On the source and magnitude of income mobility in Germany*

Philippe Van Kerm

CEPS/INSTEAD, G.-D. Luxembourg

June 2002
Draft 1.0

Abstract

This paper has two objectives. Firstly it sets out a methodology for the analysis of income mobility that permits a visual inspection of what portion of the distribution contributes the most to the aggregate level of income mobility in the context of 'distance-based' mobility measures (typically à la Fields & Ok). Secondly the paper presents some results on income mobility in Germany. This illustrates the use of the suggested methodology. The main insight of the approach is that most of the contribution to mobility is from the lower 10% of the distribution. Average relative income changes are generally the same for the rest of the individuals (but the richest 5%). This pattern is observed both for Western and Eastern Germany as well as in Luxembourg, Hungary and the United Kingdom in the 1990s.

1 Introduction

The measurement of income mobility, when one crucially is concerned with the aggregation of individual income changes in a society forms a body of vivid literature. Several studies have recently documented the level of income mobility in a series of industrialised countries using a variety of different approaches to measurement.[1]

*Paper prepared for the 5th German Socio-Economic Panel conference, Berlin, July 3-4 2002. This paper is part of a research project supported by the European Commission under the Transnational Access to major Research Infrastructures programme (Contract No. HPRI-CT-2001-00128) hosted by IRISS at CEPS/INSTEAD Differdange (Luxembourg). Contact: `philippe.vankerm@ceps.lu`.

[1]See among others Aaberge et al. (1996), Burkhauser & Poupore (1997), Canto-Sanchez (1998), Galasi (1998), Hoet-Mulquin & Van Kerm (1998), Schluter (1998), Bogomolova & Tapilina (1999), Schluter & Trede (1999), Fields et al. (2000), Van Kerm (2001).

Most analyses use mobility indices that aggregate in a single figure the changes in individual incomes over time, and thence put their focus on temporal or cross-country comparisons at an aggregate (country-wise) level. Studies that attempt to analyse in greater detail the causes of mobility or identify the sources of cross-national differences are relatively rare. A notable exception is Schluter & Trede (1999) addressing the puzzling evidence that income mobility might be higher in Germany than in the USA.[2] It is mainly in the more specific context of poverty dynamics (when one dichotomises the income distribution between 'the poor' and the 'non-poor') that attempts have been made to unravel the causes of mobility as embodied in 'poverty exits' and 'poverty entries'.[3] The main objective of this paper is to propose a methodology for assessing income mobility levels that offers a flexible and intuitive framework to help identify the source of mobility and to help account for differences thereof over time or across countries. An application to Germany illustrates the methodology.

At present, most of the literature on income mobility has been concerned either with (i) *positional* mobility measures that focus on the evolution of individual positions across quantile groups or income ranks, (ii) with the evolution of the relative income of individuals, that is the change in their income share, and its impact on measures of inequality, or (iii) with the *origin dependence* of individual incomes by attemtping to capture the degree of correlation between today's and yesterday's income levels. In this paper I concentrate on mobility measurement of a very different nature. The focus is put on assessment of the magnitude of individual income changes. This approach, which has been referred to as the study of income *movement* captures the variations of the incomes of individuals in the economy irrespectively of considerations of reranking or longer term inequality. This is meant to give direct information about the income flux that takes place in the society, and to identify how (un-)stable have been the incomes of individuals in a given time period. The leading aggregate measures of this kind are those advocated and axiomatised in Fields & Ok (1996) and Fields & Ok (1999) that assess the level of income mobility in a society by means of a simple averaging of individual income changes.

The outline of the remainder of the paper is as follows. Section 2 is the heart of the paper: it presents the class of mobility measures on which the paper focuses and the graphical representation thereof that will be the basis for the analysis. The empirical analysis of mobility in Western and Eastern Germany is presented in

[2]See e.g. Burkhauser & Poupore (1997), Schluter (1998), Schluter & Trede (1999), Van Kerm (2001).

[3]See among many others Bane & Ellwood (1986), Duncan & Rodgers (1991), Stevens (1994), Stevens (1999), Jenkins (2000), Cappellari & Jenkins (2002), Devicienti (2002).

Section 3. A brief conclusion ends the paper.

2 Methodology

Let X and Y denote two correlated random variables representing respectively the distribution of income in an initial and a final time period. Denote by F their joint cumulative distribution function. Define also F_X, F_Y as the two marginal distributions, and $F_{X|Y}$, $F_{Y|X}$ as the two conditional distributions. (In the sequel, lowercase f will refer to the density functions counterpart of the uppercase F cumulative distribution functions.) Let $M(X,Y)$ be a mobility index.

As stated in the Introduction, the paper concentrates on income *movement* indices à la Fields & Ok. The standard version of these measures can be defined in the continuum as

$$M^{AFOK}(X,Y) = \int\int |y-x|\, f(x,y)dxdy \tag{1}$$

for the 'absolute' version (Fields & Ok 1996) and

$$M^{RFOK}(X,Y) = \int\int |\log(y) - \log(x)|\, f(x,y)dxdy \tag{2}$$

for the 'relative' version (Fields & Ok 1999).

These two mobility measures can be put in a more general framework by using the concept of a distance function between incomes. A 'distance' function, $d(x,y)$, between an initial and a subsequent income level is chosen to evaluate the degree of mobility experienced by each individual over the time interval. The overall assessment of mobility is achieved by taking the expectation over all individual mobility experiences:

$$M(X,Y) = \int\int d(x,y)f(x,y)dxdy. \tag{3}$$

Note that this class of mobility indices includes both the 'directional' and 'non directional' version of the Fields & Ok indices, as well as generalisations proposed in Fields & Ok (1999).

The mathematical simplicity of the class of mobility indices defined by (3) offers a variety of decomposition possibilities to isolate the sources of income mobility and thence help account for cross-national or inter-temporal differences. The stepping stone of this paper is to formulate such a mobility index as a functional of a *conditional mobility* function, the conditioning being made on the level of income at the base period. In other words, separate mobility levels are estimated for each starting position in the initial income distribution, and the resulting *conditional* *mobility* function is plotted to obtain an evocative picture of the repartition of mobility levels accross different parts of the distribution. Aggregate mobility levels are obtained simply by integrating the *conditional mobility* function. This approach makes it straightforward to identify the portions of the distribution that have the largest impact on the overall level of mobility, whether it is the rich, the poor or the middle class that experience the greatest mobility and to assess their respective impact on the overall mobility level.

