An International Comparison of Lifetime Labor Income Values and Inequality

Audra J. Bowlus
University of Western Ontario

Jean-Marc Robin
Paris School of Economics - University Paris 1,
and University College London

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1 Introduction

It is well conceded that one-year earnings inequality offers an incomplete picture of economic inequality. Among the many individual economic attributes that should be considered are unemployment risk and, more generally, earnings mobility. In this paper, we compare and contrast earnings mobility across the United States, Canada, France, Germany and Great Britain at the turn of the 21st century. We construct and estimate a flexible model of individual earnings dynamics for each country and simulate individual earnings trajectories given base-year earnings (1999). The ratio of lifetime earnings inequality to base-year earnings inequality provides a measure of how much equalizing mobility is in each country (Fields, 2005b).

The following conclusions can be drawed from the literature on earnings mobility that we review below. First, there is no available study for after 1995. Second, there is some evidence that the U.S. exhibit more mobility than other industrial countries, yet how much equalizing is unclear. Third, there does exist a fair amount of cross-country comparative studies of earnings mobility but far less than empirical studies of cross-sectional earnings inequality (see the surveys of Levy and Murnane, 1992, Gottschalk and Smeadling, 1997, Katz and Autor, 2000). The reason is that to compute measures of permanent income most authors rely on actual individual or familial income trajectories of a length of at least five years. The scarcity of long panels is thus a limiting constraint in most countries. Fourth, most studies allow for very few conditioning variables and always through coarse sample clustering. Fifth, the use of five-year-or-more individual earnings aggregates as a measure of permanent income has the drawback of mixing up structural mobility (changes in the steady-state equilibrium wage distribution) and exchange mobility (earnings dynamics in a particular steady-state equilibrium). Sixth, results differ for pre- or post-tax, individual or family income.

In this paper we develop a flexible semi-parametric model of pre-tax, individual earnings cross-sectional distribution and dynamics. We use a copula approach to model the dynamics of marginal distributions separately from the dynamics of individual ranks within the marginal distributions. The cross-sectional distributions are conditional on education, experience and calendar time. The copula is conditioned by education and experience. By this way we can separate structural mobility (changes in marginal distributions) from exchange mobility (ranks dynamics). We assume a first-order Markov copula which allows to identify the model over panel data as short as two years. On the other hand, we model the first-order autoregressive dynamics of ranks in a very flexible way. Specifically, we estimate a transition probability matrix for earnings deciles and use linear interpolation for the simulation of continuous ranks.

The decomposition of mobility into structural and exchange components that one finds in the literature (see below) involves counterfactual simulations based on very rudimentary models of structural change, as well as a rudimentary description of individual heterogeneity. In this paper, we allow for complex interactions between calendar time and education and experience. The exchange component of mobility is the amount of inequality in aggregate (lifetime) earnings obtained by simulating index trajectories from base year, shutting down structural change by removing all time trends including changing returns to education.

Our main results are as follows. First, our model of marginal earnings distributions and copulas is found to provide an excellent fit to the data. The semi-parametric copula captures tail dependence remarkably well. Second, the copula estimated for the U.S. implies much less persistence than for the other countries which display very similar ranks dynamics (the U.K. being slightly less persistent than Canada, France and Germany). Third, less persistence in the U.S. induces individuals to exchange positions more often than in the other countries. Surprizingly enough, the lifetime earnings inequality that results from exchange mobility is found to be the same in all countries despite greater earnings inequality in base year (1999) in the U.S. This confirms Flinn's (2002) result for the U.S. and Italy.

Our paper is closely related to the papers of Flinn (2002) and Bowlus and Robin (2004) and to a lesser extent Cohen (1999) and Cohen and Dupas (2000). These papers use a partial-equilibrium, on-the-job, stationary search model as behavioral model and compute present values to measure individual welfare. However, very little use is made of the search model besides the simple formulas for present values that it provides. The standard on-the-job search model yet constrains earnings dynamics a lot. Bowlus and Robin (2004) tried to improve the fit by augmenting the number of parameters governing on-the-job arrival rates. Yet, the model becomes rapidly too complex for the computation of present values to be analytically tractable. This is why we opt in this paper for the computation of realized values instead of present values. Bowlus and Robin (2004) show that results using present or realized values are qualitatively identical. Moreover, realized values correspond to the aggregate or permanent earnings computed in classical mobility studies, and using a model and simulation allows to extend the usual aggregation periods of five-ten years to lifetime.

The plan of the paper is as follows. The next section reviews the methodological and empirical literature. Section 3 develops a theoretical framework for computing lifetime values. The data are discussed in Section 4. Section 5 analyzes the results. The last section concludes.

2 Literature review

There is a vast literature on economic mobility, reviewed in Atkinson, Bourguignon and Morrisson (1992), Maasoumi (1998), Fields and OK (1999) and Morgan (2005). General, non-formal discussions on the interaction between cross-sectional income mobility and earnings mobility can be found in Schumpeter (1955), Friedman (1962) and Sen (1974). The distinction between exchange and structural mobility used in the sociological literature for occupational mobility was introduced in welfare economics in the early eighties (Markandya 1982, 1984, and King, 1983). In this section, we first review the literature on measuring inequality; then we review cross-country comparisons of mobility.

Measuring mobility. Several mobility indices have been proposed in the literature to quantify the change in long-run earnings inequality induced by mobility. Different mobility indices produce different rankings as they all measure different facets of mobility (see e.g. Dardadoni, 1993, Maasoumi, 1998, Checchi and Dardadoni, 2003, Buchinsky et al., 2003, Fields, 2005a). Fields (2005a) lists the "six facets" of earnings mobility as: "time-independence, positional movement, share movement, flux, directional-income movement, and mobility as an equalizer of longer-term incomes." There are two classes of mobility indexes. The first class of indexes aim at characterizing some properties of the transition kernel of Markovian earnings processes. The second class compares a welfare index of aggregate income to a counterfactual one.

