13] 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.

addressing measurement error by averaging earnings across two years at the beginning and end periods. As discussed in Section 3, this approach can only dampen measurement error, by a maximum of a half under classical measurement error assumptions for two period averages, but will also remove genuine earnings mobility that occurs between the paired years. The measure of initial inequality falls a little (3 Gini points) but the fall in the progressivity of earnings growth is larger at nearly 5 Gini points. This could be in part driven by the sample selection that this more data intensive approach requires, with a loss of nearly 15% of the sample, but comparing with a common sample the progressivity of earnings growth is similar to the difference observed in the data.

Figure 2 presents the non-linear estimates of the mobility profiles bounded by our two preferred approaches to dealing with measurement error. Thus we present the mobility profiles of annual earnings on the rank of this data (no correction for measurement error), annual earnings on the rank based on the alternative annual earnings measure (upper bound of mobility) and predicted annual earnings growth on the original rank (lower bound of mobility).[14] The upper bound profile 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 upper and lower bound 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 2SLS approach (the lower bound profile), this may reflect that there are few good predictors of earnings movements among high earners. For the upper bound profile the concern is 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 (see Appendix Figure A2). Therefore we are confident that a significant part of the mobility observed at this top decile is due to measurement error.

Interestingly the extent of mobility occurring in the bottom quintile differs using 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. By integrating the area under these

[14] Results from the earnings growth regressions forming the basis of the lower bound estimates are presented fully in Table 7 and will be discussed when exploring the predictors of mobility later.

curves we are then able to derive the approximations 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 Gini points lower than our original estimate. This estimate is very similar to that reported from using 2 year averages in Table 3. This is however likely to be a coincidence as the averaging approach will net out some portion of true mobility that occurs but removes less of the measurement error. 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 third over seven years compared to the 40% reduction observed without addressing measurement error. Alternatively the 2SLS approach gives us a lower bound estimate of progressive earnings mobility of 0.072 points when approximated using the non-linear mobility profile.[15] Hence the unadjusted assessment of inequality reduction through mobility appears substantially over stated but is still of the order of 25% less.

Explaining directional mobility

Tables 5 and 6 present the results of decomposing the slope term as per equation 27, which enables us to see how each of the set 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. 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 pro-poor 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 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 or not. This remains true as we include more regressors, this strongly suggests that the

[15] We also undertake the more usual exercise of predicting the RHS rank variable with initial personal and job characteristics. Using a rank measure of this prediction, which should also eliminate measurement error under the assumption that error is not correlated with job characteristics, produces a Gini reduction from earnings growth of 0.92. This is somewhat closer to our upper bound estimate.

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. Here it is potentially the young and more educated seeing faster earnings growth through experiencing more opportunities for job promotion and career advancement than other life-cycle groups examined. 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).

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. This is important to understand if one is interested in examining who it is that may be left behind in times of overall earnings growth.

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 factor 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.[16]

The first section of the table covers the life cycle age-earnings profiles by education group where the findings are consistent with the literature on age-earnings profiles (for instance see Manning, 2000 and Gosling et al. 2000). It is very 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 with children also experienced significant earnings growth over the period. The fully interacted model means that many terms are not

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

individually significant, however.

Column 2 shows that the earnings growth experienced by the young is typically 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 a 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 are focused 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 slower but has no major progressivity.

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 these 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 (Jacobson et al. 1993, Farber et al. 1993 and Arulampalam et al. 2001), 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. Interestingly we find that the earnings penalties associated with job displacement were largely concentrated to the lower end of the distribution, and therefore were significantly regressive in effect. Likewise the earnings penalties associated with becoming a casual employee in the final period were experienced by those 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

There have been a number of recent advances in literature discussing economic mobility. This paper is the first to offer an integrated framework that directly links economic mobility to conventional inequality measures, assesses the contribution of measurement error to observed 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 to observed 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 earnings mobility in Australia and its impact on overall inequality. Using data from the Australian HILDA survey we find that the strong earnings growth that occurred over the period between 2001/2 and 2008/9 was strongly progressive and led to a substantial decline in earnings inequality compared to where people started, although measurement error considerably exaggerates this 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, reduces the degree of original inequality by a third over seven years.