This methodology is closely related to the procedures presented in Schluter & Trede (1999) and Schluter & Van de gaer (2002). The same objective is indeed shared but the approach is applied here in the different and largely simplified context of 'distance-based' mobility measures.

Mathematically the suggested decomposition is obtained by rewriting (3) as

$$\begin{aligned} M(X,Y) &= \int \left(\int d(x,y) f_{Y|x}(y) dy \right) f_X(x) dx & (4) \\ &= \int m\left(X,Y|X=x\right) f_X(x) dx & (5) \\ &= \int m\left(X,Y|X=x\right) dF_X(x) & (6) \end{aligned}$$

where $m\left(X,Y|X=x\right)$ is the *conditional mobility* function.

In practice, one will estimate and plot $m\left(X,Y|X=x\right)$ and then estimate $M(X,Y)$ indirectly by integration. Reliable estimation of $m\left(X,Y|X=x\right)$ is therefore required. This can not be achieved by estimating the mobility index on the subsample defined by $X=x$. Since X is a continuous random variable such a subsample would likely be very small and the resulting *conditional mobility* function would be too variable to provide any insightful picture. Given the structure of the class of measures defined by (3) and the suggested decomposition, this estimation problem collapses to a problem of non-parametric regression function estimation: the regression of $d(x,y)$ on x (or $F_X(x)$). Different techniques can therefore be used to estimate $m\left(X,Y|X=x\right)$, e.g. Nadaraya-Watson kernel regressions or local polynomial fitting. I will use here a single method that is fairly easily implemented in most standard statistical packages: the locally weighted regression (LOESS) introduced by Cleveland (1979).

Ease of implementation is the first advantage of this method. Its second advantage is the availability of a 'robust' version of the technique. The robust LOESS estimation, detailed in Cleveland (1979), guards against deviant points that may affect estimation of $m\left(X,Y|X=x\right)$ by attaching smaller weights in the estimation process to outlying observations (i.e. observations with an extremely large absolute 'distance' between initial and final income). Applying the robust procedure permits to keep under control the potential effect of data contamination. In particular, indirect estimation of $M(X,Y)$ by integration of the robust estimate of $m\left(X,Y|X=x\right)$ will make it robust to contamination, in contrast to standard direct estimation based on unit record data.[4] Comparing mobility estimates obtained with and without this 'robustification' may give an idea of the potential effect of measurement error on our traditional estimates.

The formulation of $M(X,Y)$ as in (6) points to a direct generalisation of this class of mobility measures to allow for putting different ethical weights to different portions of the income distribution. As such, distance-based mobility indices à la Fields & Ok do not give any special importance to who experience the largest income gains. Whether it is the rich or the poor that have the largest income changes (as measured by the d function) is irrelevant. One may yet want to give greater weight to income changes for the poor since this indicates opportunity of escaping from an undesirable position – provided the d function is directional –. Using a weighted integration of the *conditional mobility* provides such a generalisation:

$$M^{w}(X,Y)=\int w\left(x\right)m\left(X,Y|X=x\right)dF_{X}(x) \tag{7}$$

An example of a weight function that could be applied to this aim is the weighting function which is implicit to S-Gini coefficients, $w\left(x\right)=\upsilon\left(1-F_{X}(x)\right)^{\upsilon-1}$ with $\upsilon>1$, that attaches decreasing weight to individuals when moving from poorest to richest, depending on their rank in the distribution (Donaldson & Weymark 1983, Yitzhaki 1983). The speed of decrease of the weight is controlled by υ.

To conclude the exposition of the methodology adopted in this paper, let me emphasise the possibility of relating the *conditional mobility* function to exogenous individual attributes. A useful property of the *conditional mobility* function is that, just as $M(X,Y)$, $m\left(X,Y|X=x\right)$ is decomposable by population subgroups. If $A=(A_{1},\ldots,A_{K})$ is a partition of the population into K mutually exclusive states, and $P(A_{k})$ denotes the probability that an individual belongs to state k then

$$m\left(X,Y|X=x\right)=\sum_{k=1}^{K}P(A_{k})m\left(X,Y|X=x;A_{k}\right) \tag{8}$$

where $m\left(X,Y|X=x;A_{k}\right)$ is the *conditional mobility* function estimated for individuals of state k only.

This property allows an assessment of the impact of exogenous attributes on the level of mobility. The additional gain of using the subgroup decomposition of the *conditional mobility* function instead of the subgroup decomposition of the aggregate mobility index is the possibility to identify differential roles of individual

[4]See Cowell & Schluter (1998) on estimation of income mobility measures with dirty data.

characteristics at different points of the income distribution. Note that defining population subgroups by using the experience (or absence of experience) of a set of mutually exclusive events also permits to investigate more closely the effects on income mobility of potential 'triggering events' as has been done in the analysis of poverty transitions. Finally counterfactual methods can be applied to account for cross-national or inter-temporal differences in mobility levels using e.g. methods inspired from DiNardo et al. (1996) or Hyslop & Maré (2000) in the context of static income distribution funtions.

3 Income mobility in Germany, 1984–2000

Data and methodological options

The methodology presented in Section 3 is now applied to the English-Language Public Users German Socio-Economic Panel data in its incarnation in the Cross-National Equivalent data files to study patterns of income mobility in Germany over the period 1984–2000.[5] Some tentative comparisons with three other European countries are presented. These are drawn from data of the Consortium of Household Panels for European Socio-Economic Research.

The measure of income, or living standard, adopted is real annual post-government household income converted in a 'single adult equivalent' using the modified OECD scale. Household income is pooled income of all family members including labour earnings, asset flows, private transfers, and public transfers minus total household taxes. The latter are not directly available but simulated and provided with the data (Schwarze 1995).

I have implemented a robust LOESS procedure to estimate the various *conditional mobility* functions. Both local linear and local quadratic fitting have been tested. The quadratic fitting did not yield distinctively better results, hence I present only results obtained by the computationally less demanding linear fitting algorithm. A 'nearest neighbours' bandwidth was used that in effect adapts to the sparseness of observations at different portions of the income line. Sample fractions of 10% or 20% were used as nearest-neighbours depending on the sample size. See Cleveland (1979) for details on the procedure.

[5]See Wagner et al. (1993) for a presentation of the English-Language Public Users German Socio-Economic Panel, and Burkhauser et al. (1995) for more information on the Cross-National Equivalent File.

