Income Dynamics in the USA, Germany, and the UK
- Evidence from Panel Data

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Abstract

This paper is about the distributional dynamics of net household income in the US, Germany, and the UK. According to common wisdom, the US and European countries are often taken to be worlds apart. This view juxtaposes the US as a very mobile society with an immobile Europe. In particular, Germany is often caricatured as a country in stasis. As it turns out, this view is mistaken. Despite different labour market institutions and tax-benefit systems standard mobility measures attribute a greater mobility to Germany than to the US. We also show that this result is mainly driven by the substantially greater mobility of the German poor.

We highlight the problems arising from standard approaches based on mobility indices and transition matrices, which group persons into income classes of arbitrary size, and propose the use of stochastic kernels.

Finally, in order to determine whether income changes are transitory or permanent, a law of motion for income is estimated.

Keywords: income dynamics, mobility, kernel density estimates, stochastic kernels, transition matrices, covariance structure.

JEL Classification: D31, D63, I32

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Contents

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Editorial Note

Christian Schluter is a Lecturer in Economics at the University of Bristol and is an associate of CASE.

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Abstract

This paper is about the distributional dynamics of net household income in Germany, the US, and the UK. We reject the common wisdom that Germany is a country in stasis: stable cross-sectional distributions are deceptive, concealing substantial movements beneath the surface. The US and the UK underwent a process of income polarisation.

For the study of mobility, stochastic kernels are used because standard approaches based on mobility indices and transition matrices, which group persons into income classes of arbitrary size, lead to misleading conclusions. The measures attribute greater mobility to Germany than to the US, but this ranking is entirely driven by the substantially greater mobility of the German poor. In order to determine whether income changes are transitory or permanent, a law of motion for income is estimated.

1 Introduction

This paper is about distributional dynamics in three major economies - the US, West Germany, and the UK - in the 1980s and 90s. Most research has concentrated on collecting cross-sectional evidence (see, for instance, Atkinson, Rainwater, and Smeeding (1994)), but this approach cannot establish whether the distributional changes are permanent or transitory, or to what extent the chances of moving up or down the income ladder are affected. To address these important questions, we use three well-known panel datasets, the German Socio-Economic Panel (GSOEP), the US Panel Study of Income Dynamics (PSID), and the British Household Panel Survey (BHPS).

According to a common but never substantiated wisdom, the US and European countries are often taken to be worlds apart. This view juxtaposes the US as a very mobile society, which arises from labour market flexibility and the small welfare state, with an immobile Europe. In particular, Germany is often caricatured as a country in stasis, burdened by a large welfare state and regulated labour markets. As it turns out, this view is mistaken. We demonstrate that although the cross-sectional evidence at first appears to support this view, the movements underlying the distributions tell a different story. Deceptively stable cross-sectional distributions in Germany conceal substantial movement beneath the surface. In fact, standard mobility measures attribute a greater mobility to Germany than to the US. This surprising fact has also been observed - without explanation - by Burkhauser and Poupore (1997). Here we show that this result is driven mainly by the substantially greater mobility of only one income group, the poor.

An international comparison of income dynamic trends over similar points in the business cycle[1] is of additional interest since the three countries have developed differ-

[1] The US and (West) Germany moved through largely synchronised business cycles, with the US experiencing the greater amplitude. The recessions at the beginning of the 1980s lasted until 1983, after which a boom began to unfold. In the modest German boom, unemployment in the West gradually fell from 8 0% in 1984 to 4 2% in 1991, whilst output expanded steadily. In the

ent social institutions to address the risks to household incomes, encompassing social insurance, the welfare state, and more collective or consensual arrangements governing employer-employee relations. Moreover, our results are important for policy makers as understanding the forces which govern movements up or down the income ladder and whether such changes are transitory or permanent is imperative for the design of effective welfare programmes.

GSOEP, PSID, and BHPS are high quality panels, very similar in design, which are well suited for an international comparison of income dynamics. Annual interviews started in 1984, 1968, and 1990 respectively. As Germany and the US move through a largely synchronised business cycle, we examine the years 1984-1994 (GSOEP) and 1982-1992 (PSID). The youth of the BHPS only permits an analysis of the years 1990-1994. The income concept to be examined in this paper is annual equivalised post-tax post-benefit personal income, derived in all three datasets by the data providers through a tax-benefit simulation. Sample sizes always exceeded 10,000 observations. Appendix A gives a detailed description of the datasets, income definition, sample sizes, and provides pertinent summary statistics.

The structure of the paper arises from the two dimensions of income dynamics. Following Quah (1995) an insightful approach is to distinguish between shape dynamics and intra-distributional mobility. The degree to which the shape of the income distribution changes is important to record, but it is only one aspect of distributional dynamics. The second important feature is the extent to which people move up or down the income ladder. However, shape dynamics are uninformative about intra-distributional mobility, for a static shape is consistent with such diametrically opposite worlds in which people forever retain their income positions, or one in which they swap them incessantly. This paper thus divides naturally into three parts. We

US, unemployment fell from 9.5 to 5.2 by 1989 but began to grow thereafter. The UK suffered a contraction in the early 1990s but growth resumed and unemployment declined in 1993. See Table 10 in the data appendix for the complete time series.

examine both shape dynamics and intra-distributional mobility in the three countries. Then we formulate and estimate laws of motion for incomes.

More specifically, the paper is structured as follows. Section 2 looks at the changing shape of the income distributions in Germany, the US, and the UK and examines various graphical features in a statistical light. Section 3 is devoted to the study of intra-distributional mobility. At first, various mobility measures are presented, but it is demonstrated that this standard approach suffers from the arbitrariness of the imposed discretisations resulting in conflicting results and unclear value judgments. Often the supposedly static German society is accorded greater mobility than the US. It is argued that these mobility measures are poor statistics of the stochastic kernel, and a direct examination of the stochastic kernels is preferable. Finally, a model for the law of motion of household incomes based on the income decomposition between 'permanent' and 'transitory' components is proposed in section 4. Using minimum-distance methods, the model is estimated from the covariance structure of income changes. As year-to-year income changes more than two periods apart are approximated uncorrelated and the correlation of income changes in adjacent years is negative, a MA(2) specification for the transitory income component is examined in detail. Section 5 concludes.

11 Aspects of distributional dynamics

In order to make the concepts of shape dynamics and intra-distributional mobility more precise, consider the following law of motion governing incomes. Let the income distribution at time t, F_t, induce a probability measure μ_t where $\mu_t((-\infty; y]) = F_t(y)$. For low frequency data found in GSOEP or PSID t is discrete (years). A simple low order specification could be

$$\mu_t = T^*_{t-1}(\mu_{t-1}; u_{t-1}) \tag{1}$$

where u is a disturbance and T^*_{t-1} is a suitable operator (often the adjoint of the Markov operator) mapping a perturbed probability measure at time $t-1$ into the current one (see also Quah (1995)). The forces governing the income distribution are allowed to be time-varying. A more specific model is a stochastic kernel equation for the probability measure

$$\lambda_t(A) = \int K_{t-1}(y; A)\lambda_{t-1}(dy) \tag{2}$$

for all measurable A where the stochastic kernel $K_{t-1}(y; A)$ can be interpreted as the probability of moving into set A given income level y at time $t-1$. If the stochastic kernel were discrete, it would be a transition matrix. Shape dynamics are captured in the time series of F_t or λ_t, and $K_{t-1}(\cdot)$ informs about intra-distributional mobility. Whilst we do not attempt to construct the operators T^*_{t-1}, we will look directly at each aspect of the distributional dynamics. We first turn to the shape dynamics of the income distribution in Germany, the US, and the UK.

2 Cross sectional (shape) dynamics

Examining the changing external shape of the cross-sectional income distribution can shed some light on the law of motion governing incomes. A natural approach to the assessment of these shape dynamics is to depict the cross-sections using kernel density methods.

2.1 Some statistical preliminaries

The density estimator needs to take into account the individual sampling weights which arise most prominently from deliberately oversampling specific groups of the population. To accommodate the sparseness of the data in the right tail of the income distribution, an exponentially increasing bandwidth has been used which performs 'optimally' with respect to some criterion function[2]. To concentrate on the main issue - the shapes - incomes are normalised at the contemporaneous medians.

[2] See Silverman (1986) or Haerdle (1991). The estimator for the density of the weighted data $f(x)$ at point x is $\hat{f}(x) = [nh]^{-1} \sum w_i K([x - X_i]/h)$ where w_i is the weight of observation X_i and $K(\cdot)$

The graphical mode of analysis - an examination of the densities - needs to be supplemented by further statistical examinations. If the densities appear to be similar, a non-parametric two-sided Kolmogorov-Smirnov test is appropriate to test whether the income distributions are indeed identical. For sequential tests of equality of the income distributions in periods t and t+1, Table 1 reports the values of the test statistic and their approximate p-values.

Second, the number of modes of the income density can be scrutinised statistically using a bootstrap test proposed in Silverman (1981). Such information about the number of modes is important as distinct modes are indicative of mixture populations. The test is based on the fact that the number of modes of a Gaussian density estimate is non-decreasing as the bandwidth h increases. For a test of k-modality, the null hypothesis is that the number of modes equals k, against the alternative hypothesis of more than k modes. The test proceeds as follows. From the density, which has been rescaled so as to have the same variance as the original sample, draw samples with replacement. This is achieved by setting

$$x_i^* = \bar{y}^* + (1 + h^2/\sigma^2)^{-0.5}(y_i^* - \bar{y}^* + h\epsilon)$$

where y_i^* are sampled with replacement from the original sample, $\bar{y}^*$ is its mean, σ^2 its variance and ϵ is distributed as a standard normal. $(1+h^2/\sigma^2)^{-0.5}$ is the rescaling factor, and ϵ is Gaussian since the kernel is Gaussian. Next, compute the density of the bootstrap sample and count its modes. Let h_k denote the smallest value of h producing a k-modal density, and h_k^* its equivalent for the bootstrap sample. The p-value is approximated as a quantile of the h_k^* distribution by $\#\{h_k^* > h_k\}/B$, B being the number of bootstrap samples. $B = 500$ was chosen. The test has the following interpretation. A large value of h_k, indicating that a lot of smoothing is needed to generate k modes, is taken as evidence against the null hypothesis of $k-$modality.

is the kernel. The bandwidths h have been chosen 'optimally' using the method of cross-validation. The increasing bandwidth is obtained simply by estimating the density of the log of income and then exponentiating the abcissae-values.

Figure 1 here

Figure 1: Density estimates of the income distribution in West Germany, the USA, and the UK. Incomes are normalised at the contemporaneous medians. Plots are truncated at the 99% quantiles for better visual clarity. Weighted data.