Examining mobility across the earnings distribution we find evidence of relatively large amounts of upwards earnings mobility in the bottom 40% of the distribution, little movement in the mid to upper section of the distribution but only modest downwards earnings mobility in the very top of the distribution (the top 10%) after measurement error is considered. When assessing the drivers of mobility, we find that about one third of all progressive earnings mobility, after measurement error adjustment, can be attributed to the stage of the life cycle people start at. High earnings growth amongst young males and young females is typically very progressive. Continued rapid earnings growth among prime-age men, especially the well-educated, is however regressive. That is, prime-age well-educated men who are already high earners in the base period see rapid earnings growth. Hence the difference between current earnings and life-time earnings lies behind a large part of the measured 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 over the full distribution or are rare. The exception is gaining higher educational qualifications, which is progressive.

A large part of progressive earnings mobility, and indeed the progressive elements of the life cycle, are related to job change factors such as promotion, changing jobs (without experiencing 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 mainly 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 loads. 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 peoples lives such as promotions, redundancies and moves between full and part-time work, which are irregular, discrete and not always in same direction.

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

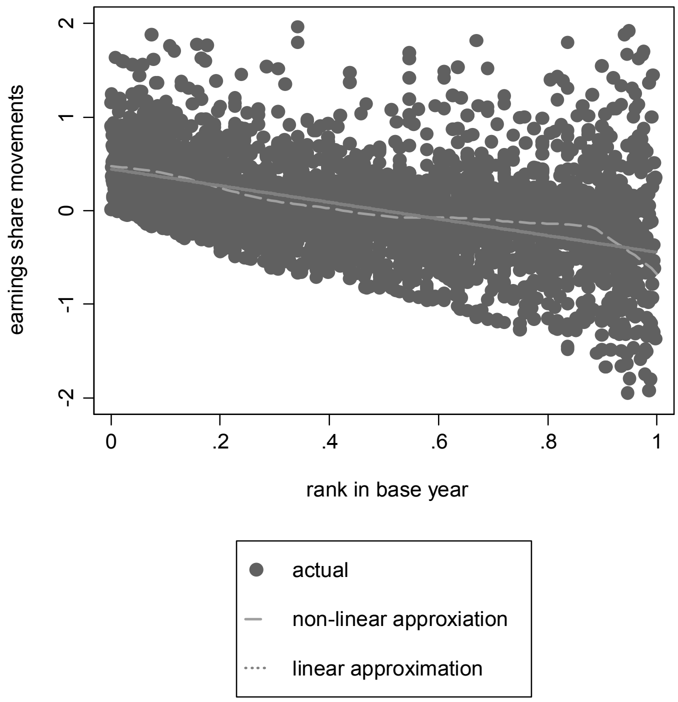


Figure 2: Mobility profiles

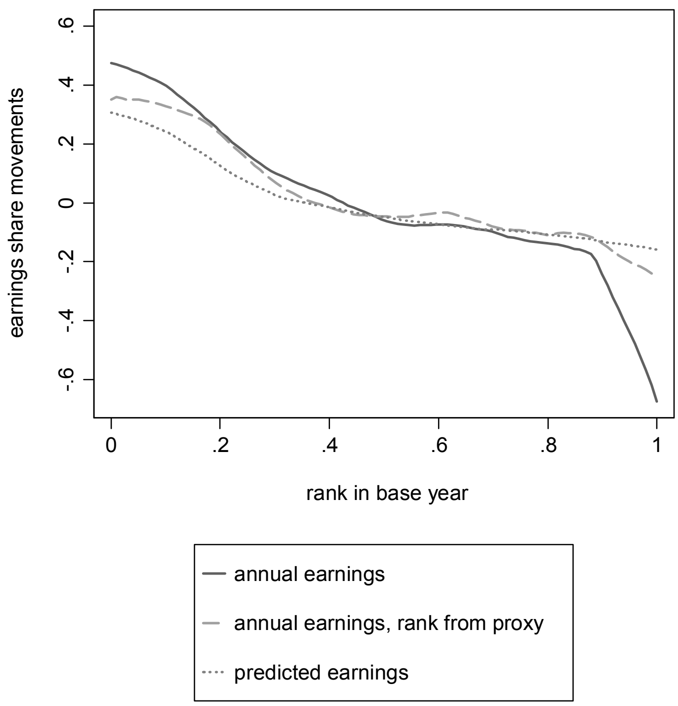


Figure 3. Weighted mobility profiles (inequality aversion parameter = 2)