Conditional mobility functions: the aggregate annual results

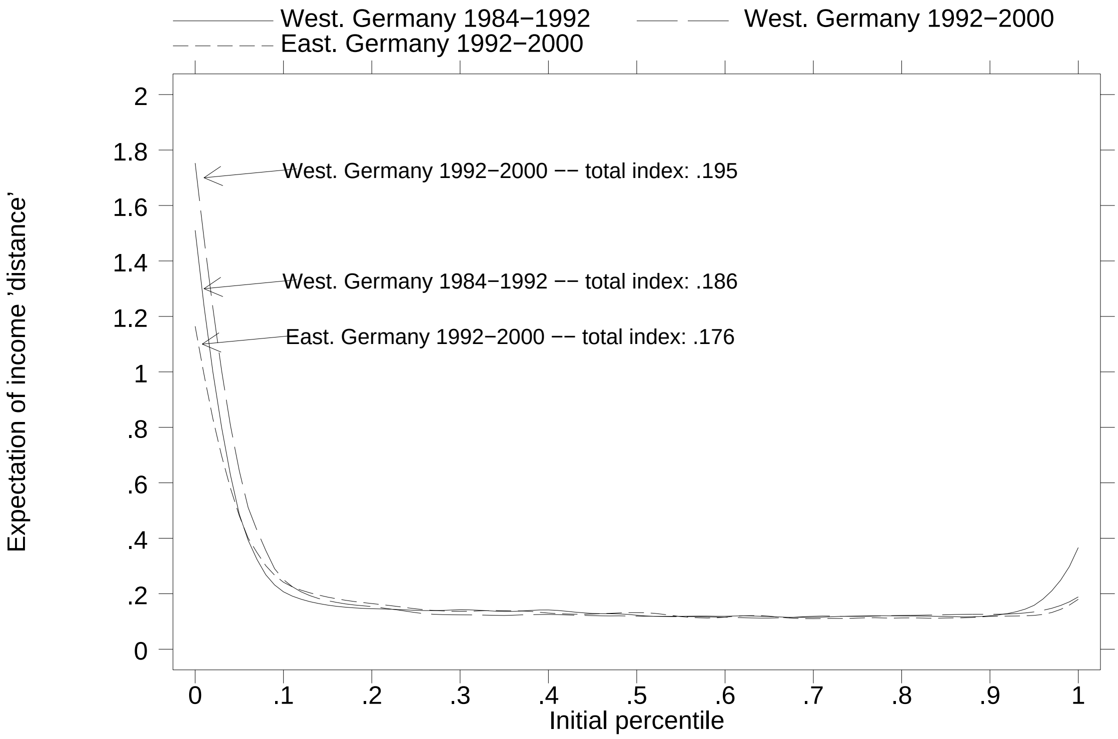
Figure 1 plots estimated *conditional mobility* functions for pooled data for Western Germany 1984-1992 and 1992-2000 and Eastern Germany 1992-2000. The distance function d in the top panel of the figure is the relative, non-directional version of Fields & Ok's index: $d(x,y) = |\log(y) - \log(x)|$. The distance function d in the bottom panel is the directional counterpart: $d(x,y) = (\log(y) - \log(x))$ (Fields & Ok 1999). Income changes between successive years are considered. The data within each of the three subsamples are pooled so that all observed year t and year $t+1$ income pairs are used to estimate the *conditional mobility* functions.

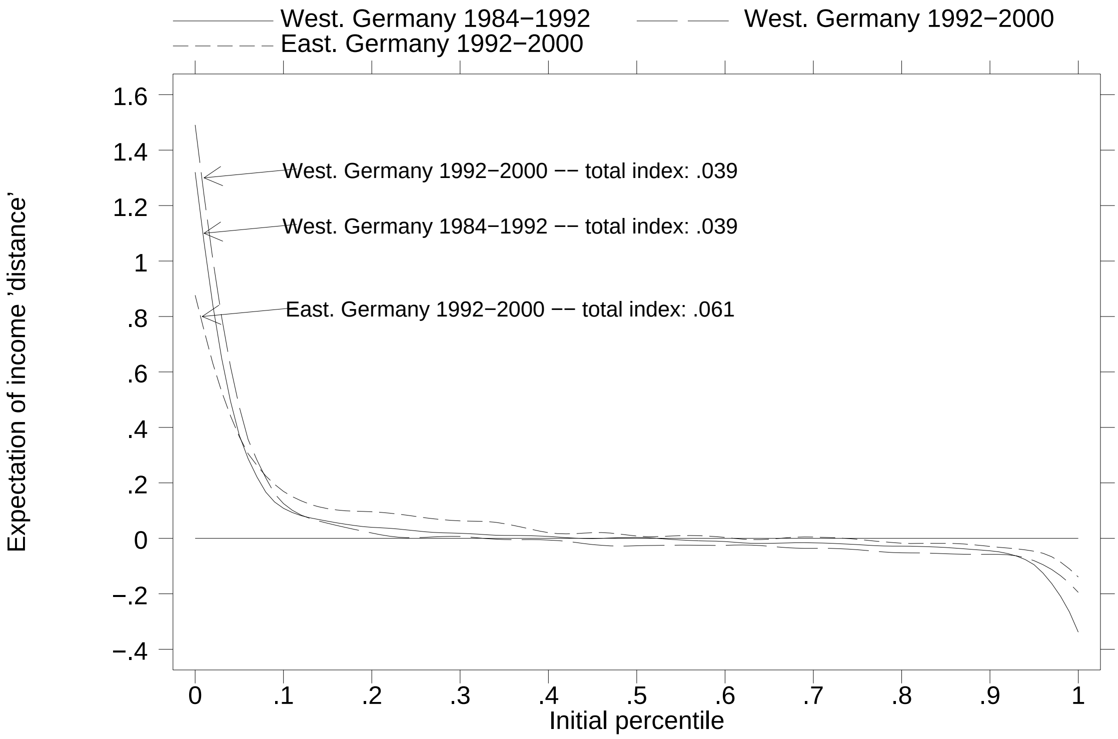
One clear pattern emerges from both pictures. The highest contribution to aggregate mobility is made by the poorest individuals in the initial distribution. Expected income increases reach 100% and above for approximately the poorest 5%. The decline is however steep and at about the first decile point the curves stabilise and remain flat until the upper decile point. Interestingly the curves for the three separate subsamples are very similar and can be distinguished only at the tails. According to the non-directional distance function, it is for Western Germany over the period 1992-2000 that annual mobility was higher (0.195), followed by Western Germany 1984-1992 (0.186) and Eastern Germany 1992-2000 (0.176). But it is particularly clear from Figure 1 that this ranking is driven by differences at the very bottom of the distribution (and somehow at upper tail as well).

