An International Comparison of Lifetime Labor Income Values and Inequality: A Bounds Approach[*]

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Abstract

In this paper, we compare and contrast earnings inequality and mobility across the U.S., Canada, France, Germany and the U.K. at the turn of the 21st century. We first construct and estimate a flexible model of individual earnings dynamics for each country that isolates mobility within a stable earnings distribution, allowing, or not, for individual fixed effects. We then simulate individual earnings trajectories given base-year earnings (1998) and construct lifetime annuity value distributions for each country. Our model provides an excellent fit to both the earnings and the mobility data despite its simplicity and limited data requirements. Our results show that equalizing mobility is positively correlated with earnings inequality with the U.S. displaying the most equalizing mobility and France the least. The models with and without fixed effects provide upper and lower bounds, respectively, on the resultant lifetime inequality levels in each country, and reveal that the countries are much more similar in terms of long run inequality than cross-section measures suggest.

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1 Introduction

Because individuals are subject to shocks that make them change and exchange positions within earnings distributions, cross-sectional survey data can only offer an incomplete picture of earnings inequality across countries or across different groups within the same country. In order to account for such sources of instability as unemployment risk and, more generally, earnings mobility, it is thus essential to consider long run measures of earnings inequality.

Long run earnings inequality studies are usually based on measures of permanent income obtained by averaging actual, individual or familial, pre- or post-tax income series over periods of at least five years with a strong preference for even longer panels.[1] However, as few countries have collected long panel data sets, the number of cross-country studies of earnings mobility and long run earnings inequality is small relative to the large literature that compares and contrasts cross-section earnings inequality across countries.[2]

Moreover, besides requiring long panel data sets, the use of five-year-or-more earnings averages has the drawback of mixing structural mobility (changes in the steady-state equilibrium wage distribution) and exchange mobility (earnings dynamics within a particular steady-state equilibrium) – the dynamics of the economy and that of individuals.[3] It is therefore arguable that a model of earnings dynamics is useful both to filter out macroeconomic trends and to simulate lifetime earnings.[4]

Our aim in this paper is to develop a model that is at the same time highly flexible, for the simulations to remain credible even over long time spans, and easy enough to estimate and simulate for a large cross-country comparison study to be feasible. We start by detrending the

[1] See Moffit and Gottschalk (2002) for a discussion as to why at least five years are necessary for averaging.

[2] Examples of comparative studies of mobility include the following. Aaberge et al. (2002) compare the U.S. and Scandinavian countries (Denmark, Norway and Sweden). Burkhauser, Holtz-Eakin and Rhody (1997), Burkhauser and Poupore (1997), Maasoumi and Trede (2001), and Schluter and Trede (2003) compare post-government-tax family income in the U.S. Panel Study of Income Dynamics (PSID) and the German Socio-Economic Panel (GSOEP) in the 1980's before the reunification of East and West Germany. Van Kerm (2004) compares Belgium (Belgium Socio-Economic Panel), Western-Germany (GSOEP) and the U.S. (PSID) as far as post-tax-and-transfer disposable household income in 1985 and in 1997 is concerned. Buchinsky et al. (2003) and Fields (2005b) look at earnings mobility in France and the U.S. between 1970-1995 using PSID data and the French DAS/DADS register data. Cohen (1999) and Cohen and Dupas (2000) use a search model to compute lifetime welfare functions for French and American workers and compare the cost of unemployment in both countries. Flinn (2002) compares Italy and the U.S. in 1988-1989. For cross-country comparisons of earnings inequality see the surveys of Levy and Murnane (1992), Katz and Autor (1999) and Gottschalk and Smeeding (2000).

[3] In addition, this constraint makes it difficult to study different time periods as lengthy representative panels are then required for multiple time periods. When a single panel is available for such a long period, e.g. the Panel Study of Income Dynamics (PSID) in the US or the German Socio-Economic Panel (GSOEP), authors often argue that the full panel should be used to get a more accurate measure of permanent income rather than breaking up the panel to study different time periods. See Gangl, Palme and Kenworthy (2007) regarding the former argument and Baker and Solon (2003) as an example of the latter.

[4] Lillard (1977) is one of the first paper to use this approach to measure human wealth and its dispersion. See Haider (2001), Flinn (2002) and Bowlus and Robin (2004) for recent applications.

earnings data to remove any structural mobility. The earnings process is then assumed to be a function of standard observable characteristics such as sex, education and experience. While the analysis is conducted separately for males and females, parametric forms are assumed for the dependence of earnings and its dynamic process on education and experience. We also allow for unobserved heterogeneity through an individual fixed effect in log wage means and for heteroskedasticity conditional on education and experience. The distributions of the fixed effects and the residuals are estimated nonparametrically. Next we use a flexible copula approach (the continuous equivalent of matrices of transition probabilities across earnings quantiles) to model the dynamics of individual ranks of the standardized residuals within the marginal distributions. We then put these two components together and compute simulated realized values needed to construct our lifetime earnings measures.[5] Finally, the amount of equalizing mobility is measured by the ratio of lifetime earnings inequality to base-year earnings inequality (Shorrocks, 1978, Fields, 2005b).

We model the autoregressive dynamics of the ranks of the standardized residuals in a flexible way by combining multinomial logit models for movements between earnings deciles and employment states over time with a smooth nearest-neighbor procedure for within decile placement. Hence, like the more traditional literature on earnings mobility (e.g. Gottschalk, 1997, Buchinsky and Hunt, 1999), we also consider relative mobility and model, as nonparametrically as possible, the joint distribution of consecutive ranks. In this way, we do not impose any undue symmetry.

In addition, our model also incorporates some of the features of the dynamic earnings models found in the literature.[6] It has the familiar factor structure with a deterministic component, a permanent component, and a transitory, covariance-stationary component. Yet, the dynamics of the transitory shocks are less complex. In particular, the permanent component is a standard fixed effect and the transitory component is only first-order Markov. With respect to the former our model allows for very little unobserved heterogeneity compared to Alvarez et al. (2007), Altonji et al. (2007) and Pavan (2008), for example. With respect to the latter, our transitory innovations are much simpler than, for example, the ARCH process in Meghir and Pistaferri (2004).

We treat the individual-specific, unobserved factor as a fixed effect and we do not allow for measurement error. This makes the model very straightforward to estimate. However,

[5]An alternative would be to use present values (Lillard, 1977). Bowlus and Robin (2004) show that results using present or realized values are qualitatively identical.

[6]See, for example, Moffitt and Gottschalk (1995, 2002), Baker (1997), Haider (2001), Baker and Solon (2003), Geweke and Keane (2000, 2007), Meghir and Pistaferri (2004), Alvarez et al. (2007), Altonji et al. (2007) and Pavan (2008).

short panel data are likely to yield inconsistent estimates. We thus show that disregarding unobserved heterogeneity in marginal distributions over-predicts mobility. The fixed effect model reproduces the patterns of earnings rank-autocorrelations much better, despite some tendency to under-predict mobility. The two models – with and without fixed effects – therefore provide useful bounds for measuring the amount of equalizing mobility. Random-effect models such as those of Altonji et al. (2007) and Pavan (2008) are, by comparison, considerably more difficult to estimate whereas our methodology only requires standard econometric software (OLS and MLOGIT procedures) and can be easily utilized by non-academics.

The countries of our study were chosen to showcase both a range of earnings inequality levels and a range of earnings and employment mobility patterns. They include the U.S., the U.K., Canada, France, and Germany. For all five countries we use panels of three to seven years in length that cover the end of the 1990s with a base year of 1998. The use of this time period allows us to report on more recent trends in mobility as most studies - single and multiple countries - tend to use data from the 1980s and early 1990s.

Our main results are as follows. First, our model provides an excellent fit to the data; it even captures the tail dependence remarkably well. Second, the U.S. displays the most earnings mobility with the U.K. second followed by Canada, Germany and France.[7] Third, the U.S. also displays more employment mobility followed closely by the U.K. and Canada. France and Germany display far less employment mobility than the other countries. Fourth, lifetime inequality measures that incorporate only earnings mobility leave the cross-country inequality rank orderings basically the same with the U.S. displaying the most inequality. Fifth, the inclusion of employment mobility brings the countries much closer together as employment mobility is an equalizing factor in the U.S., the U.K. and Canada and a non-equalizing factor in France and Germany. Thus, despite large differences in earnings inequality in 1998, overall the countries display more similar lifetime inequality levels. How much more depends on whether or not one allows for unobserved heterogeneity.

Given our results, we speculate that mobility likely reduces earnings inequality over a lifetime by about 20-30% in the U.S., Canada and the U.K. and very little, if at all, in France

[7]The OECD Employment Outlook of 1996 draws the following conclusion about earnings mobility between 1986 and 1991 across various OECD countries including the U.S., France and Germany. "The conclusion that similar and substantial levels of mobility prevail across countries is also confirmed when movements across earnings quintiles are examined. [...] indices suggest that Denmark, the United Kingdom and the United States (and, perhaps, Finland) had somewhat higher rates of earnings mobility than France, Germany, Italy and Sweden. But the overall picture is, nevertheless, one of considerable similarity." [page 79] Contini (2002) uses the OECD (1996) data and refines the Employment Outlook's conclusion as follows. "Upward and downward mobility of the relatively better off fraction of the workforce is higher in the USA than in the European countries.[page 5] " Therefore, the cross-country mobility differences that we find seem to be a more recent phenomenon, that was amplified during the 1990's.

and Germany. Within our sample of countries, the countries with relatively higher earnings inequality are also those countries with more equalizing mobility. Thus, incorporating mobility reveals that countries with North American style labor markets are more similar to countries with Continental European style labor markets in terms of long run inequality than measures of short-run inequality would suggest.

Finally, we note that our use of simulation methods to construct lifetime earnings profiles in order to estimate long run measures of inequality is closely related to the methods used by Flinn (2002) and Bowlus and Robin (2004) and to a lesser extent Cohen (1999) and Cohen and Dupas (2000). These papers use partial-equilibrium, on-the-job, stationary search models as a behavioral model and compute present values to measure individual welfare. They all find mobility results in significant equalization in the U.S.; enough equalization to bring the U.S. close to Italy (Flinn, 2002) and France (Cohen, 1999) in terms of long run inequality. While similar in spirit and results, our model is considerably more flexible than these models both because it allows for unobserved heterogeneity and because it is not restricted by the rather stringent implications of search theory.

The plan of the paper is as follows. The next section develops a theoretical framework for computing lifetime values. The data are discussed in Section 3. Section 4 discusses the fit of the model, and Section 5 analyzes the results. Conclusions are given in Section 6.

2 The Model

In this section we explain how we model individual earnings dynamics and how we then use this model to simulate individual trajectories and compute lifetime earnings.