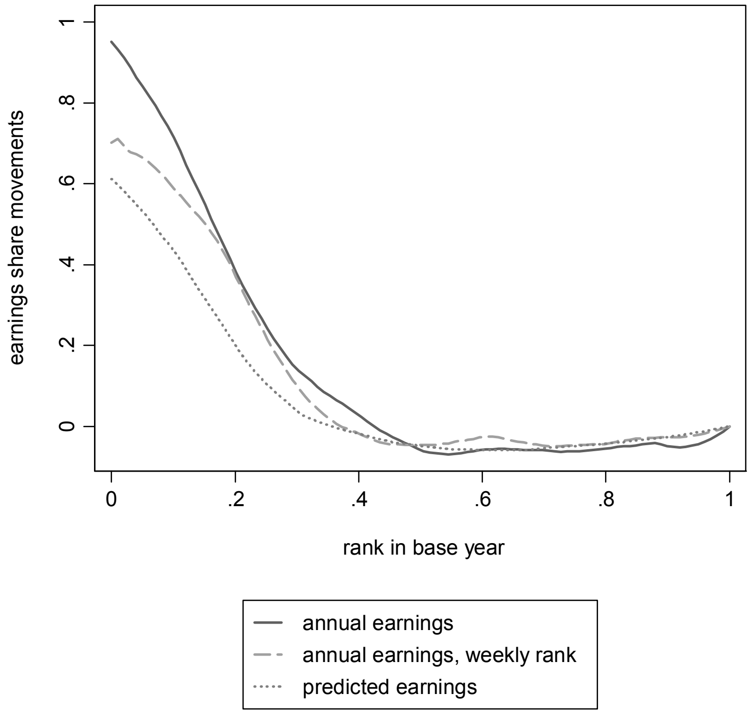


Table 1. Details of sample restrictions and result on sample size

	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
Omitting zero weekly earnings			
Mean	42,270	50,926	39,435
Standard deviation	32,232	35,037	26,472
N	3,463	3,463	3,463
Correlation between earnings measures for 2001/02			0.74

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 varying measures of earnings in 2001/2 and 2008/9[1]

	Gross annual earnings (1)	Gross annual earnings - 2 year average (2)
Initial S-Gini	0.368	0.331
	(0.006)	(0.005)
Final S-Gini	0.345	0.318
	(0.005)	(0.005)
Absolute change	-0.023	-0.013
	(0.006)	(0.005)
R-component	0.126	0.089
	(0.005)	(0.004)
P-component	0.148	0.102
	(0.008)	(0.006)
Relative change (%)	-6.2	-3.9
R-component (%)	34.1	26.8
P-component (%)	40.3	30.8
N	3,733	3,195

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

Table 4. Aggregate Pro-Poorness of earnings growth, lower and upper bounds[1]

	Gross annual earnings (1)
Observed P	0.148
Lower bound (2SLS estimate)	0.072
Upper bound (proxy rank estimate)	0.103
N	3,733

Table 5. Explaining Pro-poor 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 Pro-poor 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***
	(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)

	Coeff (se's) (1)	Contribution to β_p (2)	Coeff (se's) (3)	Contribution to β_p (4)
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
	(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	-0.001	0.007***	-0.001	0.019***

	Coeff (se's) (1)	Contribution to β_p (2)	Coeff (se's) (3)	Contribution to β_p (4)
working	(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	
	(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

Appendices

Table A1. 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

Sample characteristics	Mean	Sample characteristics	Mean
Life events occurring between initial and final period		Worked 25% to 49% of initial year	0.031
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

Table A2. Inequality decomposition of earnings between 2001/2 and 2008/9[1], raw estimates vs estimates adjusted for sample attrition