Comparing the figures for the two different distance concepts also help describing the patterns of income mobility in greater detail. For example, according to the plot for the non-directional distance concept, the majority of individuals (those between the 20th and 80th percentiles) experience on average absolute income changes of about 15%. But it appears from the plot for the directional distance that their expected net gain is close to 0: the absolute changes are a mixture of income gains compensated by income losses of the same average magnitude. It is at the tails of the distribution that the expected net gains depart from 0, reflecting a phenomenon of regression to the mean with the richest 10% expecting income losses and the poorest 20% expecting income increases (increases that might be substantial on average for the very poorest). If Eastern Germany has the lowest aggregate non-directional mobility index, remark that its population has by far the greatest expected gains. The poorest 5% in East Germany have lower expected gains that the poorest 5% in West Germany, but the expected gains for all individuals above the 10th percentile are higher in Eastern Germany than in Western Germany. These expected gains are rather large and positive up to the 40th percentile.

Time series of estimated aggregate mobility indices for 1984-2000 are reported in Table 1. Estimates for the non-directional index are reported in the first two

Figure 1: Conditional mobility functions for $d(x,y) = |\log(y) - \log(x)|$ (top) and $d(x,y) = (\log(y) - \log(x))$ (bottom). Pooled data for year t to year $t+1$ changes.





columns. These are obtained by numerical integration of *conditional mobility* functions that have been estimated either using the robust LOESS procedure of the simple (non robust) LOESS procedure. The impact of robustification is to reduce the estimated indices by about 20%. However the trends are unaffected. Trends that have been, in Western Germany, a reduction of year-to-year mobility levels during the second half of the 1980s followed by an increase in the first half of the 1990s and a reduction in the second half of the 1990s. Mobility levels have been on the decrease over the whole 1992-2000 period in Eastern Germany.

Table 1 also contains estimates of 'ethically weighted' directional mobility indices as presented in (7) using the suggested weighting function underlying the S-Gini coefficients. Four different weighting parameters giving greater relative weight to the poor have been used ($\upsilon = 1$ gives equal weight to all percentiles of the initial distribution). As expected given the shape of the *conditional mobility* functions with large gains obtained by the poorest, the value of the indices increase with the weighting parameter. Again if the value of the indices are changed by the weighting parameter, the trends are not substantially affected. This suggests that the underlying repartition of the income gains in the population have not been altered much in the period although the overall levels may have changed cyclically. Note that given the already emphasised greater gains of the very poorest in Western Germany, increasing the weight of the poorest reduces the East-West differential in favour of the West, and may sometimes reverse the ranking of the two regions (e.g. in 1994-95, 1996-97 and 1998-99).

Controlling for transitory fluctuations and mobility in a longer term

Transitory fluctuations and measurement error may influence the assessment of income mobility. To control for this I present now results using three-year moving average incomes as measure of individual living standard. This smoothes out transitory income fluctuations. I then consider longer term mobility patterns by comparing smoothed income at year t to smoothed income at year $t + 5$. Figure 2 shows the counterpart plots of Figure 1 with these different definitions. Note that the axis scales are left unchanged.

The general shape of the *conditional mobility* functions remain the same. However the peak at the bottom of the distribution is largely reduced. This indicates that once the inital ranking of the population is made after controlling for transitory income fluctuations, the gains of the poorest are much more limited than what the previous analysis suggested although the interval between income observations is now 5 years.

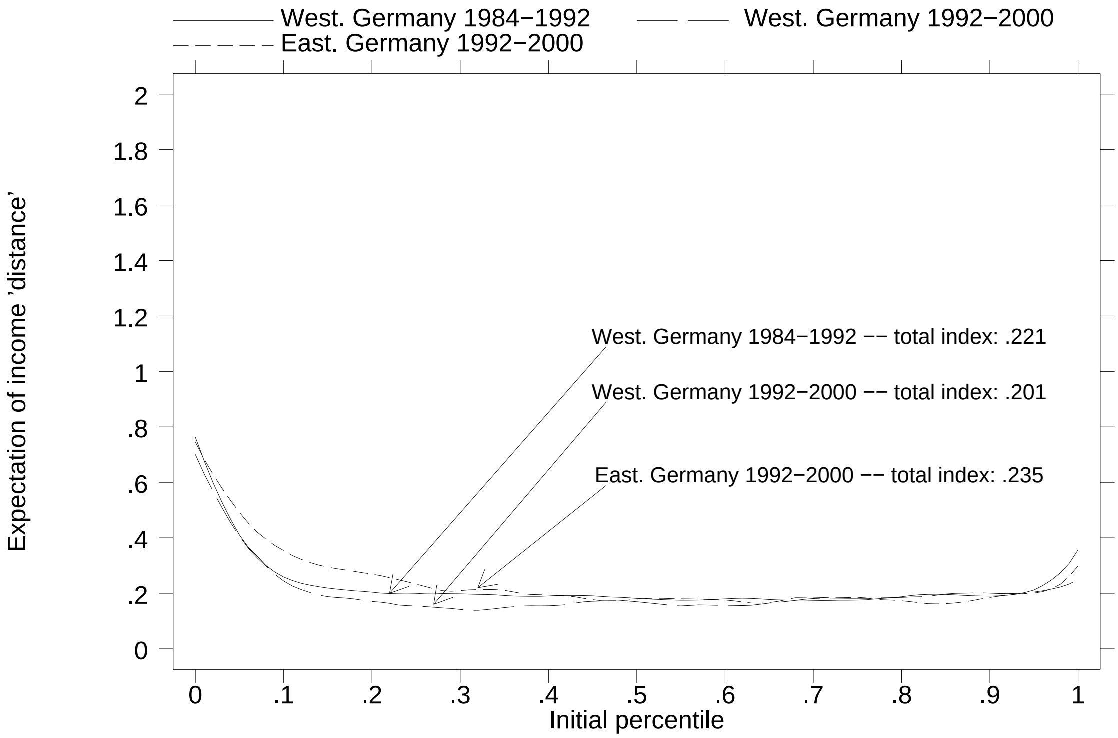
The position of the East German sample relative to the West German sample is now very different. Both directional and non-directional mobility are higher for