Our goal is to have the model satisfy the following requirements. First, it should be conditional on individual characteristics like gender, education and experience. While it is possible to cluster the population by gender and we do so, the number of potential interactions between the other covariates rules out an approach based on clustering the population by all these characteristics and modeling employment and earnings dynamics unconditionally within each population cluster. Hence, we develop a parametric index model for exogenous individual covariates that allows for non-linearity and interactions between covariates.

Second, conditional on individual characteristics, the model for the joint distribution of two consecutive earnings should be flexible. It is thus important to allow for non-symmetric dynamics. For example, wage decreases should be more likely when one is at the top of the earnings distribution and increases more likely when one is at the bottom. In addition, the model should be simple enough to make Monte Carlo simulation easy. Therefore, we adopt a nonparametric approach based on first discretizing the support of the marginal distributions and then smoothing the empirical distribution.

Third, the model should isolate the dynamics of individual positions within marginal earnings distributions separately from the dynamics of the marginal distributions themselves. To this end, we detrend the earnings data before conditioning the marginal earnings distributions on interactions between education and experience and modeling the residual stochastic dynamics of individual ranks within the equilibrium cross-sectional earnings distributions.

2.1 Model Specification

To meet the above requirements we set up the following model. First, we detrend all wages by regressing log earnings on time dummies interacted with education dummies.[8] Let w_{ht} denote the detrended earnings for an employed worker h at time t. Next, we posit a linear regression regression for log earnings

$$\ln w_{ht} = x_{ht}\beta + f_h + e_{ht}, \tag{1}$$

where x_{ht} is a vector of regressors comprising education dummies interacted fully with a quartic function of potential experience. We allow (or not, for comparison) for a fixed effect f_h. The components of the parameter β that are associated with time-varying variables are estimated by the within-group estimator. The remaining components of β and the fixed effect f_h are estimated by applying OLS to the within-group regression residuals.

We also allow for conditional heteroskedasticity of the following form

$$\operatorname{Var}(e_{ht}|x_{ht}) = x_{ht}\gamma, \tag{2}$$

where the parameter γ is estimated by regressing the squared residuals $\widehat{e}_{ht}^2$ on x_{ht}. To improve efficiency, we then re-estimate β and f_h by weighted least squares, with weights proportional to $(x_{ht}\widehat{\gamma})^{-1/2}$.

Let G be the cumulative distribution function (cdf) of the standardized residuals, $u_{ht} = \dfrac{e_{ht}}{\sqrt{x_{ht}\gamma}}$. We estimate G by the empirical cdf of $\widehat{u}_{ht} = \dfrac{\widehat{e}_{ht}}{\sqrt{x_{ht}\widehat{\gamma}}}$. Let $r_{ht} = G(u_{ht})$ be the rank of the residual u_{ht} in the distribution G. We estimate r_{ht} by $\widehat{r}_{ht} = \widehat{G}(\widehat{u}_{ht})$. Finally, let q_{ht} denote a discrete version of the ranks r_{ht},

$$q_{ht} = \max\left\{\frac{\lfloor N r_{ht}\rfloor + 1}{N}, 1\right\}, \tag{3}$$

where $\lfloor\cdot\rfloor$ is the integer part function. Note that q_{ht} is never equal to 0 even if w_{ht} is the minimum earnings. Hence, we use the notation $q_{ht} = 0$, if individual h is unemployed at time

[8] As stated above, the model is estimated separately for men and women. To simplify the notation we do not index the parameters by gender.

t. We call "state" the value of q_{ht} in $\{0, \frac{1}{N}, \frac{2}{N}, ..., 1\}$. In the empirical analysis N is set equal to 10.

Incorporating transitions between employment and unemployment is nonstandard in the earnings dynamics literature as authors often require individuals to have positive earnings in every year of the period under study. However, unemployment risk has been shown to be an important component of variation in earnings as well as measures of lifetime inequality (see Bowlus and Robin (2004), Altonji et al. (2007) and Pavan (2007)). In addition there is wide variation in unemployment risk across countries and as such its inclusion makes a difference in cross-country comparisons. Thus, we include unemployment as a state in our transition matrix in order to incorporate unemployment risk in our analysis. However, we recognize that determining the level of income during unemployment is basically an ad hoc process and so we conduct sensitivity analysis to this choice in our analysis.

Standard ARIMA models of earnings dynamics typically require only a few parameters and, therefore, characterize changes in earnings means and variances well but fail to produce a good description of tail dependence. For this reason a common practice in the literature of earnings inequality and earnings mobility is to examine matrices of transition probabilities across quintiles or deciles (e.g. Buchinsky and Hunt, 1999). We adopt this approach here as well.

Let $P(i, j|x_{ht})$ be the probability of moving from state $q_{ht} = i$ at time t to state $q_{h,t+1} = j$ at time $t+1$, with $\sum_j P(i, j|x_{ht}) = 1$. We parameterize the transition probabilities $P(i, j|x_{ht})$ using multinomial logits for each initial state i. Specifically,

$$P(i, j|x_{ht}) = \frac{\exp[x_{ht}\kappa(i, j)]}{\sum_{m=0}^{N} \exp[x_{ht}\kappa(i, m)]}. \tag{4}$$

The set of covariates for these multinomial logit models includes an experience quadratic and the set of education dummies. However, in this case we do not allow for interactions due to small sample sizes within some education*experience groups for some state-to-state transitions.

If the destination cell sizes are too small, e.g. destination quantiles distant from the quantile interval of origin, we collapse infrequent destination quantiles together. For example, if for $q_{ht} = \frac{1}{10}$ there is little chance to reach a rank at $t+1$ above $\frac{5}{10}$, irrespective of the vector of individual characteristics x_{ht}, we concatenate the whole range of ranks $r_{h,t+1}$ above $\frac{1}{2}$. Specifically, upper and lower destination deciles are combined by collapsing all destination deciles $\left[\frac{j-1}{10}, \frac{j}{10}\right]$ such that $|j - i| > k$, for some k, where $\left[\frac{i-1}{10}, \frac{i}{10}\right]$ is the decile of origin.

Having produced an approximation of the joint distribution of ranks at times t and $t + 1$ given covariates x_{ht} at discrete nodes, we then obtain an approximation over the whole range of rank values by using a nearest neighbor procedure. Given r_{ht} and x_{ht} we predict the quantile at $t+1$, $q_{h,t+1}$, using the multinomial logit models. Then we predict $r_{h,t+1}$ as the value of $r_{h,t+1}$ in the data that yields the closest match of r_{ht} and $q_{h,t+1}$.

One aspect of the earnings data that we do not model is measurement error. In general validation studies of wage and earnings data find that measurement error is nonclassical and mean reverting, i.e. individuals under report high wages and over report low wages (Bound et. al. (2001) and Gottschalk and Huynh (2007)). While classical measurement error would tend to overstate inequality, nonclassical measurement error results in an understatement of earnings inequality. In terms of earnings mobility the effect of nonclassical measurement error is less clear. Evidence from Gottschalk and Huynh using data from the U.S. Survey of Income and Program Participation (SIPP) matched to U.S. tax records (assumed to be measured without error) indicates that the effects from the nonclassical measurement error are largely offsetting when examining earnings mobility. Thus, even though the SIPP data are found to be measured with error and this results in an understatement of earnings inequality, estimates of the correlation in earnings over time from the SIPP are found to be similar to estimates from the tax records. Since we do not have access to validation data for each country nor an identification strategy for estimating the form and/or degree of measurement error, we do not attempt to incorporate measurement error into our model. We recognize that our measures of earnings inequality may understate the true levels, but we expect the reporting biases to be similar across the countries and we are encouraged by Gottschalk and Huynh's finding that our mobility measures may not be biased.

2.2 Simulation of the Value Functions

In Bowlus and Robin (2004) we computed both ex ante and ex post lifetime income values with the former based on taking expectations or averaging over expected future transition paths and the latter based on simulated paths for each individual in the sample. Here we adopt the ex post measure of lifetime income values as our unit of analysis because in our previous work we found that the results for ex post and ex ante values were qualitatively similar and ex post values are easier to compute.

To simulate an individual's remaining path from some date t onward we start them at their current employment state and salary. Next, we randomly draw a sequence of states for the periods following t until their retirement year based on their experience level, which increases with age, and their characteristics using the same marginal distribution G and the same transition probability matrix P. So doing, we allow the individual's age to change and modify the earnings process but the macroeconomic environment responsible for shifts in G

and P is held fixed in its state at time t.

While employed, individuals receive the annualized value of their earnings. Income during unemployment is equal to a country specific unemployment insurance replacement rate ρ times the previous period's annual earnings if the individual was working in the previous period and times a minimum earnings level, $\underline{w}$, if the individual was unemployed in the previous period. Finally, we set income following retirement at age $\overline{a}$ equal to 0.

Let $\mathcal{E}_{at}(w)$ be the discounted sum of the predicted future income stream for someone with age a and wage w at time t. In order to compare present values across all individuals, not only those within the same cohort, we compute the annuity value of employment rather than the stock value. To convert stock values $\mathcal{E}_a(w)$ into annuity values we use the standard formula for an annuity $\mathcal{A}_{at}(w)$ with interest rate r such that:

$$\mathcal{A}_{at}(w) = \frac{\mathcal{E}_{at}(w)}{\sum_{t=1}^{\overline{a}-a+1} \frac{1}{(1+r)^t}} = r\mathcal{E}_{at}(w)\frac{(1+r)^{\overline{a}-a+1}}{(1+r)^{\overline{a}-a+1}-1}. \tag{5}$$

In the empirical analysis r is set equal to an annual rate of 5%.

3 Data Description

In this section we describe the data used from each of the countries to conduct the above exercise. We have chosen to examine data from the U.S., the U.K., France, Germany and Canada in order to present a wide range of cross section inequality levels as well as varying mobility patterns. The inequality analysis below examines the year 1998 for all of the countries, and all five of these countries have at least three-year panel data sets that cover the late 1990's. We have tried as much as possible to make the samples consistent across the countries. We note below where this has not been possible. For the U.S. we use the Survey of Income and Program Participation (SIPP) for 1996-1999. For France we use individuals in the three-year panel from the French Labor Force Survey (LFS) for 1997-1999. [9] The 1996-2001 wave of the Survey of Labour and Income Dynamics (SLID) is used for Canada. For the remaining countries we use ongoing panel data sets including The British Household Panel Survey (BHPS) for the U.K.