	Original estimates (unweighted) (1)	Weighted (2)
Initial S-Gini	0.368	0.365
	(0.006)	(0.008)
Final S-Gini	0.345	0.338
	(0.005)	(0.005)
	-0.023	-0.027
Absolute change	(0.006)	(0.006)
	0.126	0.133
R-component	(0.005)	(0.005)
	0.148	0.160
P-component	(0.008)	(0.007)
Relative change (%)	-6.2	-7.4
R-component (%)	34.1	36.4
P-component (%)	40.3	43.8
N	3,733	3,733

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

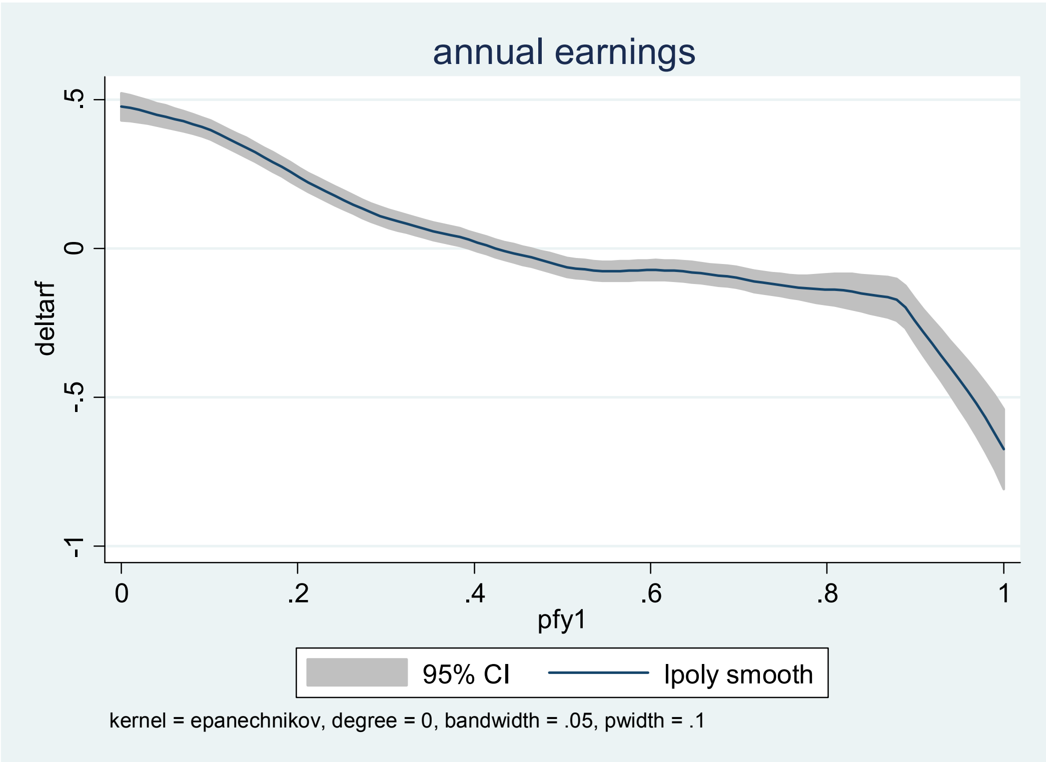
Table A3. Inequality decomposition – sensitivity to including imputed earnings

	Original estimates	Including imputed earnings where missing earnings information
Initial S-Gini	0.368	0.373
Final S-Gini	0.345	0.348
Absolute change	-0.023	-0.025
R-component	0.126	0.128
P-component	0.148	0.153
Relative change (%)	-6.2	-6.7
R-component (%)	34.1	34.3
P-component (%)	40.3	40.9
N	3,733	4,018

Table A4. Non-linear and linear approximations of pro-poor component of earnings mobility

	Annual rank	Weekly rank
Observed pro-poor component (P)	0.148	0.103
Non-linear approximations of P		
Actual earnings growth	0.144	0.120
Predicted earnings growth	0.072	0.073
Linear approximations of P		
Actual earnings growth	0.148	0.101
Predicted earnings growth	0.074	0.078