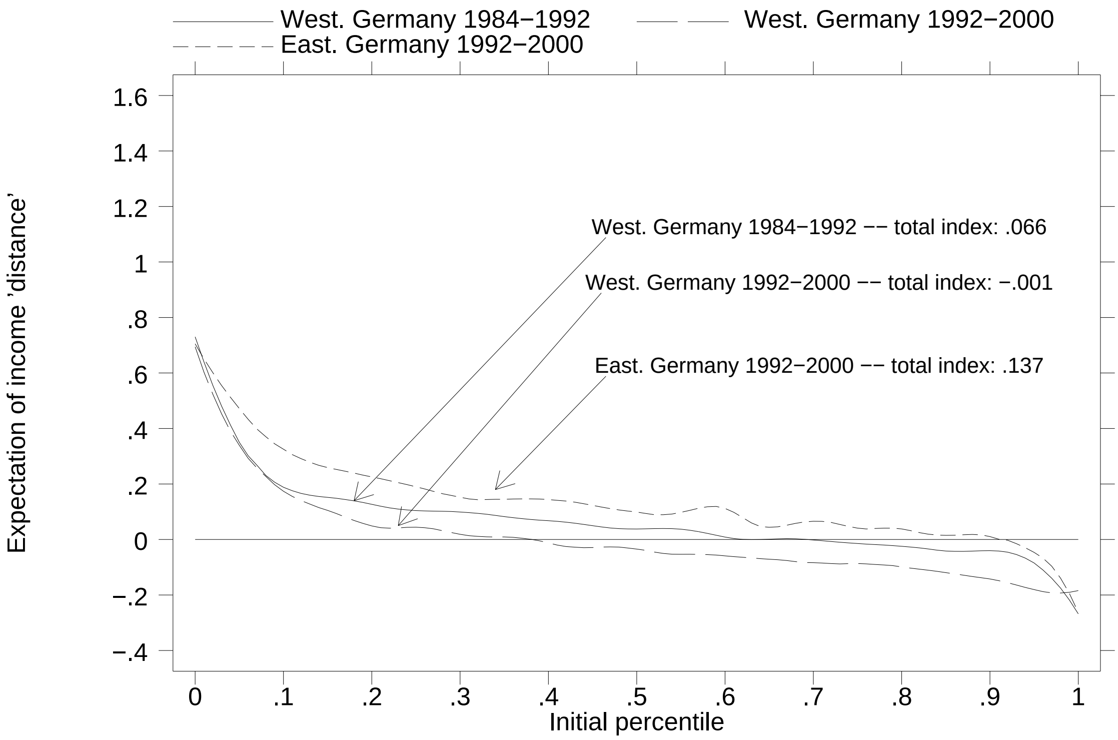
Table 1: Time series of mobility indices, 1984-2000

$d(x,y)$:	$\|ln(y) - ln(x)\|$		$ln(y) - ln(x)$			
Ethical weight ($upsilon$):	1	1	1	2	3	4
Robustification:	no	yes	yes	yes	yes	yes
Years	Western Germany					
84–85:	0.252	0.201	0.011	0.088	0.136	0.175
85–86:	0.245	0.185	0.011	0.080	0.126	0.166
86–87:	0.243	0.205	0.102	0.189	0.261	0.326
87–88:	0.219	0.174	0.032	0.091	0.130	0.164
88–89:	0.220	0.179	0.045	0.116	0.168	0.214
89–90:	0.229	0.176	0.033	0.100	0.151	0.197
90–91:	0.236	0.187	0.052	0.111	0.153	0.191
91–92:	0.245	0.189	0.036	0.101	0.154	0.200
92–93:	0.252	0.201	0.028	0.097	0.155	0.208
93–94:	0.246	0.195	0.009	0.073	0.123	0.166
94–95:	0.255	0.192	0.009	0.078	0.132	0.181
95–96:	0.265	0.214	0.050	0.150	0.227	0.294
96–97:	0.242	0.200	0.056	0.147	0.219	0.282
97–98:	0.233	0.179	0.019	0.083	0.134	0.180
98–99:	0.242	0.194	0.051	0.126	0.187	0.241
99–00:	0.238	0.188	0.088	0.162	0.221	0.272
Years	Eastern Germany					
92–93:	0.271	0.241	0.148	0.220	0.270	0.309
93–94:	0.219	0.186	0.093	0.145	0.185	0.219
94–95:	0.208	0.169	0.017	0.067	0.102	0.131
95–96:	0.209	0.168	0.031	0.087	0.125	0.156
96–97:	0.205	0.172	0.075	0.152	0.209	0.257
97–98:	0.207	0.171	-0.002	0.051	0.090	0.122
98–99:	0.193	0.154	0.055	0.116	0.161	0.199
99–00:	0.191	0.158	0.071	0.128	0.171	0.207

Note: All estimates are obtained by numerical integration of estimated conditional mobility functions. Weighted integration is used for the ethically weighted indices. See text for details.

Figure 2: Conditional mobility functions for $d(x,y) = |\log(y) - \log(x)|$ (top) and $d(x,y) = (\log(y) - \log(x))$ (bottom). Pooled data for year t to year $t+5$ changes using three-year moving average incomes.