[9] The French LFS is a rotating three-year panel that starts a new three-year wave every year. Here we include only those individuals from the 1997 wave who are in the panel all three years. Inclusion of individuals from the 1996 and 1998 waves for the years 1997-1999 results in too many individuals with only two wage observations. Estimating the fixed effect model with only two wage observations leads to residual terms that are equal in absolute value and the negative of each other. This leads to a transition matrix that has very little weight on the diagonals and a lot of weight on opposite decile transitions such as 1-10, 2-8, 3-7, etc. Thus to avoid this pattern which results solely because of the length of the panel we require individuals be in the panel for three periods. Because the French LFS is a residence based survey unlike the others which are individual based surveys, one implication of this restriction, and the survey structure in general, is that individuals who move during the survey period will be dropped. While we cannot test this implication on the French data we did estimate the model for the U.S. excluding individuals who move during the survey period. The two samples produced very similar results suggesting movers and non-movers in the U.S. face the same levels of mobility.

and the German Socio-Economic Panel (GSOEP) for Germany. For these latter countries we use seven years of data from 1995-2001.[10]

Unlike in Bowlus and Robin (2004) and most other inequality studies, we do not impose many sample restrictions. Instead our samples include most individuals, i.e. males and females, all races,[11] and full- and part-time workers. For each year of the panel we exclude individuals who are self-employed,[12] in the military, and those out of the labor force.[13] The latter includes those who are retired, enrolled in school and who work less than 10 hours per week. Finally, our sample is restricted to individuals between the ages of 16 and 65 for the U.S., U.K. and Canada and ages 16 to 60 for France and Germany with the latter reflecting the earlier retirement age in those countries.

For the transitions we use the labor force status of the individual at the time of the annual surveys in France, the U.K. and Germany. For Canada we use the labor force status in the month of March, and for the U.S. we use the month the individual was first surveyed in 1996. We then examine the transitions of individuals who are employed or unemployed (as classified by the surveys) in adjacent years.

To standardize all annual earnings values we use a full-year earnings measure. For the U.S. and France we multiply the monthly earnings by 12.[14] U.S. figures are reported in U.S. dollars, while the French earnings measure is divided by 6.55957 to convert to Euros. For Canadian earnings we divide annual earnings by weeks worked and multiply by 52 and report the figures in Canadian dollars. Figures for the U.K. are reported in British pounds and are calculated by multiplying the monthly wage by 12. Finally, for Germany the monthly wage is multiplied by 12 and then divided by 1.95583 to convert to Euros. All earnings measures are deflated by consumer price indices for each country with a base year of 1990. To deal with top-coding in the SIPP data we use the imputed base year averages given in the SIPP for top-coded values multiplied (prior to deflation) by a growth factor of 1.019 raised to the number of months since the base year.[15] Top-coding is not an issue for the other countries although in the French LFS

[10]The sample sizes of the BHPS and GSOEP are substantially smaller than the SIPP and the French LFS. So to increase the sample size we use a longer time period. However, we do not use the full available panels for the U.K. and Germany in order to make the results more comparable with the other countries.

[11]We do not include race in x because race is not identified in the data sets for all countries.

[12]We also exclude unpaid family workers under self-employed in Canada. In the French LFS we use the occupation or profession variable to exclude self-employed workers. In this case we exclude self-employed farmers, craftsmen, retail and small firm executives. For Germany we exclude self-employed or free lance professional workers. In addition to those in school in the UK we exclude those in government training programs and in Germany those in apprenticeship programs.

[13]Thus an individual does not have to meet all of our requirements over the entire panel to contribute to the analysis. Only those person years in which the requirements are not met are dropped.

[14]The SIPP collects earnings for each month on up to two jobs. We sum the monthly earnings from each job to compute our monthly earnings measure.

[15]This procedure to deal with top coding follows that given in the SIPP manual.

we do delete monthly earnings greater than 900000. Finally, we weight all calculations using the appropriate weights given in each data set.[16]

We use a trim procedure to deal with outliers in the data. Minimum and maximum earnings levels are determined using the 1998 samples and then applied to the other years. We trim earnings at the top and bottom for each sex*education group. This results in mean earnings that vary appropriately across groups reflecting each group's relative position in the market. The trim levels vary with the quality of the data in each country. For the U.S. we trim 2% at the bottom and 1% at the top. For France and Germany we trim 1% off the top and bottom. For the U.K. we trim 1% off the top and 2% off the bottom and for Canada we trim 2% off the top and bottom. These trim levels are non-trivial and basically remove all of the excess kurtosis from the log wage distributions. However, our inequality indexes (ninety-ten percentile ratios and Gini coefficients) are relatively indifferent to the length of the upper and lower tails,[17] and thus the results are generally insensitive to variation in the trim levels around these values.

As noted above the regressors in the transition probability and wage models include indicators for education levels. For the U.S., Canada and France there are four education categories that correspond to less than high school, high school, some college, and university. Because of the sample size issues mentioned above as well as coding issues in their surveys we use only three education categories for the U.K. and Germany. For the U.K. the categories are less than high school, high school graduate and more than high school. For Germany the categories are based on a years of education measure grouped as follows: no more than 10 years, more than 10 but less than 14 years, 14 or more years. Experience is computed as age minus age at end of education where the latter age is standardized for each education category.[18]

The sample size is not large enough in any of the countries to get an accurate picture of the transition probabilities if only the transitions between 1998-1999 are used. Thus we use all of the year-to-year transitions observed over our sample periods to estimate the multinomial logit models. Only the U.S. has a large enough sample size and mobility level such that an 11 by 11

[16] We do not use the weights given in the BHPS. The longitudinal weights for the late 1990s require the individual to have been in the sample continuously since the survey began in 1991 otherwise the individual is given a weight of zero for that year. Since we only require the individual to be present in two consecutive years, the weight requirement is much more stringent than ours and results in a nontrivial reduction in the sample size. We also do not use the cross section weights because they are very close to 1 and also not available for all individuals in the sample in each year. Since they are very close to 1, using them makes little difference and so we opted for the larger sample size in order to better fill out our transition matrix.

[17] For a study on upper-tail inequality in the U.S. and France see Piketty and Saez (2003).

[18] To maintain consistency in terms of experience levels within an education group we set age at end of education equal to a common figure for each education level. For the U.S. and Canada this age level is 16 if less than high school, 18 if high school graduate, 20 if some college and 22 if university. For the French data we set the age at end of education equal to 16 if less than high school, 19 if high school, 21 if some college, and 24 if university. For the U.K. we set it at 16 if less than high school, 18 if high school graduate and 21 if greater than high school. Finally, for Germany we use 16 if 10 years or less, 18 if more than 10 but less than 14 years, and 21 if 14 years or more.

transition matrix can be recovered using a multinomial logit specification for each decile and unemployment. For the other countries we ran into the problem of small cell sizes and even zeros for some events. This was particularly true for the transition from the top of the earnings distribution to unemployment and vice versa. To take care of the small cell sizes, upper and lower destination deciles were then combined, as indicated before, by collapsing all destination deciles $\left[\frac{j-1}{10}, \frac{j}{10}\right]$ such as $|j - i| > k$, where $\left[\frac{i-1}{10}, \frac{i}{10}\right]$ is the decile of origin. For Canada, the U.K. and Germany, k was set equal to 3, while for France a less restrictive formulation was able to be used such that $k = 4$.

Finally we had to determine the earnings level to use to compute the income received during unemployment. Since in the 1998 sample we do not necessarily observe the previous earnings for unemployed individuals, we impute an earnings level using the regression coefficients and the characteristics of the individual with potential experience set to one year less than the current value. For future unemployment values in the simulation we either use the simulated earnings from the previous period or the minimum earnings levels by education and sex after trimming for those in unemployment more than one period. The replacement rates are taken from Martin (1996). These are gross replacement rates computed by the OECD in 1995 for an individual with a spouse at work. We use the values for the first year of unemployment. They are: 25% for the U.S., 18% for the U.K., 54% for Canada, 58% for France and 35% for Germany. As noted above we do some sensitivity analysis to this choice by also simulating lifetime values assuming income during unemployment is 0.

Because we merge several years of data we need to be concerned about any trends in earnings over the sample period, as these trends will be incorporated into the transition functions and the lifetime earnings measures if not removed. To remove any overall trends as well as trends within education groups we detrend the earnings data using year dummies interacted with the education categories. The year 1998 is taken as the control year such that these coefficients are not used when we simulate the future earnings trajectories.

In Table 1 we present the stationary equilibrium distributions that stem from our predicted transition probabilities. [19] If we have isolated only exchange mobility, the wage decile elements within each column should be the same and equal to 1 minus the equilibrium unemployment rate divided by 10. For most countries and for both men and women, the equilibrium distributions obtained from the homogeneous model show a somewhat uneven spread across the deciles. In the U.S. there is only a slight accumulation in the middle deciles. However, in the U.K. and

[19] To compute equilibrium distributions, we first average the transition probability matrix P across individual characteristics. The equilibrium distribution is the eigenvector associated with the first eigenvalue of its transpose. In the cases where the destination deciles are collapsed, we divide the predicted probabilities for entering the combined destination evenly across the deciles contained in that destination state.

Canada there is a marked accumulation in the top deciles; in France in the bottom deciles; and in Germany in both the right and left tails. Allowing for fixed effects results in a marked improvement for the U.K., Canada and Germany. In the case of France, allowing for fixed effects now induces an accumulation in the middle deciles. This is an indication that three years are not enough for a precise estimation of the fixed effects. With longer panels, our results suggest that our method of detrending the data is successful. We also do a reasonable job of matching the overall unemployment rate over the sample periods.[20]

4 Data Analysis and Model Fit

4.1 Cross-Section and First-Order Markov Dependence

In terms of fit, the proposed regression framework does a good job of capturing the features of the earnings data in both levels and logs. Tables 2 and 3 show the actual and predicted moments of the log earnings and earnings distributions for each country for males and females for the specifcations without and with unobserved heterogeneity, respectively.[21] Given our log wage specification the predicted means and standard deviations match those in the data almost exactly. In turn this yields a fairly good fit for the mean and standard deviation of the level distribution. The skewness and kurtosis predictions are not quite as good but in most cases the fit is reasonable given that these moments are not functions of the explanatory variables. While both model specifications match the mean and variance, the unobserved heterogeneity model fits the skewness and kurtosis levels better.

In order to examine how well we fit relative earnings mobility using the multinomial logit models and our interpolation procedure, we compute Spearman's correlation using the ranks from the actual and predicted log earnings data for each country. To do so we compute the rank correlations for actual log earnings in adjacent periods (combining the data across all two-year pairs in the sample period) and the rank correlations for actual log earnings in the first period and predicted log earnings from our model in the second period. We examine the rank correlations of the earnings data rather than the residuals even though our mobility model is estimated only on the residuals. Thus this test effectively captures how well the full model

[20] Since we use multiple periods to estimate the transition matrix we mitigate the problem of cyclical variation in unemployment rates to some extent. Our model matches the average unemployment rate over several years rather than the actual rate in any one year which may be high or low depending on whether the country is in a recession or boom. This is important when conducting cross-country comparisons as not all countries will be at the same stage of the business cycle during the base year. Only France with its relatively short sample period and high unemployment rate over this period is at greater risk of having its lifetime inequality measure influenced by the business cycle.