The most well known mobility index in the second class is certainly the index proposed by Shorrocks (1978a, 1978b) which compares aggregate inequality to mean inequality:

$$M_S(\mathbf{Y}) = 1 - \frac{I\left(\sum_{t=1}^{T} \alpha_t Y_t\right)}{\sum_{t=1}^{T} \alpha_t I(Y_t)},$$

where $\mathbf{Y} = (Y_1, ..., Y_T) = (y_{ht})$ is an $N \times T$ panel of earnings, $I(\cdot)$ is some relative inequality index and α_t are weights.[1]

Benabou and OK (2001) note a feature of this index which they find problematic: it treats equalizing and disequalizing changes in the same way. Fields (2005b) therefore proposes to modify Shorrocks's mobility index as:

$$M_F(\mathbf{Y}) = 1 - \frac{I\left(\sum_{t=1}^{T} Y_t\right)}{I(Y_1)},$$

by replacing the average inequality index of the denominator in M_S by the base-year earnings inequality index $I(Y_1)$. Fields's index is related to the index of Chakravarty et al. (1985) who

[1] The most natural choices for α_t are $\alpha_t = 1$ and $\alpha_t = \overline{Y_t}/\overline{Y}$, the ratio of year-$t$ average income to the average income in the pooled distributions. The latter corresponds to uniform weights for detrended individual income series.

propose to compare aggregate inequality $I\left(\sum_{t=1}^{T} Y_t\right)$ to the counterfactual aggregate inequality that would prevail in absence of mobility as follows:

$$M_C(\mathbf{Y}) = 1 - \frac{I\left(\sum_{t=1}^{T} Y_t\right)}{I\left(\sum_{t=1}^{T} \frac{\overline{Y}_t}{\overline{Y}_1} Y_1\right)},$$

where $\overline{Y}_t = \frac{1}{N}\sum_{h=1}^{N} y_{ht}$ denotes year-t mean income. If individual income have been detrended, then $M_F = M_C$.

Lastly, Ruiz-Castillo (2004) and Van Kem (2004) propose to operate a further decomposition of the mobility index into structural and exchange components by considering aggregate inequality in the counterfactual distributions $Y_{1|1} = Y_1$, $Y_{2|1}$, ..., $Y_{T|1}$, where $Y_{t|1}$ sorts the elements of Y_t in the order of Y_1. Ruiz-Castillo proposes to decompose M_C as

$$M_C = \underbrace{1 - \frac{I\left(\sum_{t=1}^{T} Y_{t|1}\right)}{I\left(\sum_{t=1}^{T} \frac{\overline{Y}_t}{\overline{Y}_1} Y_1\right)}}_{\text{structural}} + \underbrace{\frac{I\left(\sum_{t=1}^{T} Y_{t|1}\right) - I\left(\sum_{t=1}^{T} Y_t\right)}{I\left(\sum_{t=1}^{T} \frac{\overline{Y}_t}{\overline{Y}_1} Y_1\right)}}_{\text{exchange mobility}}.$$

Van Kerm isolates a growth component as follows:[2]

$$M_F(\mathbf{Y}) = \underbrace{1 - \frac{I\left(\sum_{t=1}^{T} \frac{\overline{Y}_t}{\overline{Y}_1} Y_1\right)}{I(Y_1)}}_{\text{growth component}} + \underbrace{\frac{I\left(\sum_{t=1}^{T} \frac{\overline{Y}_t}{\overline{Y}_1} Y_1\right) - I\left(\sum_{t=1}^{T} Y_{t|1}\right)}{I(Y_1)}}_{\text{dispersion component}} + \underbrace{\frac{I\left(\sum_{t=1}^{T} Y_{t|1}\right) - I\left(\sum_{t=1}^{T} Y_t\right)}{I(Y_1)}}_{\text{exchange component}}.$$

Our approach is this paper follows the same ideas as in Ruiz-Castillo and Van Kerm, except that we use a more precise model to filter structural trends from earnings dynamics conditional on individual education and experience and yet does not require a long panel.

International comparison studies of earnings mobility. 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. Approximately half of the workers in all of the countries were in a different earnings

[2] Van Kerm only considers two periods and uses Fiels and Ok (1999b) mobility index (mean absolute difference in log income at each date).

> quintile in 1991 than in 1986, and between 11 and 17 per cent (22 per cent for Finland) were at least two quintiles higher or lower than they had been, indicating large changes in relative earnings. Both 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.

The OECD study also shows that the ranking of countries depends on the mobility measure used. Lastly, 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."

Aaberge *et al.* (2002) compare the U.S. and Scandinavian countries (Denmark, Norway and Sweden) using Shorrocks's index and find that "mobility of male earnings in the U.S. is less than in Denmark and Norway in both periods (1980-1990 and 1986-1990)." However, the "ordering of countries by inequality of annual [family] income by and large remains unchanged when the accounting period [period over which individual or family income are summed] is extended up to 11 years (1980-1990). United States is by far the most unequal country even for this longer period." Nevertheless, in all the countries, the absolute level of income mobility is moderate. Earnings inequality is only reduced by 5 to 10% when individual or family income is averaged over a period of five to 11 years.

Burkhauser and Poupore (1997) and Maasoumi and Trede (2001) use a Shorrocks index[3] and compare post-government-tax family income in the U.S. PSID and the German GSOEP in the 1980's before the reunification of East and West Germany. They find that there is less cross-sectional inequality in Western Germany than in the U.S. but mobility is much higher. Burkauser and Poupore view this result as "surprising" and attribute it the smaller social welfare system and the less restrictive labor market in the U.S. The surprise originates from another study of Burkhauser, Holtz-Eakin and Rhody (1997) who find "similar patterns of quintile-to-quintile [individual earnings] mobility, slightly greater overall labor market mobility in the U.S., no difference in downward mobility and small but significantly greater extreme upward mobility in Germany than in the U.S. over the period." Schluter and Trede (2003) reveal why income mobility is higher in Germany than in the United States: "Higher German mobility in the bottom of the distribution is combined with an implicitly higher weighting by the mobility

[3] Maasoumi and Trede (2001) use in fact a generalization of Shorrocks's index that allows for different degree of complementarity of each period income in the definition of permanent income. Specifically, they follow Maasoumi and Zandvakili (1986, 1990) and use long-term income CES aggregates of the form: $\left(\sum_{t=1}^{T} \alpha_t Y_t^{-\beta}\right)^{-1/\beta}$, and they use a generalized entropy inequality index.

index at the bottom."

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 (two dates). The ranking of the U.S. depends on which mobility index is used but the reduction of inequality driven by aggregation is never very large (about 14-16% for Shorrocks's M_S index, 9-14% for Fields M_F index, 4% for Chakravarty et al.'s M_C index). The main factor driving mobility is found to be "exchange" mobility (67-76% of income change), before "growth" (20-31%) and "dispersion" (2-5%).