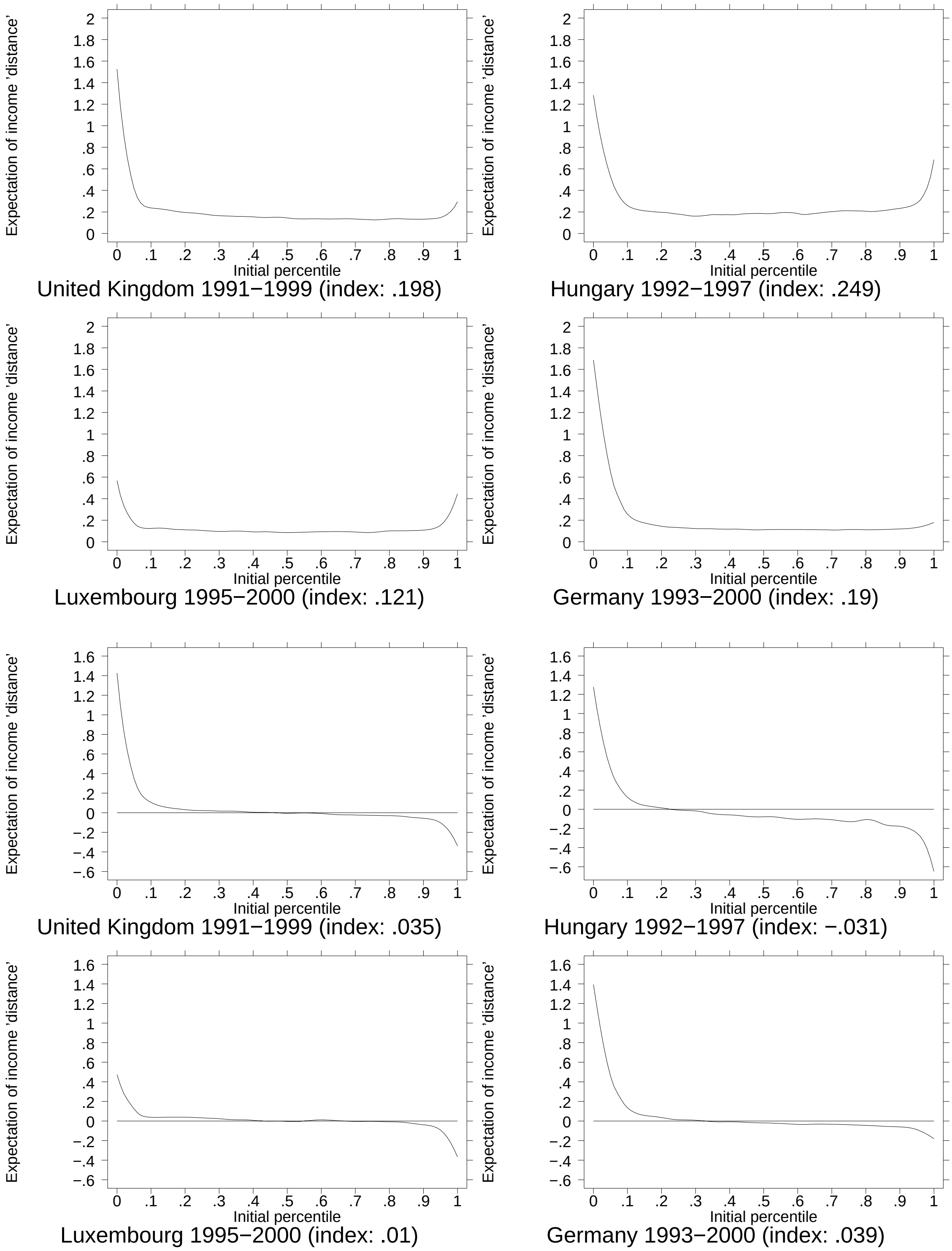
East Germany. Particularly striking is the fact that the expected income gains in East Germany have been higher than in West Germany at all percentiles of the initial distribution. The net expected income gains over the 5 years interval have been positive for all but the richer 10% in East Germany, although it was only positive for the poorest 40% in Western Germany in the period 1992-2000.

A cross-country comparison

The constancy of the general shape of the *conditional mobility* functions is also observable across different countries in the 1990s. Figure 3 presents *conditional mobility* functions for (unified) Germany and three other European countries: Hungary, Luxembourg and the United Kingdom. The estimations are based on a pre-official release of the Consortium of Household Panels for European Socio-economic Research (CHER) data. The CHER project offers a database for longitudinal household studies harmonising micro datasets from independent national panels (and from the European Community Household Panel) in a similar way to the Cross-National Equivalent File (with yet a larger number of variables and an overlapping but broader set of countries). The series national panels participating in the project includes the German Socio-Economic Panel. I have used the same income definitions as for the analysis based on the Cross-National Equivalent Files.

Aggregate levels of mobility may differ substantially between countries (estimates of aggregate mobility indices obtained by numerical integration of the *conditional mobility* curves are reported on the figures): compare the estimated 0.249 for Hungary to 0.121 for Luxembourg in Figure 3. Nevertheless an interesting constancy of the underlying *conditional mobility* functions across countries emerges. Drastically higher mobility levels are observed for the lower decile of the distribution, mobility levels are constant for the majority of the observations and then increases again at the top of the distribution. It is basically only levels that differ across countries. Note however that the German curves differ yet markedly from those of the other countries in the upper tail: higher levels of mobility, essentially downward mobility, are observed in the other three countries for individuals in the upper decile (compare with Luxembourg and Hungary). Basically the shape of the curve for Germany resembles the curve for the UK, while the situation of Luxembourg is one of much lower mobility although one might have expected a function closer to that of Germany for labour market institutions and policies are similar in both countries.

Figure 3: Conditional mobility functions for $d(x,y) = |\log(y) - \log(x)|$ (top) and $d(x,y) = (\log(y) - \log(x))$ (bottom) in four European countries estimated from CHER data. Pooled data for year t to year $t+1$ changes.



An illustration of an 'events-based' decomposition

As a final illustration I now present a rudimentary inspection of the effect of a potential triggering event of mobility: the change in the labour market participation of the household head. In a fist step, individuals are classified according to the declared labour market participation of the declared household head. Three groups are used: (i) working full-time, (ii) working part-time, and (iii) inactive. In a second step individuals are classified according to 'events' experienced regarding the change in this status between survey at year t and $t+1$. Three groups are again defined: (i) individuals with no change in the labour market participation of the household head, (ii) individuals living in a household whose head increased participation (i.e. either moved from inactive to working or moved from part-time to full-time work), and (iii) individuals living in a household whose head reduced participation (i.e. either moved from working to inactive or moved from full-time to part-time work). Separate *conditional moblity* functions are then estimated for each of these three groups. The aggregate function is obtained by summing these three functions *pro rata* their population share. If the change in the labour market participation of household head is a powerful explanation the observed mobility, we should observe the contribution of the 'no change' group to be low, i.e. the curve should be rather flat and close to zero. The other two curves should reproduce the observed mobility patterns by combining upward and downward mobility movements.

Figure 4 presents the separate year-to-year *conditional mobility* functions for the three groups underlying the aggregate curves presented in Figure 1 for Western Germany 1984-1992, Western Germany 1992-2000 and Eastern Germany 1992-2000. The striking observation is that the crude events defined here are far from sufficient to explain the observed income changes. Although most of the results are conform to intuition (e.g. increased participation leads to higher expected income gains and reduced participation tends to be associated with lower –generally negative– expected gains; see the bottom panel of Figure 4), there is not enough difference between the curves of the three groups to use it to account for most of the mobility. This is true for all three samples but particularly marked for the Eastern Germany sample that shows very small variations across the three subgroups. Crucially the curve for the 'no change' group exhibits substantial (absolute) mobility, especially at the lower tail. Given this and the fact that this group represents about 85% of the population, the contribution of this 'no change' group to the overall mobility remains substantial. Within group mobility remains high and supplementary explanations are therefore clearly required to account for a larger share of income mobility.