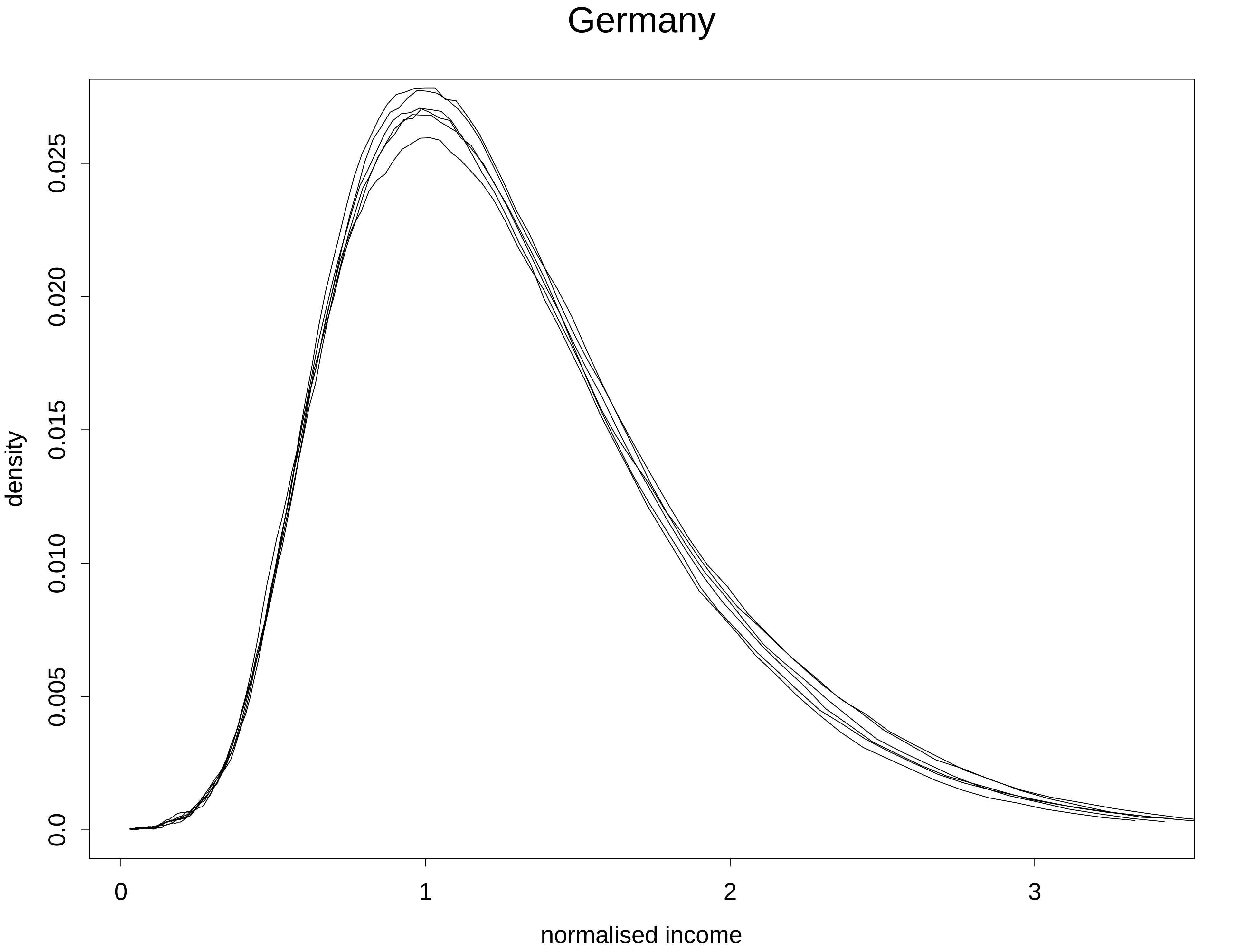
As a consequence, a large value of p is taken to support the null hypothesis, whilst a low p-value constitutes considerable evidence against it. Table 1 reports the critical bandwidths h_k and the p-values of the test.

2.2 Results

The upper panel of Figure 1 depicts the case of West Germany, the middle panel shows the income distribution in the US, and the lower panel refers to the UK. We discuss West Germany first, and then turn to the US and the UK evidence.

Surprisingly, the German distributions look very similar: all are unimodal, with modes located at 1 (the contemporaneous median). As reported in Table 1, one cannot reject the hypothesis of there being only one mode, but the Kolmogorov-Smirnov test suggest that the income distributions are statistically significantly different. These stable shapes seem to confirm visually and statistically the common wisdom of Germany as a country in stasis. The stable shape of the West German income distribution offers a picture at large, which may hide subtler absolute distributional changes with important implications for welfare. To examine this possibility, a first natural step is to examine the yearly movements of the Lorenz curves[3] as Germany moves through

[3] A Lorenz curve ordinate ©(p) is defined as the cumulative income share of the poorest fraction p of the population. Beach and Davidson (1983) show that the usual estimator of ©(p) is asymptotically normally distributed and derive a non-parametric variance estimator.


Germany
density
0.0
0.005
0.010
0.015
0.020
0.025
0
1
2
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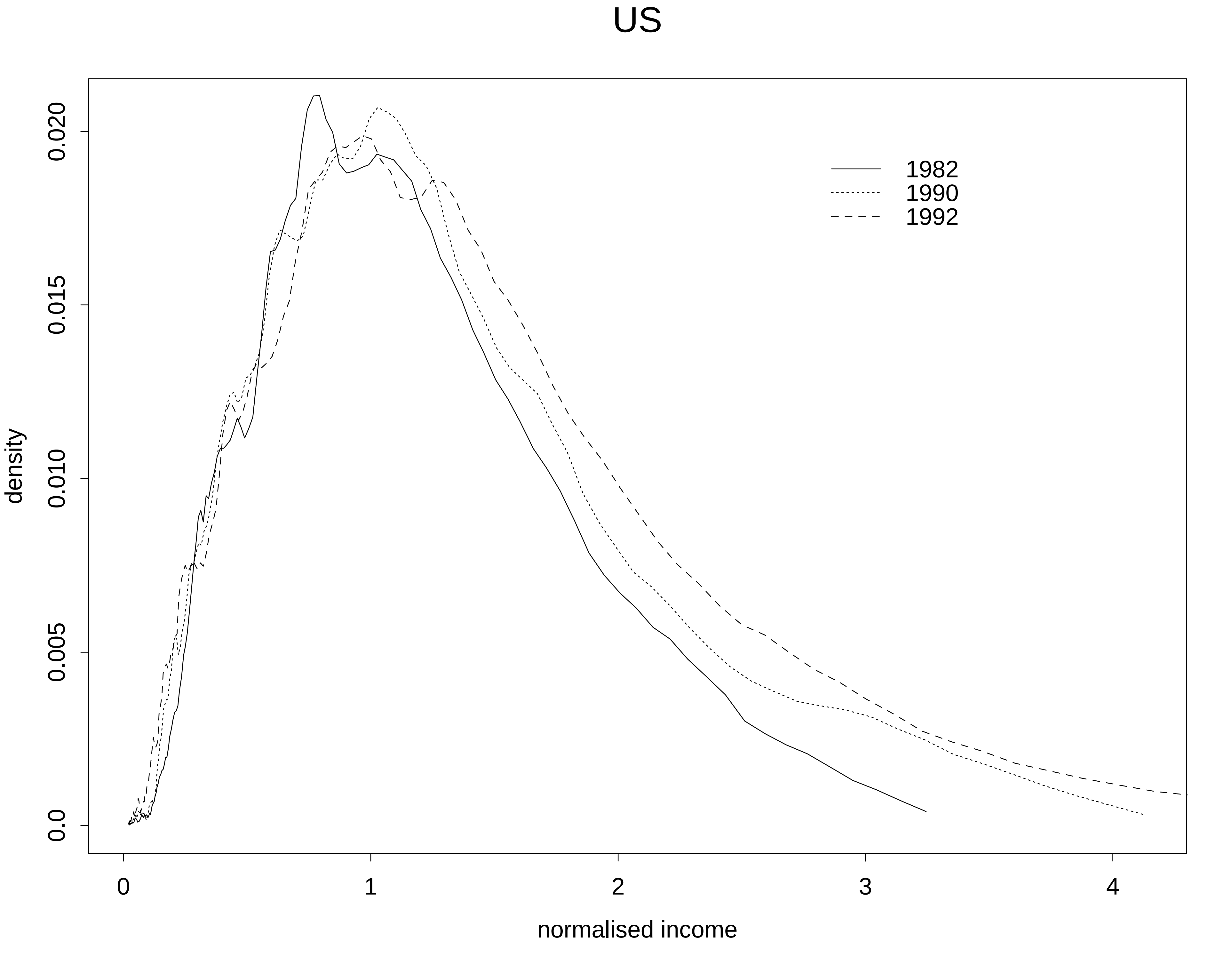
normalised income


US
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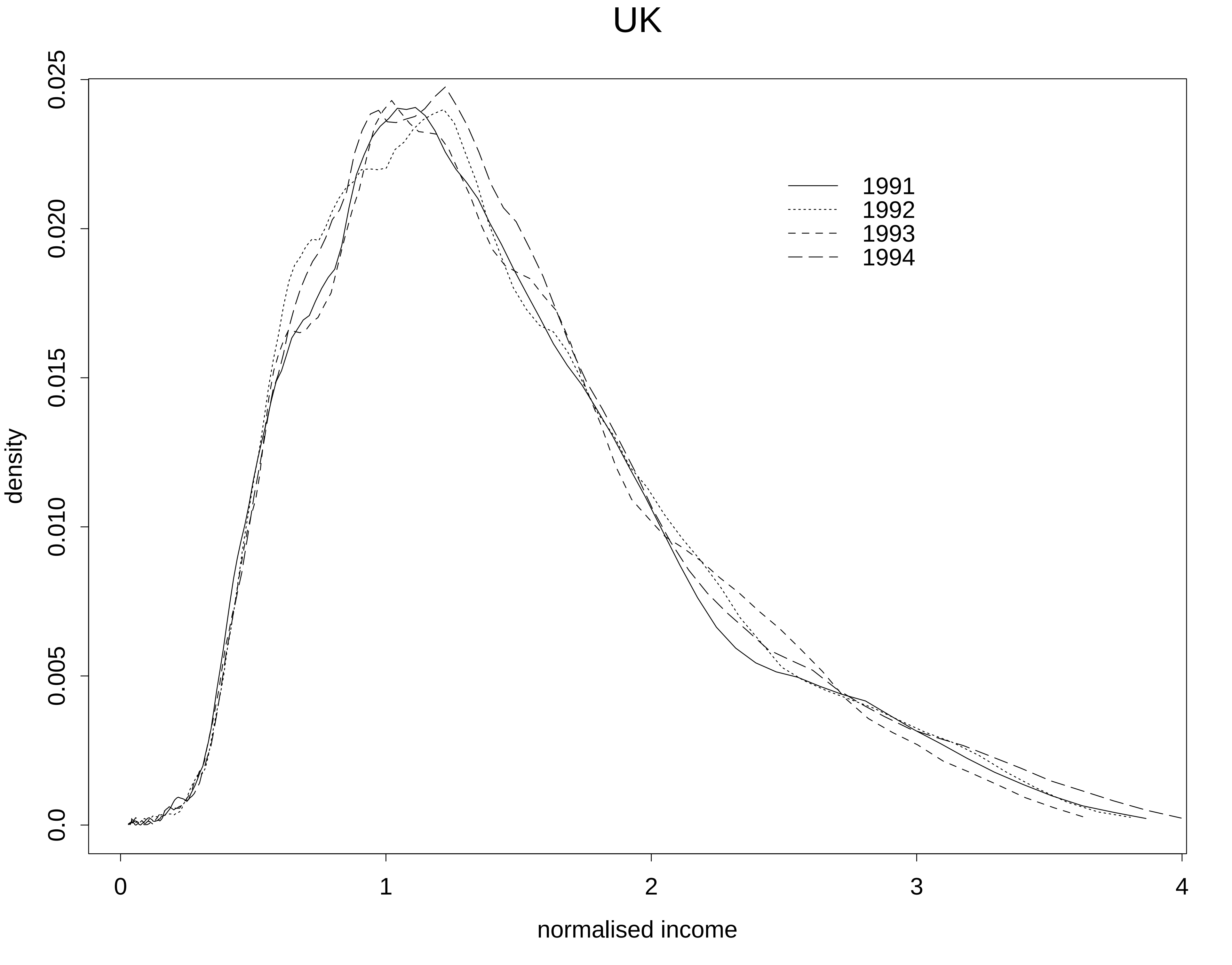
UK
1991
1992
1993
1994
density
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0.005
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0.025
0
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3
4
normalised income

a moderate business cycle from trough to boom to trough. The Lorenz curves are reported in Table 2.