Buchinsky et al. (2003) look at earnings mobility in France and the U.S. between 1970-1995, using PSID data and the French DAS or DADS register data. Their main message is that in both the U.S. and France different indices produce different rankings (of accounting five-year periods, genders, education and experience groups). Fields (2005b) focusses on the results obtained by Buchinsky et al. using his mobility index M_F. Less equalizing forces are at work in the U.S. than in France. In both countries, mobility is less equalizing in the 1980's than in the 1970's and in the U.S. mobility even stopped to be an equalizing force in the 1980's. 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. The discrepancy between the lifetime earnings of an employed and that of an unemployed worker are found to be similar in the two countries (9 monthly wages in the US and 13 monthly wages in France). The generous French unemployment insurance system compensates for much longer unemployment incidence and duration.

Dickens (2000) estimates a decomposition of individual earnings growth into permanent and transitory components in the same fashion as Gottshalk and Moffitt (2002). Dickens uses the Britain New Earnings Survey Panel from 1975-1995 while Gottshalk and Moffitt use the PSID from 1967-1996. They respectively find that a share of 40% and 50% of the variance of wage growth can be explained by permanent shocks.

Flinn (2002) compares Italy and the U.S. in 1988-1989. The Italian data come from a survey conducted by the Italian Statistical Institute in Lombardia and the U.S. data come from the NLSY. Flinn builds and estimates a search model of employment and wage mobility that he uses to simulate lifetime income. He finds that, although the cross-sectional wage distribution of young Italian males are much more compressed than are the comparable distributions of young white U.S. males, the estimated search model implies that the distribution of lifetime welfare (lifetime discounted earnings) is no more disperse in the U.S. than it is in Italy.

3 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.

The model should satisfy the following requirements. First, it should be conditional on individual characteristics like gender, race, education and experience. However, the number of potential interactions between these variables 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.

Second, conditional on individual characteristics, the model for the joint distribution of two consecutive earnings has to be flexible. It is thus important to allow for non symmetric dynamics, for example allowing wage cuts to be more likely when one is at the top of the earnings distribution and rises more likely when one is at the bottom. In addition, the model has to be simple enough to make Monte Carlo simulation easy. We therefore adopt a nonparametric approach based on discretizing the support of the marginal distributions and empirical distribution smoothing.

Thirdly, we want to analyze the dynamics of individual positions within marginal earnings distributions independently of the dynamics of the marginal distributions themselves. We therefore condition marginal earnings distributions on interactions between education and both calendar time and age, and we allow for residual stochastic dynamics of individual ranks within the equilibrium cross-sectional earnings distributions.

3.1 Cross-sectional (marginal) labor earnings distributions

We characterize a worker h at time t by a vector x_{ht} of characteristics, that includes potential experience and squared experience, education dummies, interactions between experience terms and education dummies, time dummies, and interactions between education dummies and a linear time trend.

At time t, worker h can be employed or unemployed. Let $G_t(y_{ht}|x_{ht})$ denote the marginal distribution function of logged labor earnings y_{ht} given x_{ht}. We assume that

$$G_t(y_{ht}|x_{ht}) = G\left(\frac{y_{ht} - x_{ht}\beta}{\sqrt{x_{ht}\gamma}}\right), \tag{1}$$

where $x_{ht}\beta$ and $x_{ht}\gamma$ are parametric specifications of the mean and variance, respectively. We use the same vector of regressors in means and variances to simplify the notations but it need not be so. We capture the dependence of G_t on calendar time by including deterministic trends interacted with education in x_{ht}.

We use the following procedure to estimate β and γ. First, using a pooled sample of individual observations (y_{ht}, x_{ht}), we regress y_{ht} on x_{ht}. Next, taking the squared residuals from this regression, we regress them on x_{ht} to yield an estimate of γ. Lastly, we reestimate β using weighted least squares. Once β and γ have been estimated, the distribution function G can be estimated using the empirical distribution of standardized residuals

$$u_{ht} = \frac{y_{ht} - x_{ht}\beta}{\sqrt{x_{ht}\gamma}}. \tag{2}$$

For later reference, let $r_{ht} \equiv G(u_{ht})$ denote the rank of log-earnings y_{ht} in the conditional earnings distribution of time t given covariates x_{ht}. Let also q_{ht} denote a discrete version of 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. In the empirical analysis N is set equal to 10.

Note that q_{ht} is never equal to 0 even if y_{ht} is the minimal wage. Hence we thus use the notation $q_{ht} = 0$ if individual h is unemployed at time t. We call "state" the value of q_{ht} in $\{0, \frac{1}{N}, \frac{2}{N}, ..., 1\}$.

3.2 The labor earnings/employment mobility process

Standard ARIMA models of earnings dynamics typically require few parameters and therefore characterize changes in earnings means and variances well but fail to produce a good description of tail dependence. This is the reason why a common practice in the literature of earnings inequality and earnings mobility prefers to examine matrices of transition probabilities across quintiles or deciles. We adopt this approach here also.

Let $P_t(i, j|x_{ht})$ 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 $\sum_j P_t(i, j|x_{ht}) = 1$. We parameterize the transition probabilities $P_t(i, j|x_{ht})$ using multinomial logits for each initial state i. Specifically,

$$P_t(i, j|x_{ht}) = \frac{\exp[x_{ht}\kappa(i, j)]}{\sum\limits_{\widetilde{j}=0}^{N} \exp[x_{ht}\kappa(i, \widetilde{j})]}. \tag{4}$$

The typical set of covariates for these M-logit estimation includes an experience quartic and education dummies. However, in this case we do not allow for interactions.

If the destination cell sizes are too small–and this happens for destination quantiles distant from the quantile interval of origin–we collapse infrequent destination quantiles together. For example, if $q_{ht} = \frac{1}{10}$ there is little chance to reach a rank at $t+1$ above $\frac{5}{10}$, irrespective of the vector of individual characteristics x_{ht}, and we may concatenate the whole range of ranks $r_{h,t+1}$ above $\frac{1}{2}$ together. Specifically, upper and lower destination deciles may be combined 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. When the destination deciles are collapsed, we divide the probability for entering the combined destination evenly across the deciles contained in that destination state.