[21] The actual moments for log earnings differ across the two specifications because the weights are adjusted for the variance model which differs across the specifications. The unadjusted sample weights are used for the level calculations.

reproduces the observed earnings mobility. In addition we examine rank correlations rather than level correlations because we are interested in capturing exchanges within the distribution, not level changes. Further, in the simulation exercise the marginal distribution is fixed and mobility results entirely from rank dynamics. Table 4 presents the results by earnings decile of origin. The fit is very good with a slightly better fit for the middle deciles than the extreme deciles. Both specifications produce a good fit to the data in the middle deciles; for most countries the specification with unobserved heterogeneity produces a slightly better fit in the extreme deciles.

Several features of the data stand out in this table: 1) the U.S. exhibits much lower correlations than any of the other countries, 2) the correlation is larger at the extreme deciles of the distributions than in the middle, 3) it is larger for the top than the bottom, and 4) the correlation levels for males and females within each country are quite similar. The second and third conclusions are important as they justify our nonparametric approach. That is, one single correlation parameter does not permit a full characterization of the earnings autocorrelations throughout the entire distribution.

4.2 Long Run Dynamics

Given the flexibility of our model specification, it is likely not surprising that the model can return the main features of the data used in estimation. For a model of lifetime earnings the true test is long run dynamics. To measure the performance of our model over a longer period (as allowed by the length of each panel) we compute Spearman's correlation using the ranks at all possible orders. That is, for each 2-year, 3-year, 4-year, etc. pair observed in the data we compute the rank correlations between the actual earnings levels and the rank correlation between the actual earnings in the initial year and the earnings level predicted 2, 3, and 4 years later, respectively.[22] Table 5 displays the Spearman correlations at all possible orders for each country.

There is definite evidence that the model with no fixed effect fails to fit the long run dynamics. In particular, it predicts too much mobility over time resulting in correlations that decrease much faster with time than those found in the data. For example, in the U.S. the correlation in the data falls from 0.76 for 1-year differences to 0.66 for 3-year differences, while the model predicts a much lower correlation of 0.49 for 3-year differences. This pattern is found for both males and females in all of the countries. In comparison the fixed effect model

[22] For example for the U.S. we have 4 potential earnings observations for each respondent (1996, 1997, 1998 and 1999). Thus we have at most two 2-year observations (1996-1998 & 1997-1999) and one 3-year observation (1996-1999) for each respondent. Only respondents who are working in both periods enter into the calculations for the actual figures, and only respondents who are working in the initial period and predicted to be working in the latter period enter into the calculations for the predicted figures.

does a much better job, although it predicts more persistence in earnings over time than there actually is in the data. In fact the fixed effect specification produces very little decrease in the correlation over time suggesting that the fixed effects essentially maintain individuals' ranks within the distribution.[23] Given these two specifications produce results that encompass the observed correlations, they provide useful benchmarks or bounds on the amount of mobility in each country.

The figures in Table 5 support the previous finding that the U.S. exhibits much more mobility than the other countries with no other country coming even close to the low correlations for the U.S. The U.K. exhibits the second highest mobility levels, while Canada and Germany appear, perhaps surprisingly, to be quite similar. Finally, France is the most immobile country of all with the highest 1-year correlations and no apparent drop for 2-year correlations. Interestingly males and females exhibit the same correlation patterns despite differences in the earnings distributions themselves.[24]

The full sample correlations in Table 5 are much higher than the conditional correlations in Table 4. This pattern indicates that a significant part of the overall (auto)correlation is between deciles with the remainder within deciles. This finding is particularly true for the U.S.

It is interesting to examine whether the correlation patterns vary by education or experience. Table 6 shows the education results for male workers, while Table 7 shows the experience results.[25] In general we find that younger and less educated individuals exhibit higher levels of mobility and therefore less persistent earnings trajectories. This is confirmed by the multinomial logit coefficients for education and experience which for all countries tend to be negative across most initial*destination deciles. The education patterns are the strongest for the U.S., the U.K and Germany, while the relationship is much weaker for Canada and France. In terms of experience the variation across the countries is more similar with France and Canada again showing less variation. Finally, in terms of 1-year differences the model fits the data just as well within education or experience groups as in the whole population. Over time the same pattern emerges with the homogeneous model under fitting mobility and the fixed effect model over fitting.

[23]In some cases the rank correlation in the fixed effect specification actually increases from 1-year differences to 2-year differences. This happens when the panel lengths are shorter, e.g. the U.S. and France, because the mobility matrix in short panels tends to produce oscillating patterns such that individuals have a high probability to move away from and then back to the initial residual decile. This produces correlations that are high for even-year differences. See footnote 9 for further details.

[24]See Tables 2 and 3 for the differences between males and females.

[25]The results for females are similar and are available upon request.

5 Lifetime Inequality

Having demonstrated that our empirical specification provides a good fit of the observed data, we now move on to the calculation of lifetime inequality. As mentioned above we construct our measure of permanent income from simulations of ex post income realizations using the estimated transition and earnings processes. Because we have calculated a value of unemployment, we can calculate the average annuity value based on the full sample including individuals unemployed in the base year or based only on the employed sample as with earnings. In general, the average taken over all respondents is lower than that for the employed sample because the unemployment values are, on average, lower than the employment values. This difference is more pronounced in countries that have longer unemployment durations (i.e. lower exit rates out of unemployment). In addition, lifetime inequality levels based on the full sample are higher because inclusion of the unemployed lowers the left tail of the distribution. Since we do not have income values while unemployed for our base sample, we use only those employed in the base year in our calculations of current and lifetime inequality. In this way we have comparable samples across all of our calculations.

5.1 Education and Experience Earnings Differentials

To get a sense of how the annuity values differ from earnings Table 8 presents earnings and value differentials across education and experience groups by gender. Focusing first on gender differences, we find that within each country there is a substantial gender differential. This differential is present in both current earnings and annuity values at similar levels. Thus mobility does not alleviate nor exacerbate gender differences. The gender differences reported here are larger than those often found in the literature because of the inclusion of part-time workers combined with the fact that more women work part-time than men. In countries where the fraction of women working part-time is particularly high, e.g. the U.K. and Germany, the male-female differential is quite large.

With regard to education and experience we find that, in all cases, the education premiums increase when comparing earnings differentials to annuity value differentials. In contrast, the experience premiums decrease. Thus mobility reinforces education differences and basically eliminates differences across experience groups. The latter is because low experience levels incorporate future growth in earnings in the annuity value measure, while higher experience levels incorporate flat to declining future profiles. In terms of inequality, these findings indicate that educational differences tend to enhance long run inequality, while differences in experience levels tend to reduce it.

The above patterns hold for both the model with no unobserved heterogeneity and the fixed effects model. Thus, incorporating unobserved heterogeneity does not affect these comparisons.

5.2 Earnings and Lifetime Income Inequality

We now turn our attention to a comparison of earnings and lifetime inequality. Table 9 shows the levels of inequality for earnings and annuity values using 90-10 ratios and Gini coefficients for males and females separately for each country for the model with no unobserved heterogeneity. Table 10 shows the same results for the fixed effect model. These tables also display counterfactual exercises aimed at measuring the effects of earnings mobility and unemployment risk on long run inequality.[26]

Starting with earnings inequality and comparing across countries, we find that for males the U.S. exhibits the highest level of earnings inequality. Canada and the U.K. exhibit similar levels that are between the U.S. and France and Germany where the latter have the lowest levels. For females, the U.S. has again the highest level. However, the U.K. is now closer to the U.S.; Canada remains in the middle; and France and Germany exhibit low levels of inequality. The cross-country ordering presented here for males is similar to that given in Katz and Autor (Table 10, 1999) for all full-time workers with the exception of France. In their table France has a higher level of inequality than the U.K. while here we find the opposite.

Turning to annuity values, we find that, as in Bowlus and Robin (2004), the level of annuity value inequality is in general lower than the level of earnings inequality. The exception to this finding being France. As might be expected the U.S. exhibits the largest differential between earnings and annuity value inequality levels. After the U.S. comes Canada and then the U.K. Germany and France have the lowest levels of equalization.

Within each country females exhibit more earnings inequality than males. Similar to the explanation for the large male-female earnings differentials, this is due to the fact that a greater fraction of women work part-time and part-time workers have lower earnings and therefore pull down the earnings distribution. This is again particularly true for countries such as the U.K. and Germany that have high rates of part-time work among females. Females also have higher lifetime inequality levels than males although the male-female gap is reduced for all countries. It is likely that mobility between full- and part-time employment for women aids in reducing

[26]To compute these calculations we use the 1998 sample only. Because the sample sizes for a single year are relatively small for the U.K., Germany and France, the inequality measures can vary across simulations. Thus we implement the following Monte Carlo: after n iterations of the counterfactual simulations let $x(n)$ be the mean of the n statistics of interest (e.g. 90/10 ratio); stop if $|x(n) - x(n-1)|$ is less than 1% of $x(n-1)$. To save space we list the standard deviation of these means for only the full mobility counterfactuals. The others are available upon request. We note that the 90/10 ratios exhibit more variation than the Gini coefficients, females exhibit more variation than males, and Germany with the smallest sample size exhibits more variation than the other countries.

this gender differential.

To determine the relative importance of different forms of mobility we simulate the lifetime annuity values under various scenarios. We start with earnings mobility only and examine the level of long run inequality that results if we allow for only upward earnings mobility, only downward earnings mobility and both.[27] Our results show that both upward and downward mobility have equalizing effects and that together the decrease in inequality is even greater.

While the inclusion of earnings mobility results in a reduction in inequality levels for all countries, it does not change the relative rankings across the countries. The U.S. still exhibits the most inequality. This is particularly true for the fixed effect model where the degree of equalization due to earnings mobility is similar across the countries. This result is in line with other cross-country studies of long run inequality that have used 5 or 10 year earnings averages as a measure of permanent income (e.g. Burkhauser and Poupore (1997) and Gangl, Palme and Kenworthy (2007)).[28]

Our inclusion of unemployment risk, however, shows a different pattern.[29] When we allow for mobility only between employment and unemployment we find that the equalizing effect is much lower and in some countries unemployment risk actually increases inequality in the long run. This is especially true for countries such as France and Germany that have a very low exit rate out of unemployment.[30] Thus, in the long run, earnings mobility is clearly equalizing but unemployment risk is not. This explains why France, and, to a lesser extent, Germany, exhibit such a limited long run reduction of inequality, if not a small increase. Clearly ignoring unemployment risk would have resulted in the incorrect conclusion that France and Germany had equalization rates similar to the other countries and therefore substantially lower levels of lifetime inequality.