Interesting results however emerge from the pictures. Note for instance that reduced participation appears to be associated with higher (absolute) income changes than increased participation, at least if one disregards mobility of the poorest 10% or 20%. Finally the decomposition still puts forward the regression to the mean effect at both tails of the income distribution: expected income gains are positive for the poorest in all groups, even those experiencing reduced participation. Symetrically expected income gains are negative for the richest even if they experience increased participation.

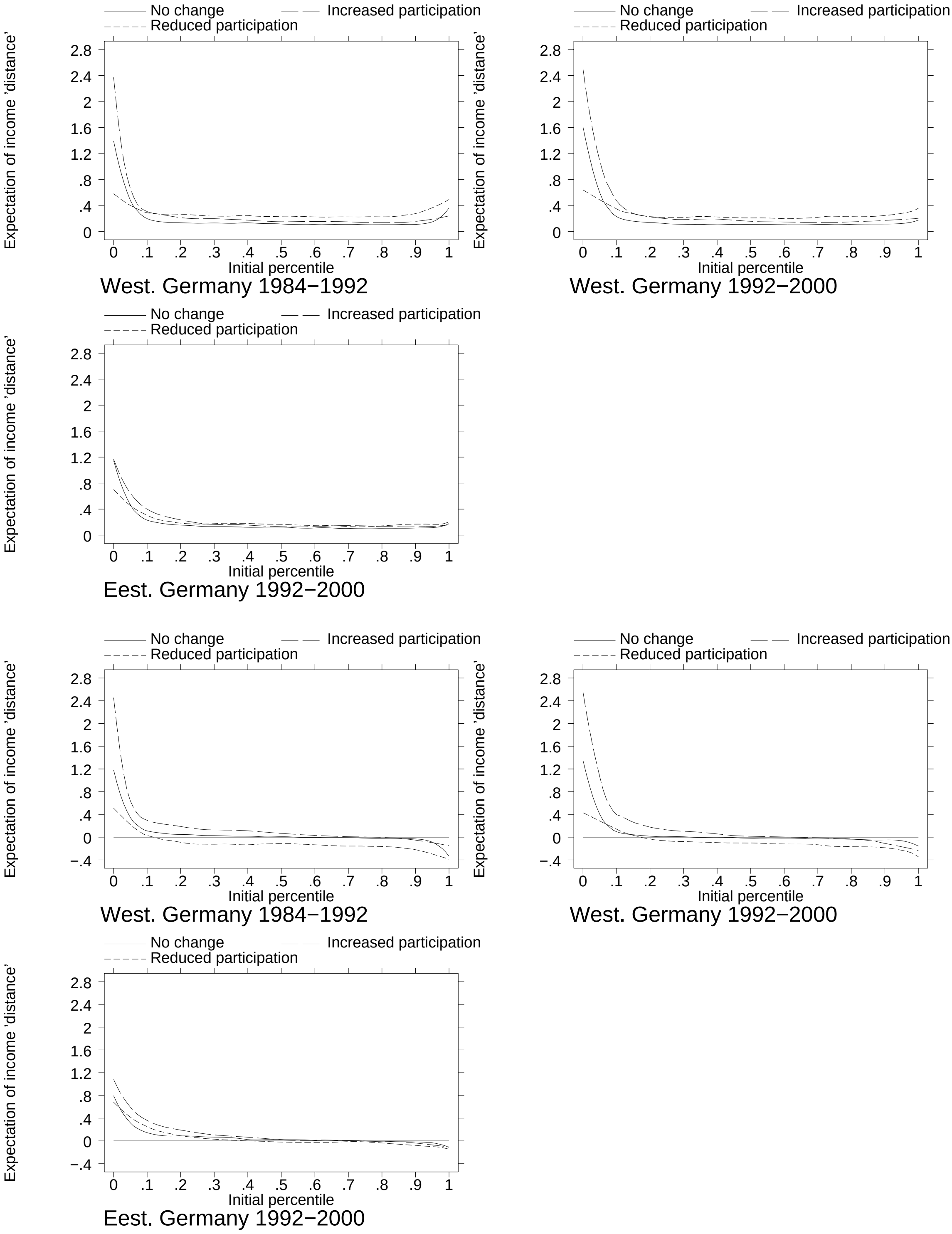
4 Conclusion

This paper provides a broad brush analysis of income mobility patterns in Germany between 1984 and 2000 using a simple graphical methodology to decompose aggregate mobility indices à la Fields and Ok (Fields & Ok 1996, Fields & Ok 1999).

The methodology suggested provides an evocative means of identifying where in the distribution are the individuals that experience the higher levels of mobility while linking this identification to a standard class of distance-based mobility indices. The methods have several other advantages. It provides a means of estimating mobility levels in a manner robust to data contamination. It also points to a generalisation of the Fields & Ok mobility indices that includes ethical weights depending on the initial position of individuals whose income changes are aggregated. This permits to contrast the mobility assessment in situations where the richer get all gains and situations where the poorer get all. Finally it conserves the additive subgroup decomposability of the distance-based mobility indices. Thence it offers a framework to help accounting for income mobility with potentially distinct explanations for different portions of the income distribution.

Application to German data obtained from the German Socio-Economic Panel data incarnation in the Cross-National Equivalent File and in the Consortium of Household Panels for European Socio-Economic Research reveals that it is among the poorest 10% (and the richest 5% to a smaller extent) that mobility is the largest. Mobility is much lower and relatively constant for the remaining majority of the population (those between the 10th and the 95th percentile). An interesting constancy of this general pattern is observed over time in Germany (both in Western and Eastern samples) as well as in three other European countries to which Germany is compared (Hungary, Luxembourg and the United Kingdom). Finally an illustration of the subgroup decomposition into potential triggering events shows how the methodology could be used to try identify the sources of mobility. The rudimentary approach applied here, although picking up some of the income changes, reveals insufficient to capture a large fraction of the overall mobility levels. In particular the regression to the mean effect is not explained by the simple events related to the labour market participation of household heads used.