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 linear interpolation. For those individuals leaving unemployment, the individual's new wage is determined by a random draw from the residual distribution conditional on the predicted destination quantile. Specifically, we model $r_{h,t+1}$ for $q_{h,t+1} \neq 0$ as

$$\begin{cases} r_{h,t+1} = q_{h,t+1} - (q_{ht} - r_{ht}), & \text{if } q_{ht} \neq 0, \\ r_{h,t+1} \sim \mathcal{U}\left[q_{h,t+1} - \frac{1}{N}, q_{h,t+1}\right], & \text{if } q_{ht} = 0, \end{cases} \tag{5}$$

where $\mathcal{U}[a,b]$ denotes the uniform distribution on $[a,b]$. Log-labor earnings $y_{h,t+1}$ finally follow as

$$y_{h,t+1} = x_{ht}\beta + \sqrt{x_{ht}\gamma}G^{-1}(r_{h,t+1}). \tag{6}$$

3.3 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 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 and randomly draw their state for the next period based on their experience level and characteristics using the same marginal distribution G_t and the same transition probability matrix P_t. So doing, we allow the individual's age to change and modify the earnings process but the macroeconomic environment responsible for shifts in G_t and P_t is frozen in its state at time t.

While employed individuals receive the value of their earnings. Income during unemployment is equal to a country specific unemployment insurance replacement rate ρ times the previous period's earnings if the individual was working in the previous period and times a minimum earnings, $\underline{w}$, if 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:

$$\mathcal{E}_{at}(w) = \frac{\mathcal{A}_{at}(w)}{1+r} + \frac{\mathcal{A}_{at}(w)}{(1+r)^2} + ... + \frac{\mathcal{A}_{at}(w)}{(1+r)^{\overline{x}-x+1}} = \frac{\mathcal{A}_{at}(w)}{r}\left[1 - \frac{1}{(1+r)^{\overline{a}-a+1}}\right]$$

hence

$$\mathcal{A}_{at}(w) = \frac{\mathcal{E}_{at}(w)}{\sum_{t=1}^{\overline{a}-a+1}\frac{1}{(1+r)^t}} = r\mathcal{E}_{at}(w)\frac{(1+r)^{\overline{a}-a+1}}{(1+r)^{\overline{a}-a+1}-1}. \quad (7)$$

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

4 Data

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., U.K., France, Germany and Canada. All five of these countries have at least two-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 twelve months of matched outgoing rotation group data for each year from the Current Population Survey (CPS). For France we use the three-year rotating panels from the French Labor Force Survey (LFS). For the remaining countries we use panel data sets including The British Household Panel Survey (BHPS) for the UK, the German Socio-Economic Panel (GSOEP) for Germany, and the Survey of Labor and Income Dynamics (SLID) for Canada. Since the U.S. data contain only two-year panels, for consistency we create two-year panels out of the other data sets. In order to maintain consistency with the sample used to compute the transition probabilities and that used to measure inequality, we use those individuals from the matched sample who are present in the year of interest for the inequality analysis.[4] For all of the countries we conduct the analysis for the year 1999.

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[5], and full- and part-time workers. We only exclude individuals who are self-employed,

[4]For all of the countries except the U.S., our sample basically is the same as the cross-section sample because almost everyone in a particular year can be matched forward or backward based on person identifiers. For the U.S. this is not the case because the CPS is a household, not individual, based survey that does not include person identifiers. We have used a matching routine based on household, age, race, sex and education to match individuals across sample years, but not all individuals can be matched due to moving or inconsistent responses. Thus, our U.S. sample is more stable than the full cross-section resulting in a lower unemployment rate and higher mean earnings.

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

in the military, and those out of the labor force.[6] 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 16 and 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 survey for all of the countries except Canada for which we use the labor force status in the month of March. We examine the transitions of individuals who are employed or unemployed (as classified by the surveys) in both years.

To standardize all annual earnings values we use a full-year earnings measure. For the U.S. we multiply the weekly earnings figure asked of all workers in the outgoing rotation group samples by 52 and report the figures in US dollars. In the French LFS a monthly earnings figure is given that we multiply by 12. We also divide the French earnings measure 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. In the U.S. top-coded values are multiplied by year-specific constants that were calculated to ensure the means of log earnings after correcting for top-coding are consistent with the means predicted by a regression model that assumes a normal error distribution and properly incorporates top-coded values in the log likelihood function. Top-coding is not an issue for the other countries although in the French LFS we do delete monthly earnings greater than 900000. Finally, we weight all calculations using the appropriate weights given in each data set.[7]

To deal with outliers in the data we determine minimum and maximum earnings levels using the 1999 samples. We trim earnings at the top and bottom for each sex cross education group. This results in earnings values that vary appropriately across groups reflecting each

[6] 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.

[7] 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 consequtive years, the weight requirement is much more stringent than ours and results in a non-trivial 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.

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 1% at the bottom and none 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 2% off the bottom. Note that this is quite a lot of trimming. It basically remove all excess kurtosis from log-wage distributions. However, our inequality indexes (ninety-ten percentile ratios and Gini coefficients) are relatively indifferent to the length of upper and lower tails. (For a study of upper-tail inequality in the U.S. and France, see Piketty and Saez, 2000).

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.[8]

The inequality analysis below examines the year 1999 for all of the countries using only those from the matched samples that appear in 1999 taking care to eliminate duplicate observations. However, 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 were to be used.[9] Therefore, for the countries with relatively large sample sizes - the U.S., France and Canada, we augmented the 1998-1999 transition sample with transitions from the matched data from 1999-2000. We also used the combined three year sample to estimate the earnings function parameters. For the U.K. and Germany the sample sizes were much smaller and this augmentation was not enough to avoid zeros in some cell sizes. For these countries we augmented the transition sample further using all transitions from 1996-2002. As before the earnings function parameters were estimated off of this larger sample. Even with these extended data sets for most countries an 11 by 11 transition matrix could not be recovered using a multinomial logit

[8] 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 US 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 UK 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.

[9] For all countries we ran into the problem of small cell sizes and even zeros for some events. This is particularly true for the transition from the top of the earnings distribution to unemployment or vice versa.

specification for each decile and unemployment. Only the U.S. had a large enough sample size and mobility level to estimate the full transition matrix controlling for education and experience. For the other countries upper and lower destination deciles were 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 $k = 4$.

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 include a linear trend variable interacted with the education categories and dummy variables for each two-year matched panel interacted with the education categories in both the mean and variance functions for earnings. The year 1999 is taken as the control year such that these trend 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.[10] For most countries and for both men and women, the distributions show even representation across the deciles and thus suggest that our method of detrending the data is successful.

All of the estimation and simulation steps are done separately for each sex. We must also determine the earnings level to use to compute the income received during unemployment. Since in the 1999 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 everyone. For future unemployment values that take into account staying in unemployment more than one period we use the minimum earnings levels by education and sex after trimming. 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.