The point estimates seem to suggest a clear-cut story which ensues from several Lorenz dominances: inequality fell unambiguously from 1984 to 1986. After this period, the fruits of growth became less equally distributed. Inequality increased from 1986 to 1987 and fell in the subsequent year. After 1991, the economic downturn took hold and inequality rose unambiguously for the rest of the period. The Gini[4] coefficient, reported in the last column of Table 2, necessarily confirms the distributional rankings of the Lorenz dominance criterion.

However, in line with the stable densities, most year-to-year movements of the Lorenz curves are not statistically significant[5]. As regards the years in which the Lorenz curves intersect, different value judgements may lead to different rankings. To examine this possibility, Table 4 collects results for the Generalised Entropy[6] inequality index GE_α. The lower the sensitivity parameter α, the more sensitive the index is to the bottom of the distribution; several values have been chosen. The inequality measure is computed on the weighted data. Only four cases out of 33 voice disagreement between the indices, despite the different implicit weights attached to the different subgroups of the population. Table 5 collects all distributional rankings. The overall picture thus is indeed one of stasis: inequality has changed at most slightly, with falls initially but slight increases later on.

By contrast, the US income distribution has undergone dramatic changes. In

[4] The Gini coefficient is defined by $1 - 2\int \Phi(p)dp$. Hoeffding (1948) shows that the usual estimator of the Gini coefficient is asymptotically normally distributed and derives a variance estimator.

[5] The tests are reported in the discussion paper version of this paper (Schluter 1998a).

[6] The Generalised Entropy index $GE_\alpha(F)$ is defined by $(\alpha^2 - \alpha)^{-1}((\mu_\alpha/\mu_1^\alpha) - 1)$ where $\mu_\alpha = \int y^\alpha dF(y)$. Its usual estimator is asymptotically normally distributed since it is a functional of asymptotically normally distributed statistics. The variance estimator can be found using the delta-method. Note that with weighted data the speed of convergence falls to $\sqrt{n/(1+v^2)}$ where v^2 is the squared coefficient of variation of the weights. See Sandström (1987).

1982, the US distribution already exhibits bimodality. The income mountains have been subject to erosion, and twin-peaks have emerged from a redistribution of mass both to the left and to the right - income have polarised. Over time, the mountain is subject to further erosion, mass is shifted to the right, but twin-peaks persist. The rightward shift suggests both income improvements for most households and also disproportionate income gains by the middle class over the entire period. The Kolmogorov-Smirnov test, reported in Table 1, confirms these distributional changes to be statistically significant, and the Silverman test affirms the bimodality distribution. In fact, the hypothesis of a larger number of modes cannot be rejected.

These observed dramatic distributional changes are mirrored in a large increase in all inequality indices from the beginning to the end of the period reported in Tables ?? to 5. But a glance at the Lorenz curves reveals that the inequality increase is not monotonic nor uniform across income groups: Lorenz curves either shift out or intersect. The beginning of the economic upturns in the early 1980s had different welfare consequences. In contrast to the US, Germany experienced some initial equalising effects. Only later did the fruits of growth become more unequally distributed.

The US is not alone in experiencing distributional change, which is also evident, albeit on a more modest scale, in the UK. The two peaks are 'close' and both near 1 (the contemporaneous medians). The Silverman test does not reject this bimodality. Using cross-sectional data, Jenkins (1995) suggests that a process of income polarisation has started in the mid 1980s. Consistent with the evidence presented here, he observes that "The shift away from the middle class in both directions is strong evidence that the 'middle class' was shrunk, however one defines the middle." Over time, the densities change slightly but sufficiently for the Kolmogorov-Smirnov test. As regards inequality, the evidence for the UK is less clear-cut, since all Lorenz curves intersect. The other inequality indices suggest a rise in the second year but later give conflicting assessments, including the year of the upturn. The changes in the Lorenz curves are not unambiguously significant, and the inequality indices change modestly.

The UK thus assumes an intermediate position in terms of the cross-sectional changes observed in Germany and the US.

Thus basing one's judgement solely on the cross-sectional evidence, the common wisdom appears to be justified. Large distributional changes have occurred in the US, implying a substantial increase in inequality. By contrast, Germany seems to be a country in stasis, as the income distributions and thus inequality have hardly changed.

3 Intra-distributional mobility

Assessments of income dynamics cannot be based on cross-sectional evidence alone, since it is uninformative about the extent to which persons move up or down the income ladder. As it turns out, standard mobility measures attribute a greater extent of mobility to Germany than to the US. This common approach to intra-distributional mobility is to compute certain statistics of the stochastic kernel of equation (2). We demonstrate that severe problems might arise from such standard attempts to quantify mobility. A much clearer picture emerges from examining the stochastic kernels directly.

3.1 Measuring mobility

The literature contains several approaches to the problem of quantifying mobility[7], which are not necessarily mutually exclusive. However, a common framework is absent since, in contrast to the role of the transfer principle in the literature on inequality measurement, no single principle commands universal consensus.

The point of departure of the first approach is to define and to estimate transition

[7]For a derivation of the asymptotic distribution of the estimators of the mobility measures used below see Trede (1995) or Schluter (1998b). Standard errors of the estimates are not reported here for the sake of brevity but are available on request from the author.

matrices $P_t = [p_{ij}(t)]$ where $p_{ij}(t)$ is the conditional probability of occupying state j in time t given that i was occupied in the previous period. The maximum likelihood estimator is $\hat{p}_{ij}(t) = n_{ij}(t)/\sum_j n_{ij}(t)$; the fraction of people who occupied state i and now occupy state j.

Such transition matrices are arbitrary discretisations of an underlying continuous process. For the income partition, both number and width of the income groups have to be selected. Two types of discretisations will be examined. First, four income groups are determined with respect to the contemporaneous median in period $t-1$. The width of the first three income groups is constant - one half of the contemporaneous median - but the number of people falling into these income groups (the marginal probabilities) varies across cells. By contrast, a discretisation according to deciles results in constant marginal probabilities, but the width of the income intervals varies. The associated transition matrices are denoted by P_{med} and P_{decile} respectively.

A mobility index is a function over the space of transition matrices. A popular index is the Prais-Shorrocks index

$$M_S(P) = \frac{n - tr(P)}{n-1} = \frac{n}{n-1}\left[\frac{1}{n}\sum_i (1 - p_{ii})\right] = \frac{n - \sum_i \lambda_i}{n-1} \qquad (3)$$

where $tr(P)$ is the trace of the nxn transition matrix P, and λ_j its js ordered eigenvalue. Since $1 - p_{ii}$ is the probability of leaving state i, the index is the inverse of the harmonic mean of the expected durations of remaining in a given income group. Note that this index only weights the incidence of leaving a given state and ignores the size of the income change. Mobility is deemed greater the larger the index is.

Another index is given by

$$M_E(P) = \frac{n - \sum_i |\lambda_i|}{n-1} \qquad (4)$$

This index captures the speed of convergence of the underlying Markov process since all eigenvalues of the stochastic matrix are bounded by one. $M_S(P)$ equals $M_E(P)$ if P's eigenvalues are all real and non-negative (which they actually happen to be for the chosen income partitions and the data under scrutiny). The approach focussing on the convergence speed can be simplified by concentrating on the dominant convergence term, viz. the second largest eigenvalue λ_2, $M_{LE}(P) = 1 - |\lambda_2|$. This index would be attractive if the economy followed a (first order) Markov process. However, as is demonstrated below, the transition probabilities are time-varying and, as shown elsewhere (Schluter (1997)), a simple first order Markov process does not describe the data well.

A second class of mobility indices - often labelled stability indices - avoids the discretisation problem, takes account of the size of the income jumps and implicitly attaches different weights to different parts of the distribution. Despite these advantages, the trade-off between these two and the implicit value judgements is not made explicit. This class, proposed by Shorrocks (1976) and Maasoumi and Zandvakili (1986), is based on the comparison between the inequality of income averaged over the entire period and a weighted average of contemporaneous inequalities. Let F_t denote the cross-sectional income distributions at times $t = 1; \ldots; T$, F the distribution function of income averaged across this observation period, and I the chosen inequality measure. The proposed mobility index is

$$M = 1 - \frac{I(F)}{\sum_{t=1}^{T} w_t I(F_t)} \tag{5}$$

where the weights w_t are often defined to be the contemporaneous mean divided by the mean of average income. The inequality index we have selected is a member of the class of Generalised Entropy indices $GE_\alpha(F)$ defined above. This inequality index exhibits greater sensitivity to the bottom of the distribution the smaller the sensitivity parameter is. M inherits this property. In order to compare this index to the Prais-Shorrocks index, we restrict attention to two consecutive years.

3.2 Results

The point estimates of the mobility indices are depicted in Figure 2, and some staying probabilities for the `median' income partition in Figure 3. Consider Germany first. The figure makes clear that the stable shapes of the cross-sectional distributions disguise substantial movement beneath the surface. Comparing the values of the indices amongst the three countries reveals that intra-distributional mobility in Germany is large. The view of Germany as a country in stasis has to be rejected.

The figure also picks up some interesting changes of mobility over the business cycle. The Prais index of the median and decile income partitions suggest a similar downwards trend in mobility, except for an increase in 1986/87 and 1990/91, but disagree in the last year. This simple picture becomes more blurred when examining the time series of the staying probabilities - an important step since the Prais index simply aggregates the incidences of leaving a given state, which often move in opposite directions. During the boom, the rich ($p_{4:}$) enjoy increased staying probabilities, whereas the poor ($p_{1:}$) only benefit in its initial phase. After 1986, the increase in p_{11} may reflect the increased fraction of the long-term poor who failed to escape poverty during the economic expansion. This series exhibits a large jump at the onset of the recession. Comparing the magnitudes of all changes in Figure 3, it is evident that p_{11} drives the overall Prais index. The stability indices present a more volatile picture, but despite some disagreement also suggest a downward trend in mobility. The top-sensitive M_{GE_2} picks up the improved fortunes of the rich during the boom, but the bottom-sensitive $M_{GE_{-1}}$ implies an increase in mobility after 1988/89. Such conflicting evidence reveals the problem embodied in the index: the value judgement determining the trade-off between the size of the income jump and the weights attached to different parts of the distribution is not made explicit.

The indices for the US suggest, similarly, that mobility has fallen except for the last year. The Prais index for the decile partition has a visible downward trend, but the index for the median partition is almost constant. A glance at the staying

Figure 2 here

Figure 2: Mobility in Germany, the US, and the UK. Weighted data. The indices and income partitions are defined in the text.