Further confirmation of the inequality-enhancing role of unemployment risk in France and Germany can be found in Tables 11 and 12 for the homogeneous and fixed effect models, respectively. These tables display the results of a counterfactual simulation assuming the replacement income level during unemployment is 0. In countries such as the U.S., the U.K. and Canada where unemployment risk is minimal the results are basically unchanged. However, for France and Germany the long run inequality levels are now all higher and often greater than the

[27]Here we set the probability of exiting to unemployment to zero and transfer that probability to remaining in the current state. Likewise for the case of only upward (downward) mobility we set the probability of transiting to lower (higher) deciles to zero and transfer that probability to remaining in the current state.

[28]It is not surprising that our fixed effect model produces results that are similar to 5 or 10 year averages since the fixed effects effectively contain this average for our sample periods which range from 3 to 7 years.

[29]This pattern is more apparent in the 90/10 ratios than the Gini coefficients. This is because the addition of unemployment risk primarily affects the lower tail of the distribution. The 90/10 ratio picks up this change more than the Gini coefficient which focuses on the middle of the distribution.

[30]For example, the exit rate out of unemployment is 0.27 for France compared to 0.75 for the U.S.

cross-section levels.

The finding that unemployment risk is an important component of lifetime inequality is supported by Altonji et al. (2007) and Pavan (2008) who also find important links between unemployment risk and earnings. Our results incorporating full mobility are also in agreement with studies that use structural search frameworks to incorporate unemployment risk and wage mobility through job changes such as Flinn (2002) and Cohen (2000). In particular, the homogeneous version of our model also produces the result that the levels of lifetime inequality are quite similar across the countries despite very different cross section inequality levels. The similarity in the results is likely related to the fact that these studies do not incorporate unobserved heterogeneity but do incorporate unemployment risk.

Turning now to a comparison of the models with and without fixed effects, we find, as expected, that the equalizing effect of earnings mobility is much smaller in the fixed effect model. Instead of a reduction of inequality of about 30-40%, in the case of the U.S., Canada and the U.K., when no unobserved heterogeneity is allowed for, the reduction is only 10-15% in the fixed effect model. Since the homogeneous model overstates mobility and the fixed-effect model understates it, the true measure of the equalizing force of mobility lies somewhere within the limits imposed by the two benchmark models.

As an additional sensitivity test of our results we also computed the inequality analysis using a utility based approach to see if risk aversion made a difference.[31] We used a CRRA utility function specification with an intertemporal substitution elasticity of 2.[32] In general the inequality levels for the utility based approach are much lower than those for the income based approach. The reduction in inequality due to moving to lifetime measures is also substantially smaller for the 90-10 ratios, but similar for the Gini coefficients. All of the other orderings and conclusions remain the same.

Given our results, we speculate that mobility likely reduces earnings inequality over a lifetime by about 20-30% in the U.S., Canada and the U.K. and very little, if at all, in France and Germany. Within our sample of countries, the countries with relatively higher earnings inequality are also those countries with more equalizing mobility. Thus, incorporating mobility reveals that countries with North American style labor markets are more similar to countries with Continental European style labor markets in terms of long run inequality than measures of short-run inequality would suggest.

[31] These results are available upon request.
[32] We do not incorporate a utility value for leisure.

6 Conclusions

In this paper we compare and contrast earnings inequality and mobility across the U.S., Canada, France, Germany and the U.K. at the turn of the 21st century. We are particularly interested in the degree to which exchange mobility in each country reduces lifetime inequality measures as compared to current earnings inequality measures. That is, we are interested in determining the amount of equalizing mobility in each country. To examine exchange mobility we construct and estimate a flexible model of individual earnings dynamics for each country that removes all structural mobility features in order to isolate only that mobility within a stable earnings distribution. We then simulate individual earnings trajectories given base-year earnings (1998) and construct lifetime annuity value distributions for each country. Finally, we examine current and lifetime measures of inequality across the countries.

To facilitate cross-country comparisons we designed our model so that it could be estimated on panels of relatively short lengths. Despite its simplicity and limited data requirements we find that our model provides an excellent fit to both the earnings and the mobility data. Therefore, we conclude that short panel data do not really forbid measuring the equalizing force of mobility. What is important is the ability to simulate ex post realizations of income over a longer period than that observed in the data.[33]

In our analysis we compare and contrast two different models: one which does not allow for unobserved heterogeneity and a simple fixed effect model. We find that the homogeneous model tends to predict far too much mobility over several years. The fixed effect model somewhat "overshoots" and predicts too little mobility, but the fit of higher-order rank autocorrelations is much better for this model. Thus, we use the two models as benchmarks or bounds for the measurement of the degree of equalization. Our results show that the U.S. displays both much more earnings inequality than the other countries (at least those we consider) and much more equalizing mobility. In addition countries with somewhat similar labor market structures as the U.S., such as Canada and the U.K., also display more equalizing mobility than Continental European countries such as France and Germany. The end result is that the countries we examine, which look very different in terms of current inequality, tend to look much more similar in terms of lifetime earnings inequality.

Whether this is a good or a bad thing is a matter of interpretation. On the one hand, more earnings and employment mobility moves individual positions more in the U.S. than elsewhere, so that the U.S. is not such an unequal country after all. On the other hand, income uncertainty

[33]Our simulations reveal that 10 year averages capture most of the reduction in inequality in moving to a lifetime measure, while 5 year averages capture about half the reduction.

should be negatively valued by risk-averse individuals. Our attempt to introduce risk aversion did not change the results. However, we are well aware that our welfare computations in the presence of risk aversion are not satisfactory, because insurance markets are likely incomplete. More income risk probably means more credit constraints, and this highlights the limits of the present exercise. A more satisfactory welfare computation allowing for liquidity constraints would require consumption data. The few available studies on consumer welfare (Cutler and Katz, 1992, Attanasio and Davis, 1996, Blundell and Preston, 1998, Attanasio et al., 2002) seem to indicate that there is less consumption inequality than income inequality, and possibly fewer cross-country differences. However, this approach is very difficult to implement due to the lack of consumer panels. Given the similarity of our findings to the consumption literature, both in terms of inequality levels and cross-country differences, we think our study goes a long way toward an assessment of cross-country welfare differences.

References

[1] Aaberge, R., A. Bjørklund, M. Jäntti, M. Palme, P.J. Pedersen, N. Smith and T. Wennemo (2002), "Income Inequality and Income Mobility in the Scandinavian Countries Compared to the United States," *Review of Income and Wealth*, 48(4), 443-69.

[2] Alvarez, J., Browning, M. and M. Ejrnæs (2002): "Modelling Income Processes with lots of heterogeneity," CAM Working Paper, 2002-01, University of Copenhagen.

[3] Altonji, J., A. Smith, and I. Vindangos (2007), "Modeling Earnings Dynamics," Yale University.

[4] Attanasio, O. and S. Davis (1996), "Relative Wage Movements and the Distribution of Consumption," *Journal of Political Economy*, 104(6) , 1227-1262.

[5] Attanasio, O., G. Berloffa, R. Blundell, and I. Preston (2002), "From Earnings Inequality to Consumption Inequality," *The Economic Journal*, 112, C52-C59.

[6] Baker, M. (1997), "Growth-Rate Heterogeneity and the Covariate Structure of Life-Cycle Earnings," *Journal of Labor Economics* 15(2), 338-375.

[7] Baker, M. and G. Solon (2003), "Earnings Dynamics and Inequality among Canadian Men, 1976-1992: Evidence from Longitudinal Records, " *Journal of Labor Economics* 21(2), 289-321.

[8] Blundell, R. and I. Preston (1998), "Consumption Inequality and Income Uncertainty," *Quarterly Journal of Economics* 113 (2), 603-640.

[9] Bound, J., C. Brown, and N. Mathiowitz (2001), "Measurement Error in Survey Data, "in J. J. Heckman and E. Leamer, eds., *Handbook of Econometrics*. Amsterdam: Elsevier Science B. V., Chapter 59, pp. 3707-3745.

[10] Bowlus, A. J. and J.-M. Robin (2004), "Twenty Years of Rising Inequality in U.S. Lifetime Labor Income Values," *Review of Economic Studies*, 71(3), 709-743.

[11] Buchinsky, M. and J. Hunt (1999), "Wage Mobility in the United States," *Review of Economics and Statistics*, 81 (3), 351-368.

[12] Buchinsky, M., G. S. Fields, D. Fougère, and F. Kramarz (2003), "Francs or Ranks? Earnings Mobility in France, 1967-1999," Working paper, CREST-INSEE.

[13] Burkhauser, R. V., D. Holtz-Eakin and S. E. Rhody (1997), "Labor Earnings Mobility and Inequality in the United States and Germany during the Growth Years of the 1980s," *International Economic Review*, 38(4), 775-794.

[14] Burkhauser, R. V. and J. G. Poupore (1997), "A Cross-National Comparison of Permanent Inequality in the United States and Germany," *The Review of Economics and Statistics*, 79(1), 10-17.

[15] Cohen, D. (1999), "Welfare Differentials Across French and U.S. Labor Markets: A General Equilibrium Interpretation," CEPREMAP Working Paper 9904 and CEPR Research Discussion Paper 2114.

[16] Cohen, D. and P. Dupas (2000), "Trajectoires comparées des chômeurs en France et aux Etats Unis," *Economie et Statistique*, 322-323, 17-26.

[17] Contini, B. (2002), "Earnings mobility and labor market segmentation in Europe and U.S.A.: preliminary explorations", LABORatorio R. Revelli, Working Paper, March 2002.

[18] Cutler, D. M. and L. F. Katz (1992) "Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980's," *American Economic Review* 82 (3), 546-551.

[19] Fields, G. S. (2005b), "Does Income Mobility Equalize Longer-Term Incomes? New Measures of an Old concept," Cornell University.

[20] Flinn, C. J. (2002), "Labour Market Structure and Inequality: A Comparison of Italy and the U.S.," *Review of Economic Studies*, 69, 611-645.

[21] Gangl, M., J. Palme, and L. Kenworthy (2007) "Is High Inequality Offset by Mobility? " University of Mannheim.

[22] Geweke, J., and M. Keane (2000): "An Empirical Analysis of Income Dynamics among Men in the PSID: 1968-1989," *Journal of Econometrics*, 96, 293-356.

[23] Geweke, J., and M. Keane (2007): "Smoothly Mixing Regressions," *Journal of Econometrics*, 138, 252-290.