Figure A1. Mobility profiles – confidence intervals



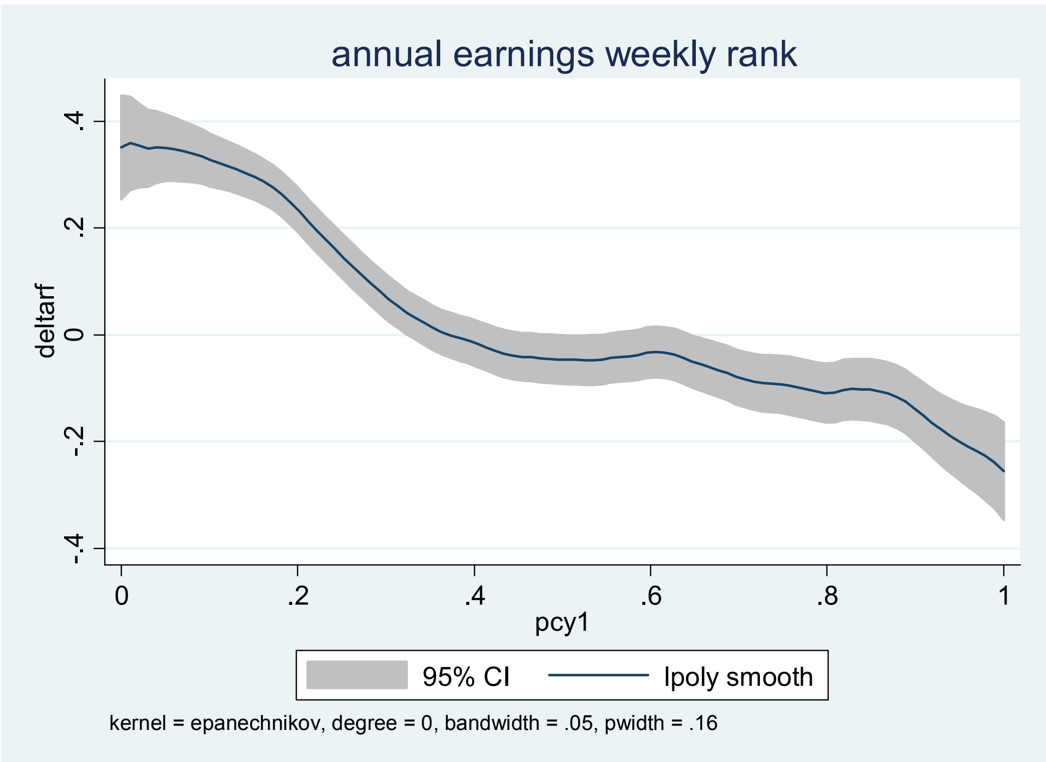


Figure A2. Kernel densities of earnings distributions, observed annual earnings vs proxy measure of annual earnings