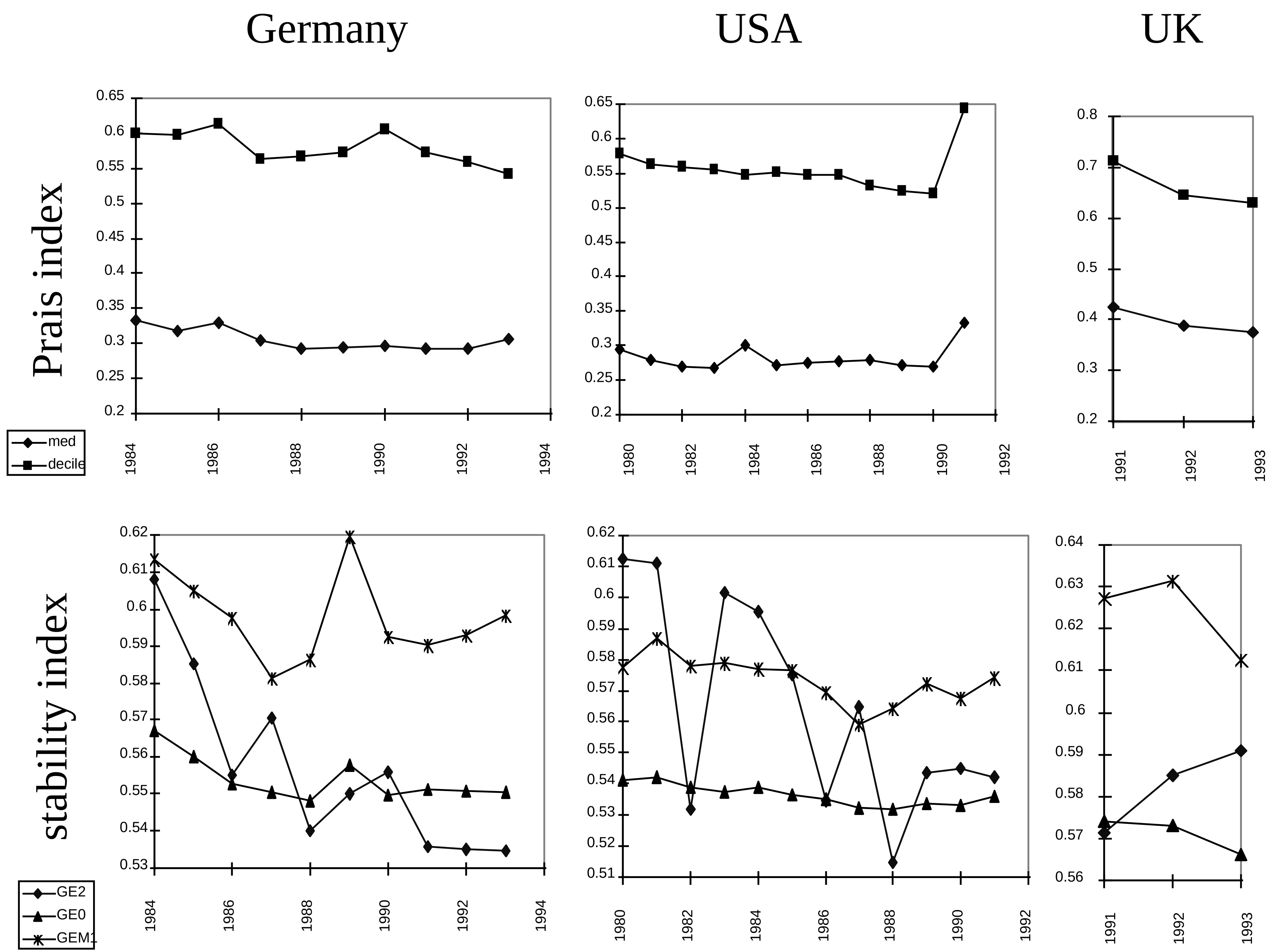
Figure 3 here

Figure 3: Staying probabilities for the 'median' income partition in Germany, the US, and the UK.

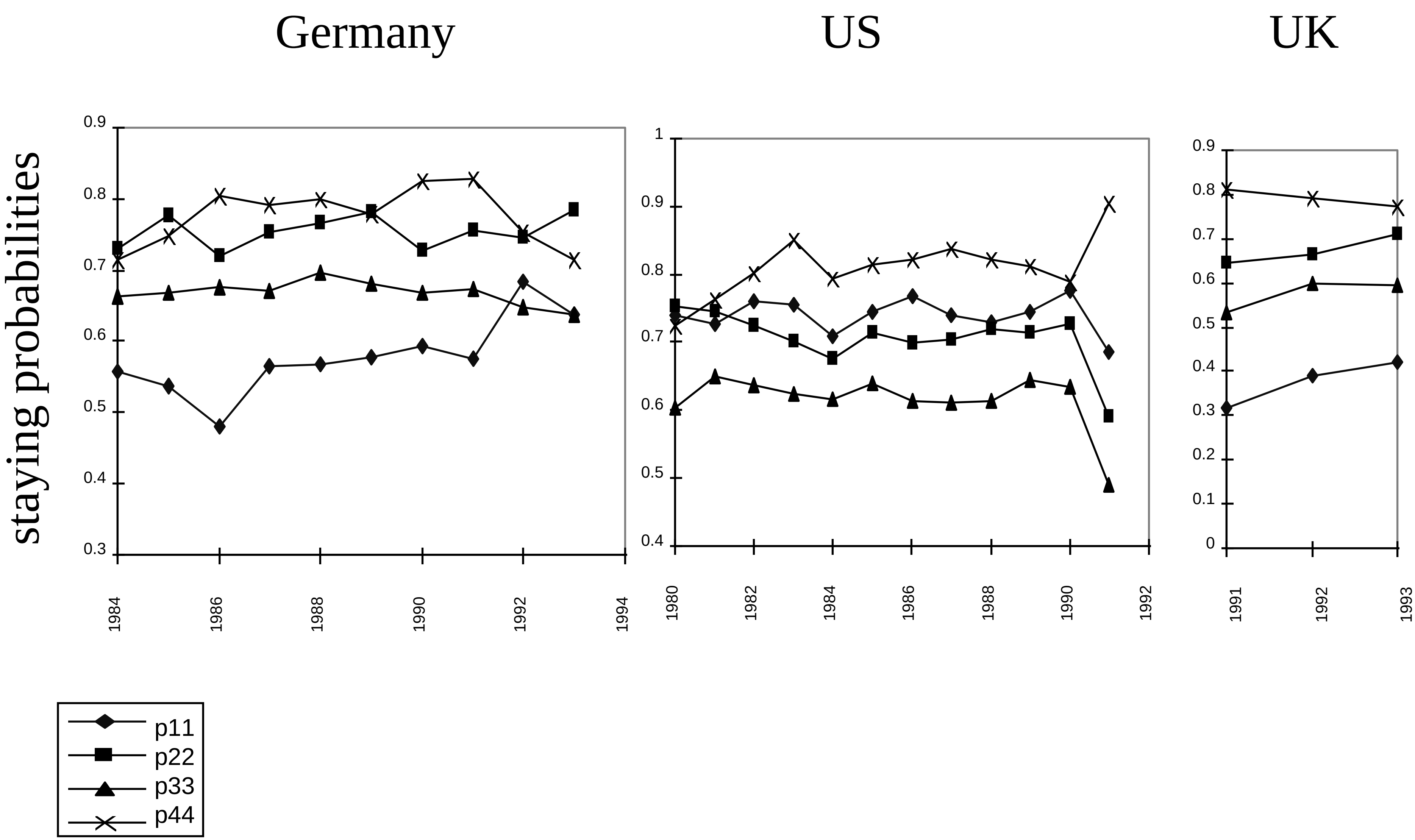
probabilities reveals that these often move in opposite directions, but, contrary to the German case, no single staying probability drives the index. The top-sensitive stability index M_{GE_2} is most erratic, but the others move more in line.

The Prais indices suggest a fall in mobility in the UK, which results from a sufficiently large increase in all staying probabilities except p_{44}. All these probabilities are lower than both in Germany and the US, but, as shown below, this is a consequence of the arbitrary discretisations. Increasing the first income interval would substantially increase p_{11}. The increase in p_{44} may explain the different overall assessment of the top-sensitive M_{GE_2} which entails an upward mobility trend whilst the other stability indices suggest a downwards trend.

Comparing the results for the US and Germany, the US is often deemed to be the less mobile society. This seeming paradox is resolved, however, by examining the various staying probabilities. The poor in Germany are substantially more mobile than in the US, and this difference is sufficient to tip the overall balance in Germany's



Germany
USA
UK
Prais index
stability index
med
decile
GE2
GE0
GEM1



Germany
US
UK
staying probabilities
0.9
0.8
0.7
0.6
0.5
0.4
0.3
1984
1986
1988
1990
1992
1994
1
0.9
0.8
0.7
0.6
0.5
0.4
1980
1982
1984
1986
1988
1990
1992
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1991
1992
1993
p11
p22
p33
p44

favour as the more mobile middle class in the US cannot compensate this effect. Thus despite different labour market institutions and tax-benefit systems, the US and Germany exhibit similar income mobility patterns. Of some worry to policy makers should be the dramatic immobility of the poor in the US, which calls into question the effectiveness of policies aimed at poverty reduction. By contrast, the likelihood of escaping poverty in Germany is substantially greater.

3.3 Stochastic kernel density estimates

The previous section illustrated that the standard approach to estimating mobility suffers from insuperable problems which arise from arbitrary discretisations of a continuous process, and the stability measures do not make explicit the inherent value judgements. An alternative approach to the problem - which might be preferable - is to estimate the stochastic kernels directly. These have been estimated non-parametrically using kernel density methods[8], and Figure 4 depicts their contour-plots. These can be read as continuous generalisations of transition matrices. The degree of immobility is expressed in the concentration of the contours around the 45 degree line. A society in which incomes in two periods are independent would have horizontal contours, i.e. the conditional distributions would be the same.

As regards Germany, the spread of the contours confirms that there is substantial intra-distributional mobility beneath the stable cross-sectional distributions. However, the contours have changed only little over time except for the very highest incomes, yet a slight upwards trend during the boom is evident, reflecting the improved fortunes in the expansion for most income groups, which increases as income

[8] The joint distribution of income in periods t and $t+1$ have been estimated using the kernel $K(x) = (1 - x'C^{-1}x)^2$ if $x'C^{-1}x \leq 1$ and 0 otherwise. C is the covariance matrix of incomes in the two periods, and $x'C^{-1}x$ centres the elliptical window along the line of correlation. Weights account for varying sample inclusion probabilities. The conditional density is derived in the usual fashion. Income is normalised at the contemporaneous median in period t. The bandwidth is uniform for both income dimensions since the variances are of the same magnitude, and has been chosen subjectively.

Figure 4 here

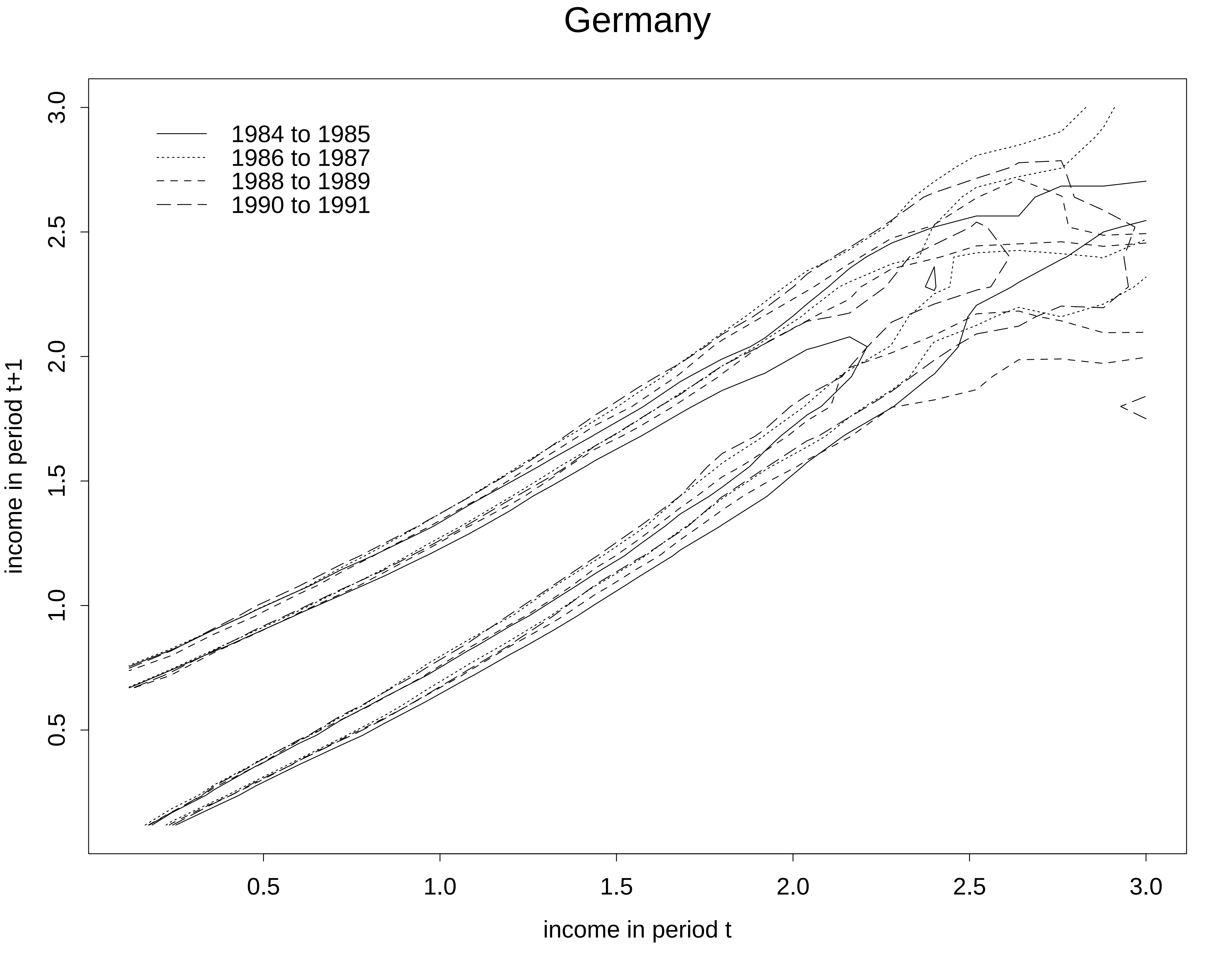
Figure 4: Germany, the US, and the UK: contour plots of the stochastic kernel estimates. Incomes are normalised at the contemporaneous median in period t. Weighted data. The degree of immobility is expressed in the concentration of the contours around the 45 degree line. A society in which incomes in two periods are independent would have horizontal contours, i.e. the conditional distributions would be the same.

rise. At the same time more frequency mass is shifted onto the main diagonal. The changes amongst the highest incomes may be attributable to the small number of observations.