[24] Gottschalk, Peter (1997), "Inequality, Income Growth, and Mobility: The Basic Facts," *The Journal of Economic Perspectives*, Vol. 11, No. 2, pp. 21-40.

[25] Gottschalk, P., and M. Huynh (2007): "Are Earnings Inequality and Mobility Overstated? The Impact of Non-Classical Measurement Errot," Boston College.

[26] Gottschalk, P. and T. Smeeding (2000), "Empirical Evidence on Income Inequality in Industrial Countries," in A. Atkinson and F. Bourguignon, eds., *Handbook of Income Distribution, 1,* North Holland, *261-307.*

[27] Haider, S. (2001), "Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991," *Journal of Labor Economics* 19(4), 799-836.

[28] Katz, L. F. and D. H. Autor (1999), "Changes in the Wage Structure and Earnings Inequality," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, 3, North Holland, 1463-1555.

[29] Levy, F. and R. J. Murnane (1992), "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations," *Journal of Economic Literature* 30(3), 1333-81.

[30] Lillard, Lee A. (1977), "Inequality: Earnings vs. Human Wealth,", *The American Economic Review*, Vol. 67, No. 2, pp. 42-53.

[31] Maasoumi, E. and M. Trede (2001), "Comparing Income Mobility in Germany and the United States using Generalized Entropy Mobility Measures," *The Review of Economics and Statistics*, 83(3), 551-559.

[32] Martin, J. P. (1996) "Measures of Replacement Rates for the Purpose of International Comparison A Note," OECD Economic Studies, 26, p.99-115.

[33] Meghir, C., and L. Pistaferri (2004), "Income Variance Dynamics and Heterogeneity," *Econometrica* , 72, 1-32.

[34] Moffitt, R., and P. Gottschalk (1995), "Trends in the Covariance Structure of Earnings in the U.S.: 1969-1987," John Hopkins University, mimeo.

[35] Moffitt, R., and P. Gottschalk (2002), “Trends in the Transitory Variance of Earnings in the U.S.,” *The Economic Journal*, 112, C68-C73.

[36] OECD (1996), “Earnings inequality and mobility, Chapter 3 of OECD Employment Outlook 1996,” *Countering the risks of labour market exclusion*, 59-109.

[37] Pavan, R. (2008), “A Flexible Model of Individual Wage Dynamics and Job Mobility Outcomes, ” University of Rochester.

[38] Piketty, T. and E. Saez (2003), “Income Inequality in the United States: 1913-1998,” *Quarterly Journal of Economics*, 118 (1), 1-39.

[39] Schluter, C. and M. Trede (2003), “Local versus Global Assessment of Mobility,” *International Economic Review*, 44, 1313-1335.

[40] Van Kerm, P. (2004),“What Lies Behind Income Mobility? Reranking and Distributional Change in Belgium, Western Germany and the U.S.A.,” *Economica*, 71(282), 223-239.

	MALES					FEMALES				
	U.S.	Can.	U.K.	Fra.	Ger.	U.S.	Can.	U.K.	Fra.	Ger.
					Homogeneous Model					
UNEMPLOYMENT										
Equilibrium	0.023	0.051	0.045	0.139	0.059	0.020	0.047	0.025	0.161	0.069
Actual	0.033	0.072	0.069	0.137	0.081	0.031	0.077	0.037	0.169	0.090
WAGE DECILES										
1	0.089	0.085	0.097	0.117	0.119	0.081	0.076	0.056	0.104	0.088
2	0.098	0.097	0.096	0.117	0.096	0.093	0.082	0.065	0.103	0.091
3	0.102	0.087	0.088	0.107	0.085	0.099	0.078	0.073	0.101	0.083
4	0.100	0.081	0.081	0.097	0.076	0.102	0.083	0.076	0.088	0.078
5	0.100	0.082	0.080	0.088	0.072	0.102	0.087	0.077	0.094	0.071
6	0.100	0.080	0.082	0.077	0.072	0.102	0.088	0.090	0.086	0.077
7	0.098	0.085	0.088	0.066	0.078	0.103	0.093	0.102	0.079	0.077
8	0.098	0.096	0.101	0.066	0.092	0.099	0.107	0.121	0.070	0.096
9	0.098	0.114	0.112	0.063	0.108	0.100	0.120	0.144	0.059	0.119
10	0.091	0.143	0.130	0.065	0.144	0.098	0.140	0.172	0.056	0.151
Actual	0.097	0.093	0.093	0.086	0.092	0.097	0.092	0.096	0.083	0.091
					Fixed Effect Model					
UNEMPLOYMENT										
Equilibrium	0.024	0.055	0.045	0.142	0.057	0.021	0.052	0.027	0.171	0.075
Actual	0.033	0.072	0.069	0.137	0.081	0.031	0.077	0.037	0.169	0.090
WAGE DECILES										
1	0.086	0.085	0.087	0.066	0.085	0.084	0.075	0.078	0.066	0.086
2	0.093	0.094	0.090	0.078	0.087	0.096	0.096	0.086	0.081	0.088
3	0.101	0.097	0.083	0.104	0.088	0.101	0.097	0.094	0.093	0.078
4	0.101	0.104	0.101	0.106	0.103	0.104	0.111	0.103	0.107	0.089
5	0.095	0.109	0.103	0.100	0.104	0.100	0.106	0.109	0.103	0.104
6	0.110	0.110	0.105	0.110	0.098	0.104	0.117	0.113	0.099	0.108
7	0.102	0.091	0.098	0.100	0.090	0.105	0.091	0.100	0.093	0.095
8	0.103	0.081	0.094	0.070	0.093	0.101	0.081	0.095	0.070	0.094
9	0.097	0.084	0.094	0.067	0.099	0.099	0.084	0.097	0.061	0.092
10	0.089	0.090	0.089	0.058	0.096	0.087	0.088	0.098	0.056	0.093
Actual	0.097	0.092	0.093	0.086	0.092	0.097	0.092	0.096	0.083	0.091

Table 1: Test of Stationarity (Equilibrium Distribution of Unemployment and Earnings)

		MALES					FEMALES				
		U.S.	Canada	U.K.	France	Germany	U.S.	Canada	U.K.	France	Germany
LOG EARNINGS											
Mean	Actual	10.05	10.36	9.54	9.49	10.11	9.69	9.92	9.00	9.25	9.61
	Predicted	10.05	10.35	9.54	9.49	10.11	9.69	9.92	9.00	9.25	9.59
St dev	Actual	0.62	0.55	0.46	0.37	0.35	0.65	0.59	0.62	0.48	0.54
	Predicted	0.62	0.54	0.46	0.37	0.34	0.65	0.57	0.61	0.48	0.52
Skewness	Actual	-0.23	-0.69	0.08	0.32	0.20	-0.35	-0.61	-0.34	-0.48	-1.12
	Predicted	-0.03	-0.16	0.07	0.43	0.28	-0.05	-0.18	-0.05	-0.03	-0.26
Kurtosis	Actual	3.17	3.76	3.11	4.12	3.64	3.14	3.15	2.67	3.33	4.44
	Predicted	2.98	3.00	2.93	3.64	3.13	2.84	2.78	2.72	2.87	3.02
EARNINGS											
Mean	Actual	28,179	36,234	15,594	14,856	27,613	19,771	23,401	9,288	11,263	16,866
	Predicted	28,325	36,266	15,657	14,926	27,414	19,936	23,468	9,312	11,364	16,365
St dev	Actual	18,317	18,388	7,718	6,724	10,541	12,791	12,266	5,515	5,246	7,750
	Predicted	19,371	20,359	7,644	6,904	10,487	13,878	13,368	6,000	5,716	8,876
Skewness	Actual	2.24	1.07	1.74	2.20	1.05	1.66	0.78	1.16	1.23	0.39
	Predicted	2.41	1.47	1.53	2.61	1.02	1.97	1.20	1.63	1.50	1.03
Kurtosis	Actual	15.72	5.36	8.47	10.90	4.38	7.57	3.52	4.75	6.62	3.06
	Predicted	15.14	6.28	6.80	15.62	4.52	9.16	4.51	6.57	6.97	3.79

Table 2: Cross-Section Distribution: Homogeneous Model

		MALES					FEMALES				
		U.S.	Canada	U.K.	France	Germany	U.S.	Canada	U.K.	France	Germany
LOG EARNINGS											
Mean	Actual	10.10	10.38	9.59	9.54	10.24	9.73	9.95	8.98	9.27	9.59
	Predicted	10.10	10.38	9.59	9.54	10.24	9.73	9.95	8.98	9.27	9.59
St dev	Actual	0.62	0.55	0.46	0.39	0.37	0.65	0.59	0.63	0.48	0.55
	Predicted	0.62	0.54	0.46	0.39	0.37	0.65	0.59	0.62	0.49	0.55
Skewness	Actual	-0.25	-0.71	0.05	0.40	-0.19	-0.37	-0.64	-0.31	-0.53	-1.02
	Predicted	-0.14	-0.55	0.05	0.44	-0.14	-0.21	-0.51	-0.20	-0.45	-0.93
Kurtosis	Actual	3.19	3.83	3.11	4.05	3.47	3.16	3.20	2.59	3.38	4.07
	Predicted	3.01	3.43	2.99	3.96	3.24	2.90	3.02	2.60	3.19	3.88
EARNINGS											
Mean	Actual	28,179	36,234	15,594	14,856	27,613	19,771	23,401	9,288	11,263	16,866
	Predicted	28,265	36,284	15,597	14,860	27,599	19,868	23,495	9,303	11,303	16,890
St dev	Actual	18,317	18,388	7,718	6,724	10,541	12,791	12,266	5,515	5,246	7,750
	Predicted	18,642	18,799	7,662	6,737	10,524	13,257	12,749	5,709	5,3525	8,026
Skewness	Actual	2.24	1.07	1.74	2.20	1.05	1.66	0.78	1.16	1.23	0.39
	Predicted	2.06	1.09	1.62	2.20	1.03	1.74	0.94	1.32	1.28	0.52
Kurtosis	Actual	15.72	5.36	8.47	10.90	4.38	7.57	3.52	4.75	6.62	3.06
	Predicted	11.28	5.09	7.50	10.80	4.20	7.86	3.92	5.12	6.91	3.09