5 Results

5.1 Mobility

To begin we examine mobility levels in the five countries. As stated above we group the earnings residuals into deciles and measure the probabilities of moving across deciles as well

[10] To compute equilibrium distributions, first average the transition probability matrix P_t across individual characteristics. The equilibrium distribution is the eigenvector associated to eigenvalue one of its transpose.

	U.S.	Canada	U.K.	France	Germany
Males					
1	0.025	0.039	0.043	0.122	0.060
Actual nonemployment rate in 1999	*0.029*	*0.066*	*0.056*	*0.144*	*0.059*
2	0.095	0.088	0.105	0.090	0.095
3	0.103	0.093	0.099	0.088	0.094
4	0.101	0.093	0.093	0.095	0.084
5	0.098	0.082	0.082	0.087	0.074
6	0.099	0.078	0.081	0.082	0.072
7	0.098	0.082	0.078	0.084	0.082
8	0.095	0.088	0.085	0.086	0.092
9	0.097	0.094	0.102	0.083	0.105
10	0.096	0.117	0.110	0.083	0.116
11	0.092	0.146	0.123	0.099	0.128
Stationarity (mean of rows 2,...,11)	*0.098*	*0.096*	*0.096*	*0.088*	*0.094*
Away from stationarity (residual mean)	0.002	0.014	0.012	0.004	0.013
Females					
1	0.021	0.045	0.024	0.158	0.077
Actual nonemployment rate	*0.026*	*0.058*	*0.028*	*0.178*	*0.076*
2	0.095	0.086	0.098	0.093	0.112
3	0.101	0.091	0.099	0.084	0.106
4	0.101	0.096	0.096	0.088	0.098
5	0.100	0.094	0.089	0.076	0.077
6	0.101	0.092	0.083	0.077	0.078
7	0.093	0.083	0.083	0.074	0.071
8	0.098	0.082	0.092	0.073	0.064
9	0.099	0.099	0.099	0.081	0.075
10	0.092	0.109	0.110	0.092	0.098
11	0.098	0.124	0.127	0.104	0.144
Stationarity	*0.098*	*0.096*	*0.098*	*0.084*	*0.092*
Away from stationarity	0.003	0.009	0.009	0.008	0.019

Table 1: Equilibrium Distributions

as to and from unemployment. The full 11×11 transition matrices, actual and predicted, are not reproduced here but are available upon request. They show that the multinomial logits fit the observed cell percentages for the full samples well. However, it should be noted that covariates (education and age) do not explain much of employment and earnings mobility. The pseudo R-squared values are very low ranging from 0.005 to a high of 0.165 and most of the explanatory variables are not significant. This suggests that it is very difficult to find differences in mobility rates across education and experience groups and that most everyone has the same chance to move from one state to another regardless of common observable characteristics. This is especially true for the U.S. where almost all of the 11 R-squared values for both men and women are less than 0.01 and the highest is .019. For Canada, France and the U.K. the R-squared values tend to be in the .02-.04 range, while for Germany the values are higher in the .04-.17 range suggesting more systematic mobility differences across observable characteristics in that country.

Table 2 provides several summary statistics of the mobility process for each country. The first column examines the exit rate out of unemployment, while the second through fourth columns show an average exit rate out of the deciles as well as the exit rates for the bottom and top deciles. By far the U.S. exhibits the highest exit rates of all the countries for all four measures. Surprisingly, the rest of the countries exhibit similar exit rate levels aside from the high female exit rate out of unemployment in the U.K. and the high exit rates out of unemployment in Canada for both sexes. The following patterns emerge: 1) the exit rates out of unemployment are higher than those for the earnings deciles in the U.S. and Canada and for women in the U.K. while they are lower in France and Germany; 2) the average exit rates for the earnings deciles are higher than either of the extreme deciles indicating it is easier to exit the middle deciles than either the bottom or the top decile, and 3) the exit rate out of the bottom decile is higher than the exit rate out of the top decile except for women in Germany. In addition, we also find that it is more likely to move to a neighboring decile than one farther away, the probabilities of moving up one decile and down one decile are similar with a slight edge usually given to going down, and it is less common to move to unemployment the higher the decile. The most surprising result from this exercise is the finding that, except for transitions in and out of unemployment, only the U.S. appears to be an outlier in terms of wage mobility. The other two contenders - Canada and the U.K. - exhibit overall earnings mobility rates that are quite similar to those of France and Germany. One distinction that should be made is that both Canada and the U.K. have more probability mass in the extreme off diagonal elements than either France or Germany.

	Unemployment		Average Across Deciles		Bottom Decile		Top Decile	
Country	Males	Females	Males	Females	Males	Females	Males	Females
U.S.	0.76	0.81	0.71	0.68	0.61	0.52	0.57	0.51
U.K.	0.40	0.64	0.59	0.54	0.42	0.34	0.34	0.30
Canada	0.52	0.47	0.47	0.48	0.34	0.36	0.24	0.25
France	0.30	0.28	0.52	0.48	0.38	0.40	0.24	0.25
Germany	0.44	0.31	0.52	0.47	0.35	0.21	0.24	0.28

Table 2: Mobility Summary Statistics: Exit Rates

That the U.S. stands alone in terms of mobility is further confirmed by looking at the eigenvalues of the transition matrices. While all other countries have a second higher eigenvalue of the order of 0.80, the U.S. have it equal to 0.54. This implies that the convergence to equilibrium, starting from any initial distribution, is much faster in the U.S. that in the other countries. In other words, the employment/earnings ranks process is much more stationary in the U.S.–people exchange positions more. This will have important consequences on lifetime earnings inequality.

In order to examine how well we fit relative earnings mobility using the multinomial logit models and our interpolation procedure, we computed Spearman's correlation and Kendall's tau using the ranks from the actual and predicted wage data for each country. Table 4 presents the results of these fit tests for the overall sample and the first, fifth and tenth decile for males and females, respectively. From a fit perspective our empirical strategy does very well at capturing the overall correlation between wages in subsequent periods for all countries. The fit is also very good within deciles with a slightly better fit for the middle deciles than the outer deciles. Several features of the data stand out in these tables: 1) the U.S. exhibits much lower correlations than any of the other countries, 2) the correlation increases moving from the bottom of the distribution to the top, and 3) the correlation levels for males and females within each country are quite similar. The second conclusion is important as it fully justifies our nonparametric approach: one single correlation parameter does not permit to characterize the earnings autocorrelations throughout the entire distribution.