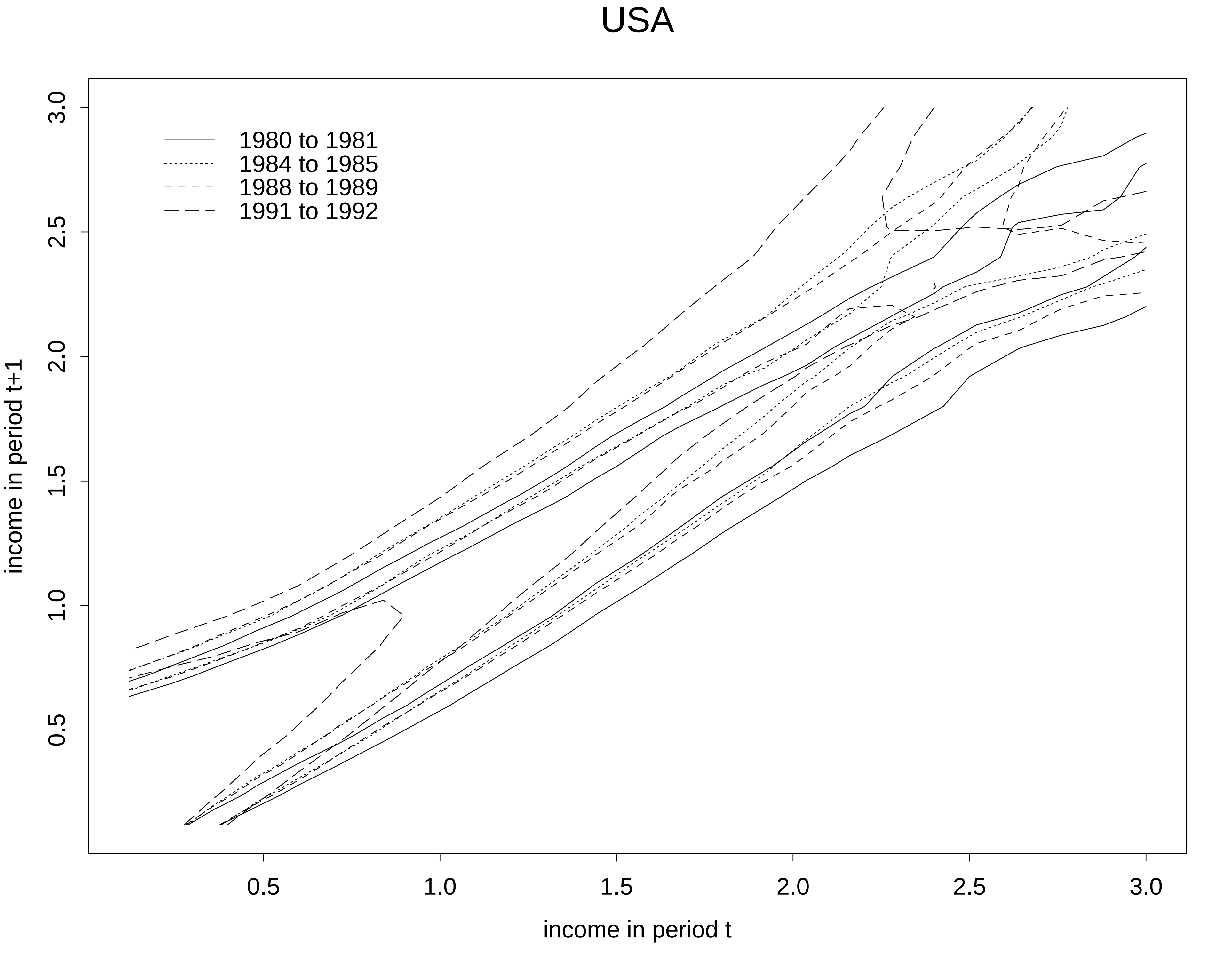
In the US, a more dramatic change has taken place: the contours have tilted relative to the main diagonal. This tilt implies an improved fortune for upper incomes but a worsened situation for the lower income groups and the poor since the conditional probabilities of an income loss have increased. Overall, the contour plots for the US register a greater extent of changes to mobility than is observed in Germany.

Two effects are at work in the UK. First, more frequency mass is shifted onto the main diagonal for lower and middle incomes. In contrast to events in the US and Germany, the contours shift downwards in all periods, implying an increased risk of income losses in the subsequent period.

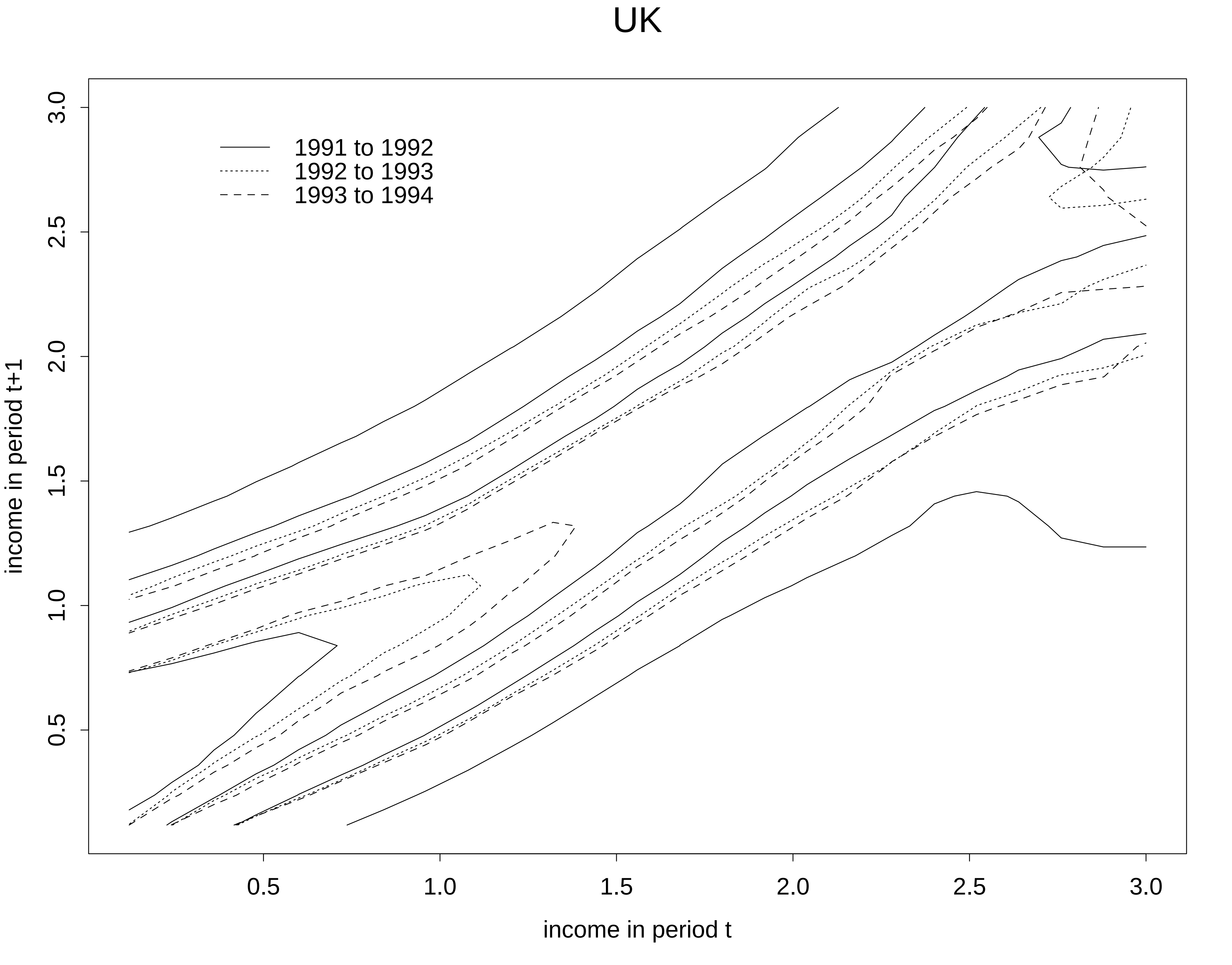
These findings suggest that the proposed plots convey important information, whilst relying exclusively on point estimates of mobility indices can produce misleading results.



Germany
1984 to 1985
1986 to 1987
1988 to 1989
1990 to 1991
income in period t+1
income in period t
0.5
1.0
1.5
2.0
2.5
3.0



USA
1980 to 1981
1984 to 1985
1988 to 1989
1991 to 1992
income in period t+1
income in period t
0.5
1.0
1.5
2.0
2.5
3.0


UK
1991 to 1992
1992 to 1993
1993 to 1994
income in period t+1
0.5
1.0
1.5
2.0
2.5
3.0
income in period t
0.5
1.0
1.5
2.0
2.5
3.0

4 The covariance structure of incomes

Further insights into the law of motion can be gained by going beyond the low order specification proposed in equation (1) and looking at the entire empirical covariance structure of income changes. The next natural step then is to propose and estimate a law of motion consistent with the data which decomposes mobility into its structural components. Schluter (1997) has examined in detail models of the form (1) when the stochastic kernel is discrete and situations in which the staying probabilities can be estimated using duration models. The complementary approach pursued here is to formulate a law of motion directly. The subsequent discussion excludes the UK because of the small number of waves available. We select households which have a complete income record for the entire eleven-year period starting from 1984 in case of Germany and 1982 for the US. The German sample consists of 2716 households and the US sample of 3850.

Tables 6 and 7 report the empirical auto-covariance and cross-covariances of the changes in the logarithm of income for the ten periods. The covariance structures are remarkably similar. These suggest a simple dynamic structure, as the covariances more than two periods apart cease to be statistically significant. Consequently, year-to-year changes in income more than two periods apart are approximately uncorrelated. Correlations between adjacent periods are negative, which implies that positive shocks are likely to be followed by negative shocks. One can therefore concentrate on the first two main diagonals. Finally, there is some evidence of non-stationarity in the empirical estimates which is not surprising since both US and Germany moved from boom to trough in this period. Temporary job or earnings losses might explain this phenomenon.

