An anatomy of household income volatility in European countries[1]

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Abstract

This paper offers an exploratory analysis of household income volatility in the 1990s in fourteen EU countries and two future member states, namely Hungary and Poland, using simple summary statistics for average income changes as advocated in Fields and Ok (JET 1996, Economica 1999). The evidence is derived from the newly generated data of the Consortium of Household Panels for European Socio-Economic Research (CHER) that contain harmonised data from the European Community Household Panel and from a series of independent panel surveys. Going a step ahead to overcome the obvious restriction of looking only at population averages as Fields and Ok suggest, both the overall distribution of individual income variations, and the variations in levels of income volatility for different starting income levels are also examined. The analysis can be viewed as looking at the primitives of income mobility at the individual level, as opposed to many of the existing analyses that assess, using other more sophisticated concepts, the aggregate outcome (like inequality of long-term income) resulting from these individual income variations.

The issue of accounting for the observed cross-national differences is addressed. Important determinants of household income, and of its variability over time, such as labour market flexibility and family formation habits vary across countries and may explain cross-national differences in income volatility. This paper attempts to evaluate how much of these cross-national differences can be accounted for by differences in the socio-demographic structure of the populations, as well as in cross-national variations in the dynamics of labour market and household formation. In particular, volatility levels are compared after controlling jointly for cross-national differences (i) in the prevalence of female-headed households, (ii) in household composition (by size, number of children, and age of household head), (iii) in the frequency of household composition changes, and (iv) in the frequency of changes in the household labour market attachment. To this aim, non-parametric (or semi-parametric) methods are derived from those developed by DiNardo, Fortin and Lemieux (Econometrica, 1996) in the context of intertemporal income distribution comparisons.

1 Introduction

Cross-national income mobility comparisons have flourished over the last decade. Many comparisons contrast Germany to the USA.[1] Other analyses have added further OECD countries in the comparison.[2] However, it remains difficult to build a comprehensive picture of how different countries (or different Welfare state regimes) fare with regard to income mobility, by contrast to what can be done with respect to income inequality. The main reason for this is probably the diverging nature of the aspects of mobility that are examined in the different studies. Income mobility can indeed be assessed in a variety of ways. It has frequently been assessed indirectly, by its impact on income inequality over time, and the degree to which it equalises incomes in the long run. Theoretical foundations for this type approach appear in Shorrocks (1978a), Chakravarty, Dutta, and Weymark (1985), Dardanoni (1993), Fields (2000) or Formby, Smith, and Zheng (2002). Most of these indirect approaches, have normative considerations and associate mobility measurement with social desirability. By contrast, other approaches attempt to capture some intuitive descriptive content of the concept of mobility. Many analyses have used transition matrices (and summary statistics thereof) to measure and compare mobility levels (as suggested in Bartholomew 1973, Shorrocks 1978b).[3] Comparisons of empirical analyses of this type are rendered difficult by the variety of ways by which transition matrices can be defined. Finally, a series of analyses have adopted various other approaches to describe income mobility, looking e.g. at correlation or rank correlation coefficients following e.g. Hart (1976) or Schiller (1977), or more recently, using simple summary statistics for average income changes as advocated in Fields and Ok (1996) and Fields and Ok (1999).[4]

This paper attempts to offer a comprehensive description of income volatility in Europe in the 1990s using this latter approach. Rather than targeting an evaluation of 'mobility', this paper documents in detail the volatility of family size adjusted household disposable income at the individual level. By volatility, I mean the change from one year to the next of the income recorded in repeated surveys. Going a step ahead to overcome the obvious limitation of

[1] See, *inter alia*, Burkhauser and Poupore (1997), Gottschalk and Spolaore (1998), Schluter and Trede (1999), Maasoumi and Trede (2001), Formby, Smith, and Zheng (2001). I do not consider here the even more prominent empirical literature on poverty dynamics (see Jenkins 2000).

[2] See, *inter alia*, Fritzell (1990), Schluter (1998), Fabig (1999), Headey and Muffels (2002), Aaberge, Björklund, Jäntti, Palme, Pedersen, and Smith (2002), Ayala and Sastre (2002), or Van Kerm (2003).

[3] See, *inter alia*, Fritzell (1990), Hauser and Fabig (1999), or Fabig (1999).

[4] See, *inter alia*, D'Ambrosio and Frick (2002), or Fields, Cichello, Freije, Menéndez, and Newhouse (2003).

looking only at population averages as Fields and Ok suggest, I look at the overall distribution of individual income variations, and examine how the degree of income variability varies with the initial income position. This simple exercise uncovers patterns which in turn may help understanding mobility differences based on other more sophisticated concepts. This analysis can be viewed as looking at the primitives of income mobility at the individual level, as opposed to many of the aforementioned analyses that assess the aggregate outcome resulting from these individual income variations. A similar approach is developed in Fields, Cichello, Freije, Menéndez, and Newhouse (2003).