5.2 Earnings

Table 5 presents the earnings differentials for education and experience for each country. The education differential is the ratio of mean earnings of the highest education group to the lowest education group while the experience differential is the ratio of mean earnings of those with 25 years of experience or more to those with 0 to 15 years of experience. The figures in Table

	U.S.	Canada	U.K.	France	Germany
Males					
1	1.000	1.000	1.000	0.995	1.000
2	0.540	0.870	0.780	0.855	0.830
3	0.379	0.768	0.651	0.761	0.732
4	0.292	0.663	0.562	0.661	0.626
5	0.224	0.558	0.519	0.553	0.519
6	0.199	0.461	0.392	0.486	0.507
7	0.160	0.426	0.271	0.386	0.380
8	0.124	0.367	0.187	0.289	0.284
9	0.094	0.295	0.137	0.219	0.227
10	0.068	0.203	0.102	0.171	0.160
11	0.059	0.203	0.092	0.086	0.102
Females					
1	1.000	1.000	1.000	0.996	1.000
2	0.602	0.839	0.823	0.879	0.864
3	0.445	0.729	0.711	0.764	0.776
4	0.338	0.639	0.596	0.653	0.668
5	0.247	0.527	0.481	0.600	0.668
6	0.195	0.509	0.350	0.511	0.580
7	0.170	0.430	0.337	0.424	0.432
8	0.138	0.333	0.260	0.343	0.338
9	0.107	0.266	0.188	0.304	0.265
10	0.075	0.232	0.135	0.246	0.215
11	0.075	0.232	0.107	0.167	0.215

Table 3: Eigenvalues of Transition Probability Matrix

		Males				Females			
		Spearman R		Kendall tau		Spearman R		Kendall tau	
Country	Sample	Actual	Pred.	Actual	Pred.	Actual	Pred.	Actual	Pred.
U.S.	Full Sample	0.69	0.69	0.53	0.52	0.73	0.72	0.56	0.55
	Decile 1	0.44	0.47	0.31	0.35	0.43	0.48	0.30	0.38
	Decile 5	0.67	0.65	0.49	0.48	0.69	0.67	0.51	0.49
	Decile 10	0.61	0.65	0.44	0.50	0.59	0.64	0.44	0.50
U.K.	Full Sample	0.87	0.83	0.72	0.67	0.90	0.87	0.76	0.72
	Decile 1	0.60	0.49	0.45	0.41	0.64	0.66	0.47	0.55
	Decile 5	0.77	0.74	0.59	0.57	0.75	0.72	0.58	0.54
	Decile 10	0.77	0.85	0.61	0.70	0.77	0.81	0.61	0.68
Canada	Full Sample	0.92	0.90	0.80	0.76	0.91	0.88	0.78	0.75
	Decile 1	0.63	0.64	0.50	0.54	0.59	0.64	0.43	0.54
	Decile 5	0.84	0.80	0.68	0.64	0.79	0.78	0.64	0.62
	Decile 10	0.81	0.87	0.65	0.76	0.81	0.81	0.66	0.70
France	Full Sample	0.93	0.92	0.80	0.78	0.94	0.94	0.82	0.81
	Decile 1	0.74	0.68	0.59	0.58	0.67	0.70	0.52	0.59
	Decile 5	0.83	0.83	0.67	0.66	0.85	0.85	0.69	0.69
	Decile 10	0.88	0.91	0.73	0.79	0.88	0.89	0.74	0.78
Germany	Full Sample	0.91	0.88	0.77	0.73	0.92	0.89	0.80	0.76
	Decile 1	0.66	0.63	0.53	0.51	0.71	0.74	0.56	0.63
	Decile 5	0.80	0.81	0.63	0.65	0.76	0.79	0.59	0.64
	Decile 10	0.88	0.92	0.72	0.81	0.82	0.83	0.67	0.73

Table 4: Wage Mobility Rank Tests

	Males		Females	
Country	Education	Experience	Education	Experience
U.S.	2.59	1.31	2.73	1.09
U.K.	1.68	1.15	2.02	0.83
Canada	1.69	1.24	2.13	1.10
France	2.06	1.17	1.97	1.01
Germany	1.86	1.31	1.66	0.97

Table 5: Earnings Differentials

5 reveal the following facts: 1) the U.S. has the highest education and experience premiums; 2) the U.K. has the lowest education premium for males and the lowest experience premiums while Germany has the lowest education premium for females; 3) females have lower experience premiums than males due to higher part-time participation rates as they age; and 4) the education premiums are much larger than the experience premiums.

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. Table 6 gives the actual and predicted moments of the log earnings and earnings distributions for each country for males and females, respectively. Given our log wage specification the predicted means and standard deviations match those in the data almost exactly. This then 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.

5.3 Lifetime values

Having demonstrated that our empirical specification provides a good fit of the observed data, we turn now to the main focus of the paper, the annuity value calculations. As mentioned above we simulate ex post realizations using the estimated transition and earnings processes. Because we have calculated a value of unemployment, one can calculate the average annuity value based on the full sample including unemployed individuals 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 order to have samples that are comparable across all of our calculations we use only the employed sample.

Table 7 presents the same education and experience differentials for lifetime annuity values that were presented in Table 5 for earnings. In all cases the education premiums have increased while the experience premiums have decreased. Thus mobility reinforces education differences while it 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 inequality.

We now turn our attention to the main focus of the paper: inequality. Table 8 shows the levels of inequality for earnings and values using 90-10 ratios and Gini coefficients for males and females separately for each country. Focusing first on earnings inequality and moving across the rows we find that within each country females exhibit more earnings inequality than males. This is due to the greater fraction of women working part-time. Across countries we find that for males the U.S. exhibits a very high level of earnings inequality with Canada and the U.K. exhibiting a similar level that is in between the U.S. and France and Germany which have the lowest levels. For females the U.K. is closer to the U.S. even surpassing the U.S. 90-10 level while Canada still remains in the middle and France and Germany exhibit low levels of inequality. (Compare to other cross-country earnings inequality studies.)