Although we examine changes in log household net income, the estimates for the US are remarkably similar to the covariance structure of male earnings in the US for 1969 to 1979 reported in Abowd and Card (1989). The estimated variances are slightly smaller, which is to be expected given the dampening effect of the tax system.

The German covariance structure is the same as in the US, but the magnitude of the effects is greater in the US. The US auto-covariances and cross-covariances average to .139 and -.047, whereas in Germany the averages are .086 and -.0238. The differences in magnitude are to be expected as the US has more flexible labour market and lower marginal tax rates.

The negative first order correlations seem to be a pervasive phenomenon as it is also discovered by Lillard and Weiss (1979) for earnings of US research scientists and by Hause (1985) for a sample of young Swedish males. These studies have looked at personal earnings whereas we look at net household income (whose principal component is earnings). Yet this similarity suggests that the same economic forces hold sway. The smaller magnitudes in Germany may then be explained by the dampening effects of the German tax-benefit system with its progressive marginal tax rates and generous benefits.

4.1 Model estimation

Economic theories of permanent income and the life-cycle suggest the distinction between permanent and transitory components of income; i.e. let the income of household $i = 1, \ldots, N$ be decomposed as

$$\log y_{it} = \mu_{it} + u_{it} \tag{6}$$

$$\mu_{it} = \mu_i \tag{7}$$

where μ_i represents the permanent component, at first assumed to be time-invariant, and u_{it} is the transitory component varying over households and time t. The aim of this section is to fit as parsimonious a model as possible. The various estimates are derived using minimum distance methods[9]. The results are collected in Tables 8 and 9.

[9] See, for instance, Abowd and Card (1989) and Chamberlain (1984). Denote by m the vector of the distinct elements of the covariance matrix of changes in log income, V the covariance matrix of

The empirical covariance matrix reported in Tables 6 and 7 restrict severely the class of admissable stochastic processes governing the transitory component. Let the transitory component follow an ARMA(p;q) process. The empirical year-to-year changes in incomes more than two periods apart are approximately uncorrelated. This feature of the data suggests the following restrictions: an autocorrelated component is either absent or rapidly fades out, and components beyond lag 2, if at all present, are not important. This simple dynamic structure of the covariance matrices suggests that a MA(2) error specification might be adequate.

Consider first a stationary MA(2) specification, i.e. let

$$u_{it} = \varepsilon_{it} + \gamma\varepsilon_{it-1} + \delta\varepsilon_{it-2} \tag{8}$$

where the disturbance $\varepsilon_{it} \sim iid(0; \sigma^2_{\varepsilon})$ is assumed to have a time-invariant variance. The estimates are reported in column 2 of Tables 8 and 9. This crude model fits the US covariance structure poorly as the goodness-of-fit statistic evaluates to $\chi^2_{[df=52]} = 1669$ which clearly exceeds typical critical levels. The model fits the German data better, the goodness-of-fit statistic evaluating to $\chi^2_{[df=52]} = 423$, and most point estimates are significant. The estimate of δ is borderline insignificant.

One problem with the income decomposition in equation (6) is that the permanent component is assumed to be time-invariant. However, if this income component

m, and f the modelling function. The estimator $\hat{\theta}$ minimises $(m - f(\theta))'V^{-1}(m - f(\theta))$: V is the optimal weighting matrix. Altonji and Segal (1994) show that $\hat{\theta}$ is biased in small samples because sampling errors in the second moments are correlated with sampling errors in the weighting matrix, but they conclude that "for most distributions the bias is very small when 1,000 observations are available to estimate each sample moment" (p 9). Consequently, the our sample sizes are sufficiently large to permit the use of the optimal weighting matrix. Let $G = df(\theta)/d\theta$. The estimator $\hat{\theta}$ has an asymptotic normal distribution $\sqrt{N}(\hat{\theta} - \theta) \to N(0; (G'V^{*-1}G)^{-1})$. To test the goodness-of-fit of the model, under the hypothesis of a correct model specification, $N(m - f(\theta))'V^{-1}(m - f(\theta))$ has an asymptotic χ^2-distribution with degrees of freedom equal to the difference between the dimension of m and the rank of the Jacobian matrix G evaluated at $\hat{\theta}$. The minimisation of the objective function was carried out using a simple iterative Newton scheme. The programmes were written in Splus.

is interpreted as a function of the ability to generate a certain income stream, a more realistic approach would allow it to change over time. One way to achieve this flexibility is to model the 'permanent' component as a random walk

$$\mu_{it} = \mu_{it-1} + \pi_{it} \tag{9}$$

where $\pi_{it} \sim iid(0; \sigma^2_\pi)$.

The estimates are reported in column 3 of Tables 8 and 9. The fit has improved dramatically at the cost of one degree of freedom in both cases, dropping to 348 and 127 respectively[10]. The point estimates for the US have changed only slightly but are poorly determined. As regards Germany, the estimate of δ has become insignificant. The estimated variance of the change in the 'permanent' component, $\hat{\sigma}^2_\pi$, explains only 27% of the theoretical variance of the overall income change.

The standard errors of the empirical covariance estimates reported in Tables 8 and 7 suggest a large degree of data variability. One source of a systematic pattern might be life-cycle factors: it is well known, for instance, that earnings mobility falls over the life-cycle. In order to examine this possibility, the sample was divided into five cohorts defined by the age of the household head at the beginning of the period. Median age is 45 years in Germany, and 37 in the US. Cohort 1 contains households whose head is aged below 30 years, cohort 2 includes the triagenarians, cohort 3 the tetragenarians etc. whilst cohort 5 includes hexagenarians and older households. The model's estimates are reported in columns 4 to 8 of Tables 8 and 9.

The point estimates for the US do not exhibit a discernible decline across cohorts, and are poorly determined. Most estimates for the separate cohorts are in the neighbourhood of the estimates for the entire sample. Factors other than the life-cycle appear to play an important role. For Germany, the imprecision of the estimates for cohorts 2 and 3 may obscure the decline in all estimates. Ignoring them suggests hat

[10] This model is expected to provide a much better fit because a constant (σ^2_π) has been added to the principal diagonal of the modelled covariance matrix.

parameters indeed fall over the life-cycle. The effect of an expected decline in earnings mobility may have been strengthened by the tax-benefit system, with linear marginal tax rates and earnings-related state pensions for the majority of the population.

Tables 8 and 9 also suggests that the empirical covariances are time-varying; evidence which is consistent with the time-varying stochastic kernels discussed in the previous section. This is not surprising since both countries completed a movement through the business cycle from economic expansion to economic downturn. A simple way to accommodate this non-stationarity is to let the variance of the error terms vary with time, i.e. $\varepsilon_{it} \sim iid(0; \sigma^2_{\varepsilon;t})$. This specification implies that the only source of change in the spread of the cross-sectional income distribution, depicted in Section 2 using kernel density methods, is the time-varying variance of the disturbance. The estimates for this non-stationary MA(2) model are reported in the last column of Tables 8 and 9.

The goodness-of-fit statistics improve again substantially at the cost of 12 degrees of freedom, to 191 and 72 respectively. The absolute values of the point estimates fall slightly in both cases. The statistically significantly changing variances are the driving force behind the empirical changes in the overall variance (the principal diagonal in Tables 6 and 7). In the German case, for instance, the average of the error variances $\sigma^2_{\varepsilon;t}$, weighted by their occurrences in the theoretical covariance matrix is 0.0349, which exceeds the estimate of 0.0298 for the time-invariant model.

To conclude, for the US, the best fit is attained by model which decomposes income into a permanent component following a random walk and a transitory component governed by a non-stationary MA(2) process. The point estimates of the MA(2) coefficients change only slightly across the models. Despite examining net household income and a different period, the fit of the model of 191 is close to the fit reported by Abowd and Card (1989) (namely 137). They do not report point estimates. By contrast, Gottschalk and Moffitt (1995) report point estimates but no goodness-of-fit for a PSID sample of white male earners. They report an estimate for γ of -.344, remarkably close to our stationary random walk model (-.369), but somewhat higher than for the non-stationary model (-253). They accept a model with a random walk specification of the permanent component and an ARMA(1,1) specification of the transitory component but conclude that the autoregressive component fades out rapidly[11]. MaCurdy (1982) accepts the stationary model for the case of personal earnings in the US, reporting a coefficient of -48 for γ. The similarity of all this evidence is surprising.

As regards Germany, the best fit is also attained by the non-stationary MA(2) model. The smaller absolute size of the point estimates is not surprising given the equalising distributional effects of the German tax-benefit system. Surprising, however, is the fact that the MA coefficient (γ;δ) have the opposite sign of their US counterparts[12]. This pattern implies that an isolated positive transitory shock in Germany elevates net household incomes above its long run value for three period whilst in the US, the first year is above and the next two years are below the long run level.

To summarise: having examined two aspects of the dynamics of income distributions - shape dynamics and intra-distributional mobility - in the two preceding sections, we have proceeded to directly specify and estimate laws of motion for household net income in US and Germany. Empirical year-to-year changes in income more than two periods apart are approximately uncorrelated, and the correlation between income changes in adjacent years is negative. The model was based on the decomposition

[11] Gottschalk and Moffitt (1995) also estimate models with factor loadings, interpreting the factors losely as `prices' of the permanent and the transitory income components. This approach has not been pursued here for two reasons. If the factors are not parametrised, 20 new parameters need to be estimated, resulting in a dramatic loss of degrees of freedom. Parametrising the unobserved factors faces the risk of misspecification error. Gottschalk and Moffitt (1995) use linear parametrisations but fail to conduct any form of misspecification analysis.

[12] Burkhauser, Holtz-Eakin, and Rhody (1997) also observe different signs for the US and Germany for male earnings, although their estimate of γ in the US is 247 compared to -344 reported by Gottschalk and Moffitt (1995).

of income into permanent and transitory components. The best fit to the data was attained when we modelled the permanent component as a random walk and the transitory component as a non-stationary MA(2) process in which the variances of the disturbances varied over time. Despite different labour market institutions and tax-benefit systems, the income processes in the US and Germany are very similar.

5 Conclusion

A fruitful approach to the study of income dynamics in the US, Germany, and the UK in the 1980s and 90s is the distinction between the cross-sectional shape dynamics and intra-distributional mobility. We reject the common wisdom that European societies are immobile vis-a-vis a highly mobile US. In particular, in Germany, stable cross-sectional distributions conceal substantial movements beneath the surface, so that the common wisdom about Germany as a country in stasis is mistaken. According to such measures, Germany is often deemed a more mobile society than the US. However, on closer inspection, this result is driven by a single income group: the lowest income group in Germany is substantially more mobile than its US counterpart, and this cannot be compensated by the greater mobility of all the other income groups in the US.

On a methodological note, stochastic kernels are shown to be useful tools for the examination of intra-distributional mobility. The problem for standard approaches based on transition matrices and mobility indices arises from the groupings of individuals into income classes of arbitrary size, i.e. an arbitrary discretisation of the continuous income process. The stochastic kernels present a more accurate and balanced view. In particular, the chances of income changes have, over time, `tilted' in the US: higher income groups benefit from increased chances of an income rise, whilst the lower income groups face an increased chance of still further losses, aggravating the process of income polarisation. In the UK, mobility has fallen across all income groups, whilst mobility in German has changed only little over the period.

Finally, a law of motion for household incomes has been proposed using the decomposition of income into permanent and transitory components. Year-to-year changes in income more than two periods apart are approximately uncorrelated, and the correlation between income changes in adjacent years is negative. A non-stationary MA(2) process for the transitory component describes the data well but the coefficients for the US and Germany exhibit opposite signs. This pattern implies that an isolated positive transitory shock in Germany elevates net household incomes above its long run value for three period whilst in the US, the first year is above and the next two years are below the long run level. Despite different labour market institutions and tax-benefit systems, the income processes in the US and Germany are very similar.

A Appendix: Data description

This appendix summarises the methods of income derivation, equivalisation, and sample selection for the three panel data sets. Table 10 reports sample sizes and other summary statistics.