Figure 4: Subgroup conditional mobility functions for $d(x, y) = |\log(y) - \log(x)|$ (top) and $d(x, y) = (\log(y) - \log(x))$ (bottom). Pooled data for year t to year $t+1$ changes.



The analysis of mobility in Germany presented in this paper remains superficial. It was essentially used to illustrate the potential usefulness of the methodology outlined in the first section. Several observations certainly require much deeper investigation, in particular the striking difference between the mobility levels of the very poorest and the rest of the population. Is this only due to noise, measurement error or temporary income fluctuations or is some more substantial processes at work? Does the constancy of the general mobility patterns hold for more countries and other concepts of 'distance' between incomes? How much of these patterns can be accounted for by 'events-based' decompositions? Deeper investigation was out of scope of the present paper but I believe the methodology suggested may serve as a support for further research in this area.

References

Aaberge, R., Björklund, A., Jäntti, M., Palme, M., Pedersen, P. J. & Smith, N. (1996), Income inequality and income mobility in the Scandinavian countries compared to the United States, Working paper series in Economics and Finance 98, Stockholm School of Economics, Stockholm, Sweden.

Bane, M.-J. & Ellwood, D. (1986), 'Slipping into and out of poverty: The dynamics of spells', *Journal of Human Resources* **21**(1), 1–23.

Bogomolova, T. & Tapilina, V. (1999), Income mobility in Russia in the mid-1990s, Working Paper 99/11, Economic Education and Research Consortium, Moscow, Russia.

Burkhauser, R. V., Butrica, B. A. & Daly, M. C. (1995), The Syracuse University PSID-GSOEP Equivalent Data file: a product of cross-national research, Cross-National Studies in Aging, Program Project Paper 25, All-University Gerontology Center, Maxwell School of Citizenship and Public Affairs, Syracuse University, New York, USA.

Burkhauser, R. V. & Poupore, J. (1997), 'A cross-national comparison of permanent inequality in the United States and Germany', *Review of Economics and Statistics* **79**(1), 10–17.

Canto-Sanchez, O. (1998), Income mobility in Spain: How much is there?, Estudios sobre la Economa Espaola EEE 17, Fundacion de Estudios de Economia Applicada, Madrid, Spain.

Cappellari, L. & Jenkins, S. P. (2002), 'Who stays poor? Who becomes poor? Evidence from the British Household Panel Survey', *Economic Journal* **112**, C60–C67.

Cleveland, W. S. (1979), 'Robust locally weighted regression and smoothing scatterplots', *Journal of the American Statistical Association* **74**(368), 829–836.

Cowell, F. A. & Schluter, C. (1998), Measuring income mobility with dirty data, CASEpaper 16, Centre for Analysis of Social Exclusion, London School of Economics, London, UK.

Devicienti, F. (2002), Poverty persistance in Britain: A multivariate analysis using the BHPS, 1991-1997, *in* P. Moyes, C. Seidl & A. F. Shorrocks, eds, 'Inequalities: Theory, Measurement and Applications', number 9 *in* 'Journal of Economics, Supplement Issues'.

DiNardo, J., Fortin, N. M. & Lemieux, T. (1996), 'Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach', *Econometrica* **64**(5), 1001–1044.

Donaldson, D. & Weymark, J. A. (1983), 'Ethically flexible Gini indices for income distributions in the Continuum', *Journal of Economic Theory* **29**, 353–58.

Duncan, G. J. & Rodgers, W. (1991), 'Has children poverty become more persistent?', *American Sociological Review* **56**, 538–550.

Fields, G. S., Leary, J. B. & Ok, E. A. (2000), Dollars and deciles: Changing earnings mobility in the United States, 1970-1995. Unpublished paper. Cornell University.

Fields, G. S. & Ok, E. A. (1996), 'The meaning and measurement of income mobility', *Journal of Economic Theory* **71**(2), 349–377.

Fields, G. S. & Ok, E. A. (1999), 'Measuring movement of incomes', *Economica* **66**(264), 455–471.

Galasi, P. (1998), Income inequality and mobility in Hungary, 1992-96, Economic and Social Policy Series, Innocenti Occasional Papers EPS 64, UNICEF, Florence, Italy.

Hoet-Mulquin, M.-E. & Van Kerm, P. (1998), Une évaluation de la mobilité des revenus en Belgique sur base des trois premières vagues du PSBH, *in* 'Portrait socio-économique de la Belgique', Treizième Congrès des Economistes belges de Langue française, CiFoP, Charleroi, Belgium, pp. 109–126.

Hyslop, D. & Maré, D. (2000), Understanding changes in the distribution of household incomes in New Zealand between 1983-86 and 1995-98, Center for Labour Economics Working Paper 24, University of California, Berkeley, USA.

Jenkins, S. P. (2000), 'Modelling household income dynamics', *Journal of Population Economics* **13**(4), 529–567.

Schluter, C. (1998), Income dynamics in Germany, the USA and the UK: Evidence from panel data, CASEpaper 8, CASE, London School of Economics, London, UK.

Schluter, C. & Trede, M. (1999), Local versus global assessment of mobility, Discussion Papers in Statistics and Econometrics 4/99, Seminar of Economic and Social Statistics, University of Cologne, Germany.

Schluter, C. & Van de gaer, D. (2002), Mobility as distributional difference. Unpublished paper, University of Bristol, UK.

Schwarze, J. (1995), Simulating German income and social security tax payments using the GSOEP, Cross-National Studies in Aging, Program Project Paper 19, All-University Gerontology Center, Maxwell School of Citizenship and Public Affairs, Syracuse University, New York, USA.

Stevens, A. H. (1994), 'The dynamics of poverty spells: Updating bane and ellwood', *American Economic Review* **84**(2), 34–37.

Stevens, A. H. (1999), 'Climbing out of poverty, falling back in: Measuring the persistence of poverty over multiple spells', *Journal of Human Resources* **34**(3), 557–88.

Van Kerm, P. (2001), What lies behind income mobility? Reranking and distributional change in Belgium, Germany and the USA. Unpublished paper, CEPS/INSTEAD, Luxembourg.

Wagner, G., Burkhauser, R. & Behringer, F. (1993), 'The English-language public user file of the German Socioeconomic Panel', *Journal of Human Resources* **28**(2), 429–433.

Yitzhaki, S. (1983), 'On an extension of the Gini inequality index', *International Economic Review* **24**(3), 617–628.