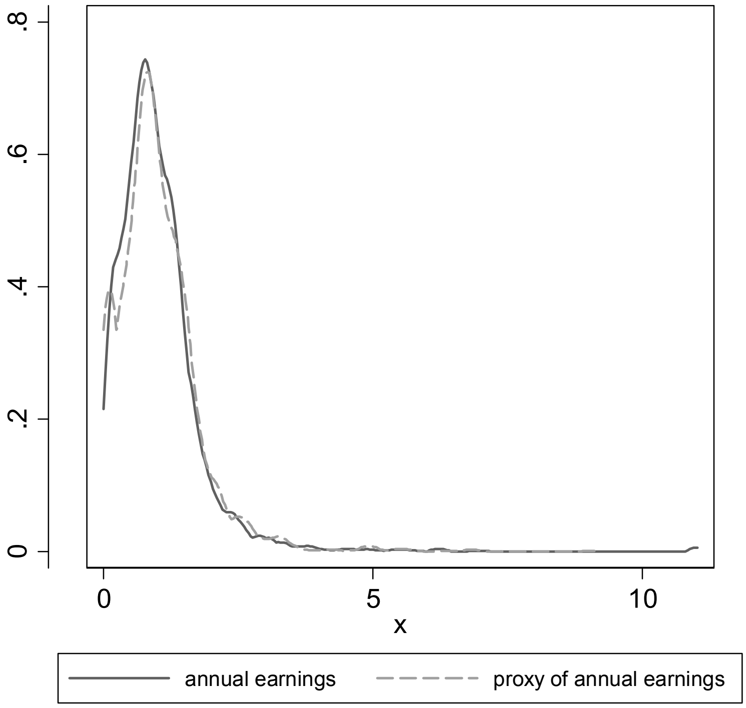


Figure A3. Mobility profiles – including imputed earnings

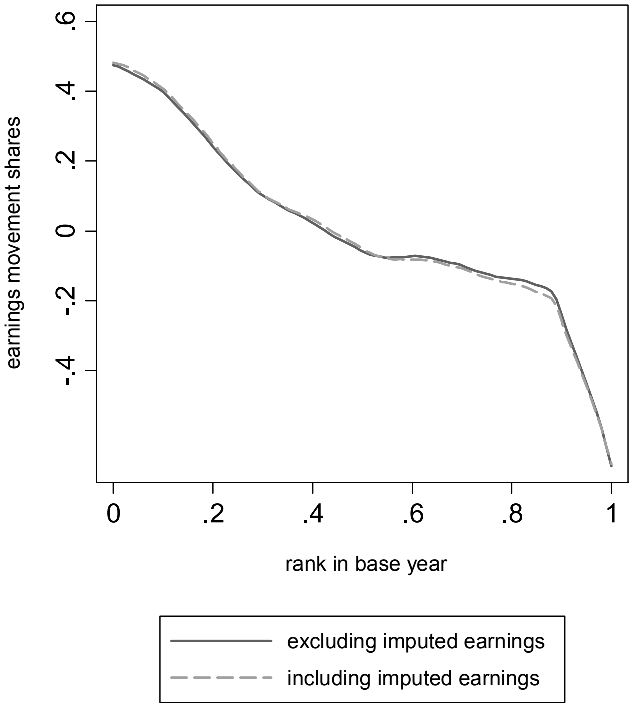


Figure A4. Mobility profiles – sensitivity to excluding non-earners

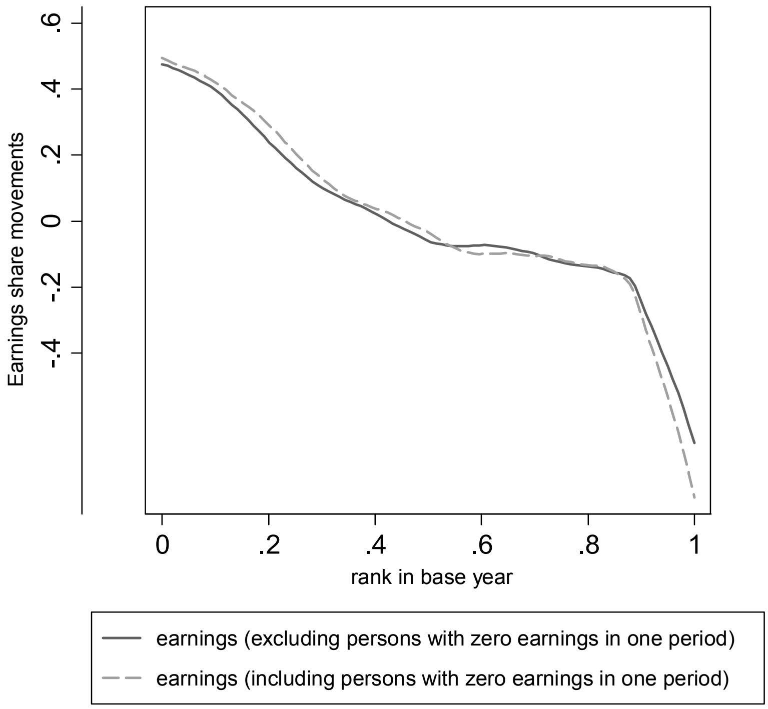


Figure A5. Zero earners in base year, rank in final year