Table 8 also shows the levels of inequality using the annuity values. As in Bowlus and Robin (2004) the level of annuity value inequality is in general lower than the level of earnings

			Males				Females			
Country			Mean	Std dev.	Skewness	Kurtosis	Mean	Std dev.	Skewness	Kurtosis
U.S.	Log Earnings	Actual	10.14	0.59	0.05	3.12	9.78	0.61	-0.07	3.15
		Pred.	10.14	0.59	0.11	2.99	9.79	0.61	0.14	3.00
	Earnings	Actual	31,903	21,540	2.39	11.92	22,177	14,890	2.48	15.21
		Pred.	31,916	21,331	2.07	9.23	22,339	15,565	2.36	12.30
U.K.	Log Earnings	Actual	9.56	0.44	0.25	2.96	9.06	0.59	-0.34	2.78
		Pred.	9.57	0.44	0.18	2.91	9.06	0.58	-0.06	2.84
	Earnings	Actual	16,170	7,916	1.85	9.14	9,853	5,709	1.20	4.96
		Predicted	16,189	7,767	1.61	7.33	9,899	6,199	1.66	6.87
Canada	Log Earnings	Actual	10.41	0.52	-0.62	3.59	9.95	0.57	-0.58	3.10
		Pred.	10.40	0.50	-0.15	2.97	9.94	0.55	-0.14	2.80
	Earnings	Actual	37,027	17,732	0.96	4.82	23,898	12,167	0.72	3.32
		Pred.	36,897	18,971	1.31	5.56	23,843	13,264	1.23	4.66
France	Log Earnings	Actual	9.47	0.38	0.45	4.26	9.26	0.48	-0.50	3.39
		Pred.	9.47	0.38	0.57	3.88	9.26	0.48	-0.07	2.87
	Earnings	Actual	15,025	7,290	2.43	12.72	11,403	5,372	1.23	6.46
		Pred.	15,051	7,412	2.58	14.11	11,402	5,763	1.46	6.61
Germany	Log Earnings	Actual	10.15	0.38	0.08	3.49	9.65	0.44	-1.13	6.09
		Pred.	10.15	0.38	0.16	2.86	9.64	0.41	-0.22	4.42
	Earnings	Actual	28,084	11,209	1.15	4.54	17,454	7,901	0.55	3.60
		Pred,	28,132	11,162	1.09	4.40	17,232	8,878	1.15	4.72

Table 6: Fit of Male Earnings Distribution

	Males		Females	
Country	Education	Experience	Education	Experience
U.S.	2.59	1.02	2.83	0.91
U.K.	1.83	0.96	2.33	0.71
Canada	1.79	0.99	2.31	0.88
France	2.44	0.92	2.27	0.84
Germany	2.13	1.04	1.55	0.98

Table 7: Lifetime Annuity Value Differentials

	Males			Females		
	Earnings	Values	Reduction	Earnings	Values	Reduction
			90/10			
U.S.	4.62	2.70	41%	4.72	2.87	39%
U.K.	3.13	2.46	22%	5.08	3.73	27%
Canada	3.59	2.63	27%	4.37	3.12	29%
France	2.61	2.75	-5%	3.88	3.68	5%
Germany	2.81	2.52	10%	3.31	3.04	8%
			Gini Coefficient			
U.S.	0.33	0.22	35%	0.33	0.23	31%
U.K.	0.26	0.20	21%	0.32	0.28	12%
Canada	0.26	0.21	20%	0.28	0.24	16%
France	0.23	0.24	-3%	0.25	0.26	-4%
Germany	0.23	0.21	9%	0.25	0.23	9%

Table 8: Earnings and Value Inequality

inequality. The exceptions to this finding are French males. French females also have an increase in inequality if one uses the Gini coefficient. As might be expected the U.S. exhibits the largest inequality differential between earnings and annuity values with a 30-40% reduction in inequality for both males and females. Inequality levels amongst annuity values are also substantially lower than earnings inequality levels for Canada and the U.K., between 15-30% lower depending on the gender and measure. France and Germany see the lowest reduction in inequality when moving to annuity values at less than 10% and as noted sometimes inequality even increases.

When comparing inequality levels across countries, the surprising feature is how similar the value inequality levels are across the countries despite the large differences in earnings inequality figures. For males France now exhibits the highest level of inequality while the U.K. exhibits the lowest; the U.S. is no longer at the top but rather in the middle. For females the U.K. exhibits the highest level of inequality with the U.S. at the bottom. The fact that the lifetime income inequality measures are higher than earnings inequality measures in France may be surprising given the overall transition matrix for this country does not look that different from that of Canada and Germany. There are several reasons for these different outcomes. First, the likelihood of remaining unemployed or becoming unemployed is the highest in France compared to all of the other countries. Transiting to unemployment reduces income because the replacement rates are far below 1. Getting stuck in unemployment reduces it even more because the unemployment income is now based on the minimum earnings level for each education group. Having these low income values reduces the lifetime values and holds down the bottom of the distribution. Second, as mentioned above Canada has more probability mass in the extremes of the off diagonals of the transition matrix. This means that the lifetime values of individuals at the low end of the earnings distribution are higher and those of individuals at the high end of the distribution are lower leading to more compression of the overall distribution. In fact if we were to hypothetically give France the Canadian mobility estimates we find that value inequality falls in France: the 90-10 ratio would be 2.20 for men and 3.02 for women. This reduction primarily comes from differences in unemployment mobility and upward earnings mobility in the two countries. Finally, France has a very polarized earnings distributions in terms of the link between education and earnings. There are very few high educated workers in the lower tails of the distributions and likewise very few low educated workers in the upper tails. This polarization is even greater after computing the lifetime values. In Canada the education distribution across the wage distribution is more stable with all groups represented at all wage levels and while the upper part of the value distribution has a higher concentration

	90/10					
	Males			Females		
	Utilities	Values	Reduction	Utilities	Values	Reduction
U.S.	2.15	1.64	23%	2.17	1.70	22%
U.K.	1.77	1.58	11%	2.25	1.95	13%
Canada	1.90	1.65	13%	2.09	1.80	14%
France	1.62	1.68	-4%	1.97	1.98	0%
Germany	1.68	1.63	3%	1.82	1.81	1%
	Gini Coefficient					
U.S.	0.17	0.11	35%	0.17	0.12	32%
U.K.	0.13	0.10	21%	0.17	0.14	13%
Canada	0.14	0.11	20%	0.15	0.13	16%
France	0.11	0.12	-5%	0.13	0.14	-8%
Germany	0.12	0.11	5%	0.14	0.13	6%

Table 9: Utility Based Current and Lifetime Inequality

of university graduates the other groups are still present pulling down the highest value levels.