The GSOEP is a high quality panel modelled on the US Panel Study of Income Dynamics (PSID), and contains most the relevant socio-economic variables. Households have been interviewed annually since 1984. In contrast to the PSID, all household members older than 15 years are interviewed individually. GSOEP does not supply a good measure of post-tax post-benefit household income; instead an estimate is furnished in the PSID-GSOEP Equivalent Data file' distributed by Syracuse University. The Equivalent Data file' comprises the years 1984 to 1994. The estimate of post-tax post-benefit household income is obtained from a tax-benefit simulation by the data provider after aggregating over household members pre-tax income from earnings (from employment and self-employment), asset flows, private and public transfers, and the imputed rental value of owner occupied housing. For some benefits, such as means-tested social assistance, only indicators of receipt are available as raw data. However, such benefits are typically set at standard rates, and take-up is very high. In order account for scale economies within the household, income was equivalised using the OECD equivalent scales, i.e. disposable income was divided by household size raised to the power 0.5[13]. Finally, incomes were standardised at 1994 prices.

The selected sample covers only households in West Germany. All samples were left-censored at DM 1,000 p.a., approximately 1/25th of mean net income in 1994, in order to eliminate obviously under-reported incomes. The sample contains foreigners who are deliberately oversampled by the data provider. Moreover, given attrition, the data must be weighted to reflect the varying sample inclusion probabilities. The cross-section in 1984 contains some 15170 persons. The mobility analysis is conducted on samples of similar magnitude.

The Equivalent Data file also contains a subset of the US Panel Study of Income Dynamics (PSID), comprising the years 1980 to 1992. Estimated post-tax post-benefit income is rendered as comparable as possible to the German income definition. Public transfers, for instance, include AFDC payments, SSI, unemployment compensation, and the face value of food stamps. Incomes are left censored at $500 p.a., evaluated at 1992 prices and equivalised using the OECD scales. As regards sample selection, similar comments apply.

The British Household Panel survey (BHPS), much younger than the other two panels, has a similar design. Jarvis and Jenkins provide an estimate of post-tax post-benefit income, also obtained through a tax-benefit simulation. For a detailed exposition, see Jarvis and Jenkins (1997). The estimate aggregates across household members earnings, income from investment and savings, private and public pensions, other market income and private transfers, social security and assistance receipts, less income tax, National Insurance contributions and local taxes. The first four waves of

[13] The choice of equivalence scales is inherently arbitrary but Burkhauser, Merz, and Smeeding (1994) show that the German Social Assistance scale implies scale economies which are too low.

the panel are included. Incomes are measured in the month prior to the interview, except for earnings which are `usual' earnings. The estimate has been converted to an annual equivalent value. Incomes are evaluated at 1995 prices, equivalised using the quasi-o±cial McClements scales, and the samples excludes households with annual incomes below $500 pa.

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	year	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
GSOEP	K-S					.0	.005	.006	.233	.471	.297	.096	.252	.0	.278	
	(D)					(.025)	(.021)	(.021)	(.013)	(.011)	(.013)	(.016)	(.014)	(.032)	(.013)	
	unimodality					.462	.904	.54	.392	.342	.768	.518	.43	.758	.496	.738
	(h_k)					(.111)	(.0634)	(.0797)	(.125)	(.135)	(.063)	(.0797)	(.103)	(.0753)	(.099)	(.087)
PSID	K-S	.020	.003	.000	.005	.111	.052	.000	.163	.060	.193	.477	.000			
	(D)	(.0156)	(.0187)	(.0276)	(.0176)	(.0122)	(.0137)	(.0214)	(.0114)	(.0134)	(.0109)	(.0085)	(.0385)			
	bimodality	.452	.57	.132	.846	.786	.894	.644	.372	.782	.384	.202	.882	.58		
	(h_k)	(.0796)	(.0796)	(.1260)	(.0869)	(.0854)	(.0796)	(.1163)	(.0989)	(.095)	(.126)	(.126)	(.0989)	(.1299)		
	trimodality	.546	.158	.494	.49	.49	.938	.238	.956	.34	.762	.164	.614	.654		
	(h_k)	(.0641)	(.0796)	(.095)	(.0834)	(.0834)	(.0709)	(.1144)	(.0680)	(.095)	(.095)	(.114)	(.095)	(.114)		
BHPS	K-S												.071	.119	.380	
	(D)												(.0172)	(.0162)	(.0126)	
	unimodality												.598	.476	.836	.782
	(h_k)												(.0989)	(.1298)	(.0951)	(.099)
	bimodality												.3	.612	.32	.53
	(h_k)												(.095)	(.0796)	(.095)	(.095)

Table 1: p-values for Kolmogorov-Smirnov test for equality of income distributions in periods t and $t+1$, and Silverman's test for unimodality. The value of the test statistic and the critical bandwidth are given in parenthesis.

	GSOEP											BHPS			
year	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1991	1992	1993	1994
per-centiles															
.1	.0370 (.41)	.03796 (.397)	.03925 (.398)	.03848 (.419)	.0389 (.42)	.0386 (.44)	.0382 (.46)	.0375 (.44)	.0372 (.46)	.0337 (.49)	.0330 (.5)	.03116 (3.756)	.03143 (4.135)	.03161 (3.884)	.03145 (4.210)
.2	.0931 (.644)	.0935 (.624)	.09559 (.627)	.09516 (.669)	.0959 (.65)	.0957 (.67)	.09469 (.69)	.0936 (.68)	.0928 (.69)	.0870 (.71)	.0861 (.74)	.07819 (6.291)	.07925 (6.707)	.07912 (6.632)	.07942 (6.841)
.3	.1590 (.884)	.15955 (.86)	.1623 (.87)	.16272 (.915)	.1628 (.87)	.1632 (.9)	.16086 (.95)	.1605 (.91)	.1589 (.93)	.1509 (.9)	.1501 (.99)	.13675 (9.161)	.13745 (9.432)	.13734 (9.487)	.13826 (9.747)
.4	.2345 (1.14)	.2356 (1.1)	.2394 (1.11)	.2389 (1.15)	.2393 (1.09)	.240 (1.13)	.2368 (1.19)	.2369 (1.1)	.2347 (1.17)	.2257 (1.18)	.2246 (1.22)	.20670 (12.03)	.20586 (12.35)	.20699 (12.60)	.20809 (12.88)
.5	.320 (1.4)	.3208 (1.34)	.3258 (1.35)	.3244 (1.4)	.3249 (1.29)	.3262 (1.3)	.3217 (1.44)	.3229 (1.3)	.3199 (1.39)	.3113 (1.3)	.3088 (1.45)	.28846 (14.71)	.28568 (15.27)	.28866 (15.59)	.28935 (15.76)
.6	.4150 (1.67)	.4165 (1.57)	.4222 (1.58)	.4199 (1.65)	.42 (1.48)	.4223 (1.54)	.4163 (1.68)	.4189 (1.54)	.4157 (1.6)	.4079 (1.56)	.4044 (1.66)	.38192 (17.18)	.37821 (18.07)	.38242 (18.30)	.38237 (18.53)
.7	.5210 (1.94)	.5241 (1.8)	.5295 (1.97)	.5269 (1.89)	.5279 (1.65)	.5299 (1.73)	.5224 (1.91)	.5262 (1.7)	.5235 (1.78)	.5172 (1.7)	.5126 (1.84)	.48872 (19.31)	.48488 (20.58)	.48991 (20.71)	.48936 (21.05)
.8	.6415 (2.2)	.646 (2.0)	.6508 (1.99)	.6476 (2.12)	.6497 (1.78)	.651 (1.88)	.6428 (2.11)	.6484 (1.84)	.6453 (1.9)	.6413 (1.8)	.6368 (1.98)	.61293 (20.87)	.60941 (22.46)	.61579 (22.60)	.61361 (23.1)
.9	.78314 (2.4)	.7888 (2.17)	.7933 (2.14)	.7882 (2.31)	.7925 (1.8)	.7935 (1.93)	.7856 (2.2)	.7908 (1.87)	.784 (1.97)	.7876 (1.78)	.7831 (2.0)	.76460 (20.94)	.76236 (23.18)	.76860 (23.39)	.76361 (23.76)
Gini	.265	.2611	.2536	.2572	.2547	.2529	.2618	.2580	.2617	.2726	.2776	.30212	.30509	.29991	.30090

Table 2: Germany and the UK: Lorenz curve ordinates, Ginis, and standard errors*1000 in parenthesis. Unweighted data.

year	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
per-centiles													
.1	.0249 (.267)	.0245 (.36)	.0238 (.2575)	.0219 (.2684)	.0216 (.2377)	.0209 (.2573)	.0206 (.2167)	.0204 (.2248)	.019 (.2384)	.019 (.24444)	.019 (.2246)	.0200 (.2294)	.0151 (.2040)
.2	.0662 (.5287)	.0652 (.6344)	.0628 (.5100)	.0591 (.5532)	.0575 (.4512)	.0563 (.5644)	.0560 (.4802)	.0554 (.4746)	.054 (.59)	.054 (.54286)	.054 (.4947)	.0551 (.4840)	.0447 (.4825)
.3	.1208 (.8163)	.1184 (1.041)	.1153 (.8353)	.1089 (.9124)	.1061 (.7286)	.1041 (.9493)	.1049 (.7819)	.1032 (.7592)	.102 (.85324)	.102 (.89756)	.1017 (.7947)	.1030 (.7757)	.0880 (.800)
.4	.1878 (1.097)	.1838 (1.499)	.1815 (1.150)	.1718 (1.319)	.1683 (1.021)	.1648 (1.394)	.1677 (1.101)	.1642 (1.062)	.16242 (1.2290)	.1631 (1.2823)	.1624 (1.119)	.1643 (1.085)	.1458 (1.170)
.5	.2673 (1.392)	.2623 (2.027)	.2604 (1.474)	.2490 (1.778)	.2450 (1.3)	.2395 (1.906)	.2440 (1.419)	.2394 (1.369)	.23707 (1.6490)	.2381 (1.7151)	.2369 (1.465)	.2393 (1.407)	.2183 (1.536)
.6	.3604 (1.694)	.3540 (2.607)	.3526 (1.814)	.3399 (2.267)	.3365 (1.66)	.3290 (2.477)	.3350 (1.735)	.3298 (1.685)	.32720 (2.1032)	.3271 (2.1850)	.3262 (1.826)	.3287 (1.731)	.3060 (1.936)
.7	.4694 (2.005)	.4605 (3.263)	.4612 (2.177)	.4474 (2.822)	.4455 (1.835)	.4353 (3.128)	.4425 (2.060)	.4380 (1.999)	.43494 (2.6064)	.4325 (2.7087)	.4322 (2.201)	.4357 (2.068)	.4115 (2.368)
.8	.5983 (2.325)	.5871 (4.012)	.5896 (2.559)	.5762 (3.450)	.5769 (2.071)	.5619 (3.863)	.5710 (2.385)	.5686 (2.310)	.56397 (3.1625)	.5590 (3.2945)	.5587 (2.584)	.5639 (2.401)	.5401 (2.831)
.9	.7549 (2.632)	.7431 (4.894)	.7479 (2.952)	.7363 (4.171)	.7403 (2.261)	.7199 (4.714)	.7320 (2.69)	.7309 (2.583)	.72502 (3.7754)	.7171 (3.9287)	.7186 (2.950)	.7236 (2.710)	.7033 (3.301)
Gini	.3300	.3402	.3410	.3579	.3605	.3736	.3652	.3700	.37462	.3776	.3779	.3733	.4054

Table 3: USA: Lorenz curve ordinates, Ginis, and standard errors * 1000 in parenthesis. Unweighted data.