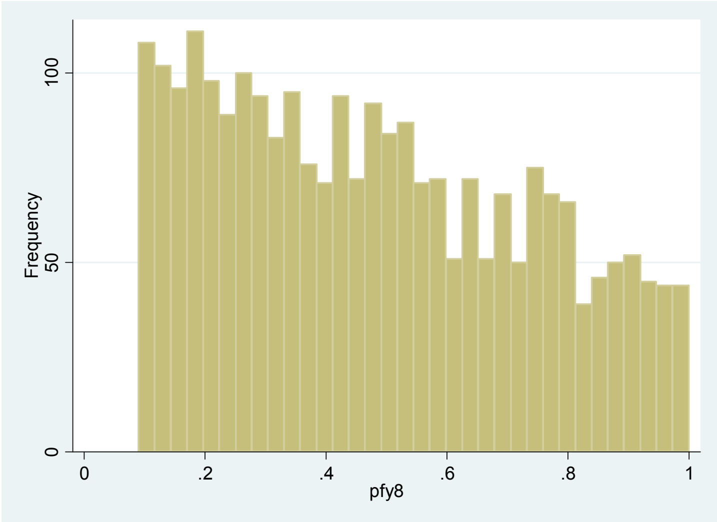


Figure A6. Zero earners in final year, rank in base year

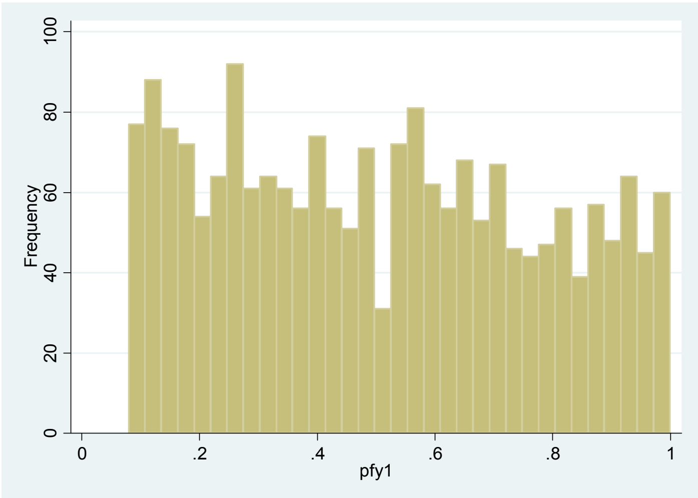


Figure A7. Mobility profiles – predicted earnings

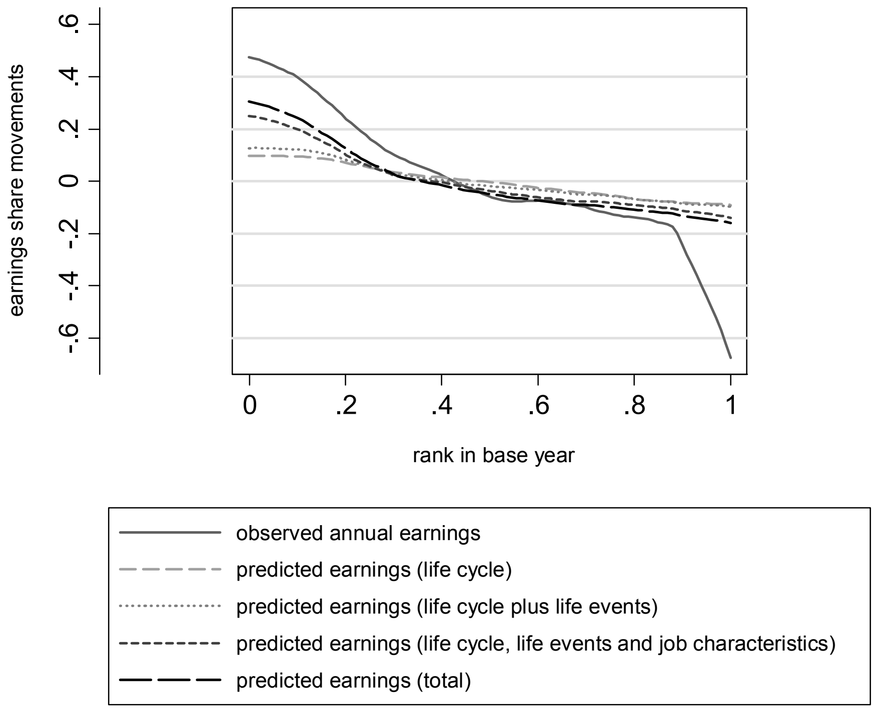


Figure A8. Mobility profiles – alternative 2SLS approaches