We also computed the inequality analysis using a utility based approach to see if risk aversion made a difference. We used a CRRA utility function specification with an intertemporal substitution elasticity of 2. These results are presented in Table 9. 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 smaller substantially smaller for the 90-10 ratios, but similar for the Gini coefficients. All of the other orderings remain the same.

To explore further the relationship between mobility and lifetime inequality across countries we conduct two exercises. First, we compute a variety of simulations under different mobility scenarios using the income based approach. These results are presented in Table 10. The first row for both males and females reproduces the 90-10 ratios for earnings from Table 8. The second row shows 90-10 ratios for lifetime annuity values that have been simulated under the assumption that only positive earnings mobility (or none) is possible. That is, there are no transitions to unemployment and one either stays in the same decile or moves to a higher one throughout their lifetime. Allowing for upward wage mobility reduces inequality substantially in all five countries for both males and females except for males in France where very little reduction occurs. The third row has the result for only downward earnings mobility. Again in almost all cases inequality is reduced. However, the reduction is generally much smaller than with upward wage mobility and for females in Germany inequality actually increases. In all countries the mean of the lifetime annuity value is lower than that of salaries when only downward earnings mobility is allowed. In Germany the bottom of the distribution

Experiment	U.S.	U.K.	Canada	France	Germany
			Males		
Annual earnings	4.62	3.13	3.59	2.61	2.81
Upward earnings mobility only	2.93	2.24	2.46	2.59	2.31
Downward earnings mobility only	3.09	2.44	3.38	2.54	2.62
Earnings mobility only	2.65	2.35	2.53	2.44	2.19
Employment mobility only	4.38	2.92	3.26	2.86	2.78
Ex post annuity values (full mobility)	2.70	2.46	2.63	2.75	2.52
			Females		
Annual earnings	4.72	5.08	4.37	3.88	3.31
Upward earnings mobility only	3.14	3.24	2.78	2.76	2.74
Downward earnings mobility only	3.47	4.07	3.99	3.90	3.85
Earnings mobility only	2.83	3.64	2.99	3.06	3.19
Employment mobility only	4.82	5.06	4.22	4.08	4.02
Ex post annuity values (full mobility)	2.87	3.73	3.12	3.68	3.04

Table 10: 90-10 Ratios Across Experiments

drops further than the top for females resulting in an increase in inequality. The fourth row shows the inequality level for annuity values that are computed assuming both upward and downward earnings mobility but no employment mobility. Here in all cases, even males in France, inequality is reduced. The fifth row shows the level of inequality when only employment mobility is allowed.[11] Not surprisingly, given the way income in unemployment is calculated, this type of mobility produces the lowest reduction in inequality in all countries and even raises it for men France and women in the U.S., France and Germany. Finally the last row contains the 90-10 ratios assuming full mobility and are reproduced from Table 8. In general the final 90-10 ratio falls in between the one for annual earnings and the highest of those from the other experiments.

Second, we compute a variance exercise also using the income based values. For each of the five countries Table 11 gives the R-squared values for regressions of earnings and ex post annuity values on each explanatory attribute for males and females, respectively. As before we only show the results for the employed sample. In terms of earnings education explains 20-28% of the variation in wages except surprisingly in Canada where it explains only 12% for males and 17% for females and in Germany where it explains only 12% for females. Experience explains less of the variation in earnings than education - less than 10% in most countries. As expected, experience explains less of the variation in female earnings than male earnings. A respondent's initial decile captures a lot of the variation in wages and combined with experience and education almost all of the variation can be explained. Turning to the annuity values education plays an

[11] Here we do allow the individual coming out of unemployment to go to any of the residual deciles. They do not have to return to their original decile.

		U.S.	U.K.	Canada	France	Germany
				Males		
Current Earnings	Education	0.24	0.20	0.12	0.28	0.22
	Experience	0.09	0.13	0.08	0.03	0.11
	Decile of Initial Residual	0.65	0.68	0.75	0.53	0.60
	All	0.96	0.96	0.95	0.95	0.94
Annuity Values	Education	0.59	0.44	0.23	0.47	0.42
	Experience	0.06	0.10	0.03	0.01	0.01
	Decile of Initial Residual	0.05	0.11	0.26	0.18	0.16
	Mobility	0.08	0.14	0.16	0.19	0.17
	Current earnings	0.39	0.41	0.44	0.57	0.46
	All	0.73	0.71	0.67	0.80	0.80
				Females		
Current Earnings	Education	0.23	0.20	0.17	0.24	0.12
	Experience	0.04	0.04	0.03	0.01	0.03
	Decile of Initial Residual	0.70	0.76	0.76	0.67	0.78
	All	0.95	0.96	0.96	0.95	0.90
Annuity Values	Education	0.56	0.40	0.31	0.38	0.09
	Experience	0.07	0.16	0.06	0.05	0.01
	Decile of Initial Residual	0.07	0.15	0.22	0.24	0.36
	Mobility	0.08	0.09	0.19	0.29	0.13
	Current earnings	0.39	0.45	0.44	0.57	0.50
	All	0.72	0.72	0.70	0.83	0.75

Table 11: Variance Analysis of Male Earnings and Annuity Values (R-squared values)

even larger role as the R-squared is two times that for earnings except for females in Germany where the explanatory power actually falls. Placement in the current earnings distribution, as indicated by the decile of the initial residual, is not important in the U.S. and the U.K. - two relatively mobile countries, but is important in France, Germany and Canada. The Canadian result is surprising given its characterization as a fairly mobile country although as shown by its mobility matrix much of this mobility is employment based. In Table 11 mobility is measured by three factors that count over the course of the simulation for each individual the number of transitions between employment and unemployment, the number of positive decile changes across the earnings residual distribution and the number of negative decile changes. Once again these measures are found to not play an important role in the U.S. and the U.K. but do in Canada, France and Germany. Current earnings has a lot of explanatory power and except for in the U.S. explains as much or more than education. Finally, all of these factors can explain between 67-83% of the variation in annuity values.

6 Conclusions

In this paper, we compare and contrast earnings mobility across the United States, Canada, France, Germany and Great Britain at the turn of the 21st century. We construct and estimate a flexible model of individual earnings dynamics for each country and simulate individual earnings trajectories given base-year earnings (1999). Our model is found to provide an excellent fit to the data. The U.S. displays more equalizing mobility than in all other countries, so much that the lifetime earnings inequality that results from exchange mobility is found to be the same in all countries despite greater earnings inequality in base year (1999) in the U.S.

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