	year	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
GSOEP	GE_2					.1785	.1825	.1636	.1740	.150	.1528	.170	.152	.159	.159	.170
						(1.43)	(1.71)	(1.78)	(1.49)	(1.08)	(1.82)	(1.66)	(1.24)	(1.64)	(1.36)	(1.60)
	GE_0					.1337	.1316	.1247	.1286	.1256	.1254	.133	.131	.141	.148	.157
						(.119)	(.128)	(.124)	(.128)	(.0954)	(.127)	(.151)	(.109)	(.146)	(.146)	(.206)
	GE_{-1}					.1843	.1687	.1671	.1622	.1594	.171	.184	.168	.197	.209	.240
						(.769)	(.732)	(.848)	(.708)	(.673)	(.993)	(1.13)	(.784)	(1.15)	(1.17)	(1.80)
PSID	GE_2	.2921	.7168	.3469	.5658	.2821	.6424	.36396	.36331	.64523	.7128	.45619	.3545	.5309		
		(8.57)	(30.5)	(10.4)	(27.7)	(3.83)	(15.3)	(6.045)	(5.789)	(15.40)	(15.75)	(6.134)	(2.96)	(10.9)		
	GE_0	.1864	.2124	.2008	.2220	.2188	.2491	.23936	.24440	.26073	.27609	.26405	.2484	.3057		
		(.31)	(.21)	(.41)	(.91)	(.24)	(.98)	(.394)	(.384)	(1.004)	(1.120)	(.536)	(.33)	(.69)		
	GE_{-1}	.2618	.2852	.2841	.3246	.3159	.3521	.35257	.36560	.37149	.39744	.38583	.3567	.4946		
		(.99)	(1.40)	(1.09)	(1.49)	(1.05)	(1.54)	(1.203)	(1.369)	(1.505)	(1.673)	(1.494)	(1.23)	(1.94)		
BHPS	GE_2												.1898	.1987	.2080	.2007
													(.837)	(1.323)	(5.39)	(1.61)
	GE_0												.1632	.1646	.1595	.1641
													(.096)	(.1573)	(.232)	(.183)
	GE_{-1}												.2185	.2208	.2097	.2212
													(.802)	(1.25)	(1.33)	(1.41)

Table 4: Inequality in Germany, the US and the UK: the Generalised Entropy Index. Standard errors*1000 in parenthesis.

	year	1980/81	81/82	82/83	83/84	84/85	85/86	86/87	87/88	88/89	89/90	90/91	91/92	92/93	1993/94
GSOEP	LD^u					F	F	C	F	C	R	C	R	R	R
	$Gini^u$					F	F	R	F	F	R	F	R	R	R
	GE_2^w					R	F	R	F	R	R	F	R	F	R
	GE_0^w					F	F	R	F	F	R	F	R	R	R
	GE_{-1}^w					F	F	F	F	R	R	F	R	R	R
PSID	LD^u	R	C	R	C	R	C	R	R	C	C	F	R		
	$Gini^u$	R	R	R	R	R	F	R	R	R	R	F	R		
	GE_2^w	R	F	R	F	R	F	F	R	R	F	F	R		
	GE_0^w	R	F	R	F	R	F	R	R	R	F	F	R		
	GE_{-1}^w	R	F	R	F	R	R	R	R	R	F	F	R		
BHPS	LD^u												C	C	C
	$Gini^u$												R	F	R
	GE_2^w												R	R	F
	GE_0^w												R	F	R
	GE_{-1}^w												R	F	R

Table 5: Summary of changes in inequality. w (u) refers to the (un)weighted data, R (F) denotes a rise (fall) in inequality, C a crossing of the Lorenz curves. Italisised items refer to periods of falling unemployment in the respective country.

¢ (log y)	period 1	period 2	period 3	period 4	period 5	period 6	period 7	period 8	period 9	period 10
period 1	0.133 (0.057)									
period 2	-0.043 (0.038)	0.131 (0.028)								
period 3	-0.006 (0.033)	-0.043 (0.041)	0.137 (0.059)							
period 4	-0.002 (0.026)	-0.005 (0.027)	-0.047 (0.038)	0.144 (0.060)						
period 5	0.003 (0.023)	-0.003 (0.022)	-0.003 (0.027)	-0.047 (0.039)	0.131 (0.061)					
period 6	0.000 (0.022)	-0.006 (0.021)	-0.003 (0.021)	-0.006 (0.025)	-0.042 (0.044)	0.122 (0.057)				
period 7	-0.002 (0.023)	0.003 (0.025)	0.001 (0.023)	-0.003 (0.026)	-0.005 (0.025)	-0.038 (0.034)	0.124 (0.053)			
period 8	-0.004 (0.024)	0.001 (0.026)	0.001 (0.024)	-0.006 (0.024)	0.001 (0.027)	0.001 (0.025)	-0.050 (0.039)	0.137 (0.069)		
period 9	-0.004 (0.025)	-0.003 (0.025)	0.000 (0.030)	0.003 (0.022)	-0.007 (0.031)	-0.004 (0.024)	-0.006 (0.024)	-0.047 (0.046)	0.135 (0.070)	
period 10	0.004 (0.028)	0.009 (0.025)	0.009 (0.024)	0.005 (0.026)	0.002 (0.025)	0.000 (0.024)	0.005 (0.023)	-0.009 (0.028)	-0.045 (0.040)	0.189 (0.069)

Table 6: USA: The empirical covariance matrix of the changes in the logarithm of equivalised net household income. Standard errors in parenthesis.

¢ (log y)	period 1	period 2	period 3	period 4	period 5	period 6	period 7	period 8	period 9	period 10
period 1	0 125 (0 0696)									
period 2	-0 0438 (0 0391)	0 0951 (0 0515)								
period 3	-0 0025 (0 0165)	-0 0245 (0 0269)	0 0864 (0 0465)							
period 4	0 0003 (0 0184)	-0 003 (0 0145)	-0 028 (0 0366)	0 0769 (0 0533)						
period 5	-0 0027 (0 0192)	-0 0021 (0 0172)	-0 0079 (0 0228)	-0 0137 (0 0245)	0 071 (0 0434)					
period 6	-0 002 (0 0173)	0 0018 (0 0183)	0 0018 (0 0139)	-0 0068 (0 023)	-0 0195 (0 0365)	0 0792 (0 0668)				
period 7	0 0007 (0 0157)	0 0023 (0 0152)	0 001 (0 0132)	0 0002 (0 0162)	-0 0037 (0 0141)	-0 0279 (0 0399)	0 0829 (0 05)			
period 8	0 0002 (0 0154)	-0 0012 (0 0158)	0 0014 (0 0148)	0 001 (0 0142)	-0 0025 (0 013)	0 0011 (0 0152)	-0 0242 (0 0233)	0 0733 (0 0463)		
period 9	-0 0036 (0 0148)	0 0009 (0 0151)	-0 0021 (0 0167)	-0 001 (0 0151)	0 0009 (0 0135)	-0 0008 (0 0219)	-0 0048 (0 0185)	-0 0256 (0 0335)	0 083 (0 0546)	
period 10	0 0015 (0 016)	-0 0012 (0 0143)	-0 0016 (0 0165)	-0 0028 (0 0161)	-0 0016 (0 015)	-0 0057 (0 0233)	0 0023 (0 0219)	-0 0054 (0 0171)	-0 0308 (0 0377)	0 0859 (0 0522)

Table 7: Germany: The empirical covariance matrix of the changes in the logarithm of equivalised net household income. Standard errors in parenthesis.

transitory component	stationary MA(2)							non-stationary MA(2)
permanent component	fixed	RW						RW
cohorts	all	all	1	2	3	4	5	all
$\hat{\theta}$	-.3490 (891)	-.3694 (1.18)	-.3530 (1038)	-0514 (491)	-4886 (2.79)	-271 (1207)	-.392 (1.387)	-253 (870)
$\hat{\delta}$	-2247 (460)	-262 (.626)	-1573 (474)	-0926 (.317)	-2637 (128)	-231 (.664)	-236 (.662)	-184 (419)
$\hat{\sigma}^2_{\varepsilon}$	0285 (030)	0247 (034)	0309 (038)	0252 (018)	0163 (048)	024 (034)	017 (029)	
$\min \sigma^2_{\varepsilon;t}$								027
$\max \sigma^2_{\varepsilon;t}$								099
$\hat{\sigma}^2_{\omega}$		033 (008)	0372 (010)	0291 (009)	0323 (015)	03 (008)	015 (008)	034 (009)
χ^2 [df]	1669 [52]	348 [51]	206 [51]	202 [51]	120 [51]	104 [51]	128 [51]	191 [39]
N	3850	3850	1234	946	562	573	535	3850

Table 8: USA: Model estimates. Standard errors in parenthesis. RW refers to the random walk model

transitory component	stationary MA(2)							non-stationary MA(2)
permanent component	fixed	RW						RW
cohorts	all	all	1	2	3	4	5	all
b	.371 (1.02 6)	1.66 (2.09)	.314 (2.98)	0.0 7 (.55)	0.63 (.34 6)	2.66 (1.88)	1.28 (2.3)	1.48 (1.99 6)
±b	1.54 (0.9 77)	0.35 (1.53)	0.64 (2.0)	0.24 (.31)	0.016 (2.31)	0.13 (1.4 3)	0.32 (1.91)	0.29 (1.504)
$¾b^2$	0.429 (0.111)	0.298 (0.12 7)	0.2 3 (0.16)	0.12 (0.11)	0.15 (0.09)	0.31 (0.12)	0.198 (0.10)	
min $¾^2_{";t}$								0.21
max $¾^2_{";t}$								0.8
$¾b^2_{¼}$		0.192 (0.0 78)	0.18 (0.11)	0.19 (0.0 7)	0.178 (0.05)	0.145 (0.08)	0.0 7 (0.0 7)	0.195 (0.0 78)
$Â^2$ [d f]	423.4 [52]	12 72 [51]	80 1 [51]	105 9 [51]	94 .5 [51]	6698 [51]	9303 [51]	71 9 [39]
N	2 716	2 716	357	609	72 6	516	511	2 716

Table 9: Germany: Model estimates. Standard errors in parenthesis.
RW refers to the random walk model

		1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
GSOEP	mean					30770.4	31462.2	31469.3	33352.4	33871.2	34659.9	35177.7	36256.6	37431.2	36964.4	3623
	median					27750.6	28422.1	28584.6	29868.8	30577.0	31189.9	31453.4	32756.2	33662.5	33812.0	3265
	N					15170	13637	13027	12805	12171	11749	11522	11482	11264	11126	1086
	growth					2.8	2.0	2.3	1.5	3.7	3.6	5.7	5.0	2.2	-1.2	2.9
	U					7.1	7.1	6.4	6.2	6.2	5.6	4.8	4.2	4.6	/	/
PSID	mean	22537.9	21843.5	20833.1	21280.5	21713.5	23187.2	23163.7	23770.6	24695.1	25399.5	25054.5	24279.0	28830.6		
	median	19726.7	18469.9	18207.5	18073.4	18764.2	19295.0	19670.7	20086.3	20343.7	20395.3	20582.1	20129.3	22700.0		
	N	18884	18885	19095	19321	19375	19582	19415	19475	19504	19530	19776	19747	20148		
	U	7.0	7.5	9.5	9.5	7.4	7.1	6.9	6.1	5.4	5.2	5.6	6.8	7.5		
	growth	-0.3	2.5	-2.1	4.0	6.8	3.7	3.0	2.9	3.8	3.4	1.3	-1.0	2.7		
BHPS	mean												16329.6	18577.5	19772.7	2075
	median												14228.3	16001.7	17219.4	1776
	N												11602	10948	10445	1044
	U												8.8	10.1	10.4	9.6
	growth												-2.0	-0.5	2.3	3.8

Table 10: Sample characteristics and economic indicators. N refers to the sample size, U to the unemployment rate, and growth to the rate of change of real GDP. U and growth are taken from the OECD Economic Outlook 1995. / refers to a break in the series