Table 3: Cross-Section Distribution: Fixed Effect Model

		MALES					FEMALES				
		U.S.	Canada	U.K.	France	Germany	U.S.	Canada	U.K.	France	Germany
Decile 1	**Actual**	**0.13**	**0.48**	**0.40**	**0.52**	**0.42**	**0.17**	**0.42**	**0.47**	**0.51**	**0.65**
	Homogeneous	0.15	0.38	0.32	0.46	0.45	0.16	0.32	0.41	0.43	0.61
	Fixed Effect	0.19	0.53	0.47	0.59	0.45	0.23	0.46	0.46	0.52	0.66
Decile 2	**Actual**	**0.16**	**0.39**	**0.25**	**0.39**	**0.30**	**0.17**	**0.34**	**0.29**	**0.47**	**0.40**
	Homogeneous	0.14	0.37	0.19	0.34	0.29	0.17	0.28	0.30	0.45	0.36
	Fixed Effect	0.18	0.42	0.26	0.37	0.29	0.19	0.38	0.34	0.45	0.45
Decile 3	**Actual**	**0.16**	**0.38**	**0.22**	**0.27**	**0.29**	**0.15**	**0.33**	**0.34**	**0.39**	**0.40**
	Homogeneous	0.16	0.35	0.18	0.27	0.26	0.15	0.27	0.27	0.37	0.37
	Fixed Effect	0.14	0.37	0.21	0.29	0.31	0.16	0.33	0.34	0.41	0.43
Decile 4	**Actual**	**0.15**	**0.34**	**0.18**	**0.29**	**0.15**	**0.18**	**0.29**	**0.22**	**0.27**	**0.38**
	Homogeneous	0.15	0.28	0.20	0.29	0.23	0.16	0.26	0.25	0.35	0.31
	Fixed Effect	0.16	0.33	0.21	0.31	0.18	0.20	0.28	0.26	0.30	0.35
Decile 5	**Actual**	**0.13**	**0.34**	**0.18**	**0.26**	**0.29**	**0.14**	**0.33**	**0.25**	**0.46**	**0.32**
	Homogeneous	0.10	0.29	0.22	0.26	0.24	0.15	0.32	0.24	0.38	0.28
	Fixed Effect	0.11	0.30	0.21	0.29	0.23	0.11	0.32	0.26	0.40	0.29
Decile 6	**Actual**	**0.14**	**0.35**	**0.23**	**0.33**	**0.26**	**0.15**	**0.30**	**0.20**	**0.45**	**0.30**
	Homogeneous	0.09	0.29	0.20	0.29	0.23	0.13	0.30	0.28	0.34	0.26
	Fixed Effect	0.13	0.32	0.20	0.32	0.22	0.14	0.30	0.24	0.39	0.25
Decile 7	**Actual**	**0.18**	**0.36**	**0.28**	**0.48**	**0.30**	**0.16**	**0.33**	**0.22**	**0.43**	**0.24**
	Homogeneous	0.16	0.29	0.22	0.42	0.22	0.16	0.28	0.22	0.33	0.24
	Fixed Effect	0.15	0.33	0.26	0.47	0.27	0.16	0.29	0.22	0.38	0.31
Decile 8	**Actual**	**0.18**	**0.35**	**0.30**	**0.40**	**0.33**	**0.22**	**0.38**	**0.35**	**0.53**	**0.42**
	Homogeneous	0.16	0.29	0.29	0.42	0.30	0.17	0.35	0.29	0.39	0.33
	Fixed Effect	0.17	0.34	0.29	0.45	0.34	0.17	0.33	0.33	0.48	0.38
Decile 9	**Actual**	**0.23**	**0.41**	**0.42**	**0.59**	**0.43**	**0.23**	**0.46**	**0.45**	**0.52**	**0.53**
	Homogeneous	0.20	0.34	0.39	0.50	0.44	0.21	0.43	0.40	0.45	0.51
	Fixed Effect	0.23	0.41	0.40	0.59	0.43	0.22	0.46	0.39	0.49	0.48
Decile 10	**Actual**	**0.43**	**0.68**	**0.65**	**0.81**	**0.71**	**0.42**	**0.72**	**0.72**	**0.82**	**0.62**
	Homogeneous	0.40	0.61	0.61	0.76	0.63	0.35	0.69	0.63	0.75	0.53
	Fixed Effect	0.42	0.66	0.63	0.82	0.72	0.38	0.68	0.65	0.81	0.61

Table 4: Earnings Mobility by Earnings Decile of Origin (Spearman's Correlation between Period 1 Earnings and Period 2 Earnings)

		MALES					FEMALES				
		U.S.	Canada	U.K.	France	Germany	U.S.	Canada	U.K.	France	Germany
1 Year Difference	Actual	**0.76**	**0.92**	**0.88**	**0.94**	**0.91**	**0.77**	**0.90**	**0.90**	**0.94**	**0.93**
	Homogeneous	0.76	0.91	0.86	0.93	0.89	0.76	0.89	0.89	0.93	0.91
	Fixed Effect	0.76	0.92	0.88	0.94	0.90	0.77	0.90	0.90	0.95	0.92
2 Year Difference	Actual	**0.71**	**0.87**	**0.83**	**0.92**	**0.87**	**0.72**	**0.85**	**0.86**	**0.92**	**0.88**
	Homogeneous	0.60	0.81	0.75	0.86	0.80	0.60	0.79	0.80	0.87	0.84
	Fixed Effect	0.82	0.91	0.87	0.96	0.89	0.82	0.90	0.88	0.96	0.90
3 Year Difference	Actual	**0.66**	**0.84**	**0.79**		**0.85**	**0.68**	**0.82**	**0.82**		**0.84**
	Homogeneous	0.49	0.73	0.66		0.72	0.49	0.68	0.71		0.78
	Fixed Effect	0.77	0.90	0.86		0.88	0.78	0.89	0.88		0.90
4 Year Difference	Actual		**0.81**	**0.75**		**0.81**		**0.79**	**0.79**		**0.81**
	Homogeneous		0.66	0.58		0.66		0.63	0.64		0.72
	Fixed Effect		0.89	0.85		0.87		0.88	0.87		0.89
5 Year Difference	Actual		**0.81**	**0.75**		**0.81**		**0.79**	**0.79**		**0.81**
	Homogeneous		0.58	0.52		0.60		0.54	0.56		0.64
	Fixed Effect		0.86	0.83		0.86		0.85	0.86		0.88
6 Year Difference	Actual			**0.70**		**0.78**			**0.73**		**0.71**
	Homogeneous			0.48		0.54			0.53		0.59
	Fixed Effect			0.83		0.86			0.86		0.85

Table 5: Higher-Order Earnings Mobility (Spearman's Correlation across 1 to 6 Years)

	1 Year Difference			2 Year Difference			3 Year Difference			4 Year Difference			5 Year Difference			6 Year Difference		
	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE
U.S.																		
< High School	**0.62**	0.63	0.62	**0.59**	0.44	0.73	**0.50**	0.26	0.66									
High School	**0.67**	0.68	0.68	**0.59**	0.47	0.76	**0.54**	0.32	0.67									
Some College	**0.70**	0.69	0.70	**0.64**	0.48	0.77	**0.57**	0.37	0.72									
University	**0.75**	0.75	0.76	**0.68**	0.56	0.79	**0.62**	0.41	0.75									
CANADA																		
< High School	**0.89**	0.87	0.90	**0.83**	0.75	0.90	**0.81**	0.64	0.89	**0.79**	0.59	0.88	**0.76**	0.52	0.86			
High School	**0.91**	0.90	0.90	**0.85**	0.79	0.89	**0.81**	0.71	0.89	**0.78**	0.61	0.86	**0.74**	0.51	0.83			
Some College	**0.91**	0.90	0.91	**0.86**	0.80	0.90	**0.83**	0.71	0.89	**0.80**	0.63	0.88	**0.76**	0.56	0.85			
University	**0.91**	0.90	0.91	**0.85**	0.79	0.88	**0.80**	0.71	0.87	**0.75**	0.63	0.85	**0.71**	0.50	0.81			
U.K.																		
< High School	**0.83**	0.82	0.83	**0.77**	0.66	0.82	**0.72**	0.54	0.81	**0.67**	0.44	0.80	**0.63**	0.36	0.78	**0.64**	0.32	0.78
High School	**0.86**	0.84	0.86	**0.80**	0.70	0.84	**0.73**	0.59	0.82	**0.69**	0.50	0.80	**0.65**	0.41	0.78	**0.61**	0.34	0.75
> High School	**0.90**	0.88	0.89	**0.85**	0.77	0.87	**0.79**	0.68	0.86	**0.72**	0.59	0.85	**0.67**	0.51	0.83	**0.59**	0.45	0.82
FRANCE																		
< High School	**0.92**	0.90	0.92	**0.89**	0.82	0.94												
High School	**0.95**	0.94	0.95	**0.92**	0.89	0.96												
Some College	**0.94**	0.93	0.94	**0.91**	0.85	0.95												
University	**0.94**	0.93	0.94	**0.92**	0.87	0.96												
Germany																		
< 10 years	**0.78**	0.75	0.79	**0.78**	0.60	0.80	**0.68**	0.49	0.80	**0.74**	0.40	0.80	**0.72**	0.32	0.82	**0.69**	0.30	0.79
10 < < 14 years	**0.87**	0.86	0.87	**0.84**	0.74	0.86	**0.81**	0.63	0.85	**0.77**	0.55	0.85	**0.77**	0.49	0.84	**0.75**	0.40	0.85
>= 14 years	**0.93**	0.90	0.92	**0.89**	0.83	0.90	**0.85**	0.75	0.89	**0.82**	0.70	0.87	**0.79**	0.64	0.85	**0.74**	0.59	0.83

Table 6: Higher-Order Earnings Mobility by Education (Spearman's Correlation across 1 to 6 Years) – Male Sample

	1 Year Difference			2 Year Difference			3 Year Difference			4 Year Difference			5 Year Difference			6 Year Difference		
	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE	Act.	Hom.	FE
U.S.																		
$0-15$ years	**0.73**	0.72	0.73	**0.68**	0.57	0.80	**0.65**	0.47	0.75									
$16-25$ years	**0.76**	0.76	0.76	**0.72**	0.60	0.81	**0.66**	0.48	0.76									
>25 years	**0.76**	0.77	0.76	**0.71**	0.60	0.82	**0.66**	0.49	0.78									
CANADA																		
$0-15$ years	**0.90**	0.89	0.90	**0.84**	0.78	0.89	**0.81**	0.67	0.89	**0.77**	0.62	0.87	**0.75**	0.57	0.86			
$16-25$ years	**0.92**	0.91	0.92	**0.87**	0.81	0.90	**0.85**	0.74	0.91	**0.84**	0.67	0.89	**0.80**	0.58	0.87			
>25 years	**0.92**	0.91	0.92	**0.88**	0.82	0.91	**0.84**	0.74	0.90	**0.82**	0.67	0.90	**0.78**	0.59	0.87			
U.K.																		
$0-15$ years	**0.86**	0.85	0.86	**0.82**	0.73	0.86	**0.79**	0.65	0.85	**0.74**	0.58	0.84	**0.72**	0.52	0.83	**0.71**	0.47	0.83
$16-25$ years	**0.88**	0.85	0.88	**0.84**	0.75	0.86	**0.81**	0.66	0.86	**0.78**	0.58	0.85	**0.77**	0.53	0.84	**0.75**	0.47	0.85
>25 years	**0.90**	0.86	0.89	**0.84**	0.74	0.87	**0.78**	0.64	0.86	**0.74**	0.55	0.85	**0.69**	0.46	0.83	**0.57**	0.45	0.80
FRANCE																		
$0-15$ years	**0.93**	0.91	0.92	**0.91**	0.85	0.95												
$16-25$ years	**0.94**	0.93	0.94	**0.93**	0.85	0.96												
>25 years	**0.94**	0.93	0.94	**0.92**	0.87	0.96												
Germany																		
$0-15$ years	**0.86**	0.85	0.84	**0.80**	0.73	0.82	**0.75**	0.62	0.81	**0.70**	0.55	0.80	**0.67**	0.50	0.77	**0.68**	0.43	0.77
$16-25$ years	**0.91**	0.88	0.89	**0.89**	0.80	0.89	**0.87**	0.73	0.89	**0.85**	0.67	0.89	**0.85**	0.59	0.89	**0.87**	0.56	0.90
>25 years	**0.93**	0.91	0.93	**0.91**	0.83	0.93	**0.90**	0.75	0.93	**0.87**	0.70	0.93	**0.88**	0.65	0.93	**0.83**	0.60	0.93

Table 7: Higher-Order Earnings Mobility by Experience (Spearman's Correlation across 1 to 6 Years) – Male Sample

		U.S.	Canada	U.K.	France	Germany
MALES and FEMALES						
Gender Differential	Current Earnings	0.70	0.65	0.59	0.76	0.61
	Ex-post Annuities, Homogeneous	0.68	0.65	0.58	0.76	0.60
	Ex-post Annuities, Fixed Effect	0.75	0.71	0.59	0.76	0.61
MALES						
Education Premium	Current Earnings	2.51	1.74	1.70	2.04	1.87
	Ex-post Annuities, Homogeneous	2.59	1.74	1.79	2.30	2.23
	Ex-post Annuities, Fixed Effect	2.65	1.73	1.70	2.27	2.07
Experience Premium	Current Earnings	1.27	1.29	1.06	1.14	1.32
	Ex-post Annuities, Homogeneous	1.04	1.01	0.89	0.97	1.03
	Ex-post Annuities, Fixed Effect	0.98	0.98	0.90	1.00	1.05
FEMALES						
Education Premium	Current Earnings	2.73	2.19	2.07	2.06	1.67
	Ex-post Annuities, Homogeneous	2.86	2.26	2.14	2.53	1.99
	Ex-post Annuities, Fixed Effect	2.72	2.41	2.12	2.19	1.68
Experience Premium	Current Earnings	1.08	1.11	0.81	1.02	0.94
	Ex-post Annuities, Homogeneous	0.92	0.88	0.70	0.91	0.86
	Ex-post Annuities, Fixed Effect	0.89	0.84	0.67	0.93	0.85

Table 8: Earnings and Annuity Value Differentials (Employed Workers Only)

	U.S.	Canada	U.K.	France	Germany
MALES					
90/10					
Annual earnings	4.88	4.02	3.20	2.55	2.66
Upward wage mobility only	2.72	2.41	2.20	2.46	2.21
Downward wage mobility only	3.30	3.55	2.57	2.38	2.39
Wage mobility only	2.67	2.51	2.28	2.23	2.17
Percentage reduction	55%	62%	71%	87%	82%
Unemployment mobility only	4.76	3.73	3.45	3.12	3.06
Ex post annuity values (full mobility)	2.76	2.65	2.40	2.65	2.55
Standard deviation (full mobility)			(0.03)	(0.03)	(0.05)
Percentage reduction	57%	66%	75%	104%	96%
Gini					
Annual earnings	0.33	0.28	0.26	0.22	0.22
Upward wage mobility only	0.21	0.19	0.17	0.21	0.17
Downward wage mobility only	0.27	0.27	0.22	0.21	0.20
Wage mobility only	0.22	0.20	0.19	0.20	0.18
Percentage reduction	65%	73%	72%	90%	81%
Unemployment mobility only	0.32	0.27	0.26	0.26	0.23
Ex post annuity values (full mobility)	0.22	0.21	0.20	0.23	0.21
Standard deviation (full mobility)			(0.002)	(0.001)	(0.003)
Percentage reduction	66%	76%	76%	103%	94%
FEMALES					
90/10					
Annual earnings	5.35	4.67	5.20	3.73	4.02
Upward wage mobility only	3.05	2.65	2.92	2.65	3.03
Downward wage mobility only	4.00	4.15	4.25	3.73	3.98
Wage mobility only	2.87	2.75	3.28	2.79	3.00
Percentage reduction	54%	59%	63%	75%	75%
Unemployment mobility only	5.40	4.41	4.95	4.50	5.01
Ex post annuity values (full mobility)	2.94	2.96	3.28	3.49	3.49
Standard deviation (full mobility)			(0.07)	(0.08)	(0.30)
Percentage reduction	55%	64%	63%	94%	87%
Gini					
Annual earnings	0.34	0.29	0.32	0.25	0.27
Upward wage mobility only	0.22	0.20	0.22	0.22	0.22
Downward wage mobility only	0.30	0.29	0.31	0.27	0.28
Wage mobility only	0.23	0.21	0.25	0.22	0.23
Percentage reduction	67%	72%	77%	89%	88%
Unemployment mobility only	0.34	0.29	0.32	0.30	0.29
Ex post annuity values (full mobility)	0.23	0.23	0.25	0.26	0.25
Standard deviation (full mobility)			(0.003)	(0.002)	(0.003)
Percentage reduction	68%	77%	78%	104%	94%

Table 9: Inequality Measures Across Experiments – Homogeneous Model

	U.S.	Canada	U.K.	France	Germany
MALES					
90/10					
Annual earnings	4.88	4.02	3.20	2.55	2.66
Upward wage mobility only	4.09	3.28	2.84	2.43	2.37
Downward wage mobility only	4.38	3.56	2.82	2.46	2.50
Wage mobility only	4.09	3.38	2.77	2.42	2.38
Percentage reduction	84%	84%	87%	95%	90%
Unemployment mobility only	4.71	3.67	3.18	2.68	2.97
Ex post annuity values (full mobility)	4.15	3.48	2.89	2.68	2.72
Standard deviation (full mobility)			(0.03)	(0.02)	(0.11)
Percentage reduction	85%	87%	90%	105%	102%
Gini					
Annual earnings	0.33	0.28	0.26	0.22	0.22
Upward wage mobility only	0.30	0.25	0.23	0.22	0.19
Downward wage mobility only	0.31	0.26	0.23	0.22	0.21
Wage mobility only	0.30	0.25	0.23	0.22	0.20
Percentage reduction	89%	89%	88%	97%	88%
Unemployment mobility only	0.33	0.26	0.25	0.24	0.23
Ex post annuity values (full mobility)	0.30	0.25	0.24	0.24	0.22
Standard deviation (full mobility)			(0.001)	(0.001)	(0.003)
Percentage reduction	90%	91%	92%	106%	100%
FEMALES					
90/10					
Annual earnings	5.35	4.67	5.20	3.73	3.94
Upward wage mobility only	4.29	3.61	4.66	3.33	3.26
Downward wage mobility only	4.74	4.11	4.95	3.50	3.49
Wage mobility only	4.27	3.85	4.69	3.38	3.26
Percentage reduction	80%	82%	90%	90%	83%
Unemployment mobility only	4.91	4.23	5.32	3.79	4.13
Ex post annuity values (full mobility)	4.31	3.95	4.78	3.78	3.67
Standard deviation (full mobility)			(0.06)	(0.04)	(0.13)
Percentage reduction	81%	85%	92%	101%	93%
Gini					
Annual earnings	0.34	0.29	0.32	0.25	0.27
Upward wage mobility only	0.30	0.26	0.31	0.24	0.24
Downward wage mobility only	0.32	0.27	0.32	0.24	0.25
Wage mobility only	0.30	0.26	0.31	0.24	0.24
Percentage reduction	88%	89%	97%	95%	89%
Unemployment mobility only	0.33	0.28	0.33	0.26	0.27
Ex post annuity values (full mobility)	0.30	0.27	0.32	0.26	0.25
Standard deviation (full mobility)			(0.001)	(0.001)	(0.004)
Percentage reduction	89%	92%	98%	105%	94%

Table 10: Inequality Measures Across Experiments – Fixed Effect Model

	U.S.	Canada	U.K.	France	Germany
MALES					
90/10					
Annual earnings	4.88	4.02	3.20	2.55	2.66
Ex post annuity values (full mobility)	2.77	2.70	2.42	2.95	2.67
Percentage reduction	56%	67%	76%	116%	100%
Gini					
Annual earnings	0.33	0.28	0.26	0.22	0.22
Ex post annuity values (full mobility)	0.22	0.22	0.20	0.25	0.22
Percentage reduction	66%	77%	77%	112%	98%
FEMALES					
90/10					
Annual earnings	5.35	4.67	5.20	3.73	4.02
Ex post annuity values (full mobility)	2.93	3.03	3.30	3.86	3.61
Percentage reduction	55%	65%	64%	104%	90%
Gini					
Annual earnings	0.34	0.29	0.32	0.25	0.27
Ex post annuity values (full mobility)	0.23	0.23	0.25	0.28	0.25
Percentage reduction	68%	79%	78%	111%	96%

Table 11: Inequality Measures Across Experiments: Homogeneous Model, Unemployment Income = 0

	U.S.	Canada	U.K.	France	Germany
MALES					
90/10					
Annual earnings	4.88	4.02	3.20	2.55	2.66
Ex post annuity values (full mobility)	4.14	3.53	2.90	2.92	2.84
Percentage reduction	85%	88%	91%	115%	107%
Gini					
Annual earnings	0.33	0.28	0.26	0.22	0.22
Ex post annuity values (full mobility)	0.30	0.26	0.24	0.25	0.23
Percentage reduction	91%	92%	92%	113%	104%
FEMALES					
90/10					
Annual earnings	5.35	4.67	5.20	3.73	3.94
Ex post annuity values (full mobility)	4.33	4.01	4.79	4.04	3.80
Percentage reduction	81%	86%	92%	108%	96%
Gini					
Annual earnings	0.34	0.29	0.32	0.25	0.27
Ex post annuity values (full mobility)	0.30	0.27	0.32	0.28	0.25
Percentage reduction	89%	93%	98%	110%	96%

Table 12: Inequality Measures Across Experiments: Fixed Effect Model, Unemployment Income = 0