Determinants of household income, and of its variability over time, such as labour market institutions, welfare state coverage, and family formation habits vary across the countries considered. Income volatility levels can therefore be expected to differ widely across countries. I also attempt to go beyond the mere description of differences in overall volatility levels, and examine the potential sources of this difference in the socio-demographic structure of the populations as well as in cross-national variations in the dynamics of labour market and household formation. In particular, I compare volatility levels after controlling non-parametrically for cross-national differences (i) in the prevalence of female-headed households, (ii) in household composition (by size, number of children, and age of household head), (iii) in the frequency of household composition changes, and (iv) in the frequency of changes in the household labour market attachment. The rationale for this analysis lies in the fact that factors (i) and (ii) have been documented as identifying subpopulations experiencing differing degrees of income mobility (see e.g. Sastre and Ayala 2002), whereas (iii) and (iv) are obvious potential 'trigger events' of family income variations.

This paper provides evidence on the levels and patterns of individual income variations in the 1990s in fourteen EU countries and two future member states, namely Hungary and Poland. It helps assess the impact that the transition had on family income variability in the years following the introduction of the reforms, and the success of the measures that were adopted to prevent excess family income falls. The evidence is derived from the newly generated data of the Consortium of Household Panels for European Socio-Economic Research (CHER).

Cross-national comparisons involve a large amount of figures. In the body of the paper, focus is put on graphical representations of data to convey information in a clean and simple way. More detailed tables are reported are available from the author on request.

The paper is organised as follows. Section 2 sets out the methods employed in the paper.

Section 3 describes the CHER data used. Empirical results are presented in Section 4 and Section 5. The concluding section summarises the main findings and contribution of the paper and briefly discusses some yet unresolved issues.

2 Methods

This paper assesses the volatility of income by the change in log-income between two consecutive survey interviews. I consider both the change and the absolute value of the change in log-income. The change in log-income is a natural tool for an assessment of an individuals' income variations. However, when aggregating the changes over a group of individuals, the losses of some offset the gains of others, and substantial individual income volatility may be hidden. The absolute value approach depicts better the overall income volatility in a population, but this is at the cost of loosing a sense of the overall 'desirability' of the changes since (undesirable) losses are added to (desirable) gains. Both approaches are therefore used as complements throughout the paper.

2.1 The quantities of interest

Define $d(x, y)$ as some 'distance' function measuring the degree of income variation in a change of an agent's income from x in an initial time period to y in a final time period. In this paper, following Fields and Ok (1999), $d(x, y)$ is either the change in log-income, $(\log(y) - \log(x))$, or the absolute value of this change, $|\log(y) - \log(x)|$. Define also X and Y as two random variables representing the distribution of income in the initial and final time periods, and let f be their joint probability density function. To document income mobility in the different countries analysed here, I start from the approach advocated by Fields and Ok (1999) focusing on the expected value of d in each country. To explore the patterns of income volatility in greater detail, I go one step further and examine also (i) its conditional mean (conditioning on first period income rank), and (ii) its overall probability distribution function. This examination permits to document patterns of income variability in greater detail than what has been done to date.

The mean of the distance function in a given country is given by

$$M(X, Y) = \int \int d(x, y) f(x, y) dx dy. \tag{1}$$

The conditional mean of the distance function, with conditioning on initial income rank , $p = F_X(x)$ where F_X is the marginal cumulative distribution function of X, is

$$M(X,Y|F_X(x) = p) = M(X,Y|F_X^{-1}(p) = x) = \int d(x,y) f_{Y|x}(y)dy \qquad (2)$$

where $f_{Y|x}$ is the probability distribution function of Y conditional on $X = x$, i.e. $f_{Y|x}(y) = f(x,y)/\int f(x,s)ds$. A plot of $M(X,Y|F_X(x) = p)$ for selected values of p gives an evocative picture of the variations of the average levels of income volatility across different parts of the income distribution (Van Kerm 2002). These plots permit to see how the initally poor fared relative to the middle class or the rich, and check whether poverty traps are at work with the poorest loosing ground, or whether forces towards a regression-to-the-mean are most prominent (and if so, at what speed).

Using similar notation, the cumulative distribution of d is given by

$$CDM(X,Y,z) = \int\int I[d(x,y) \leq z] f(x,y)dxdy \qquad (3)$$

where $I[.]$ is an indicator function equal to 1 if the assertion in square brackets is true and 0 otherwise. Finally, the conditional distribution function of d is written as

$$CDM(X,Y,z|F_X^{-1}(p) = x) = \int I[d(x,y) \leq z] f_{Y|x}(y)dy. \qquad (4)$$

Looking at $CDM(X,Y,.)$ and $CDM(X,Y,.|F_X^{-1}(p) = x)$, or its inverse, the (conditional) quantile function, permits to check what underlies the expected values embodied in $M(X,Y)$ and $M(X,Y|F_X^{-1}(p) = x)$, e.g. whether only the incomes of a few vary widely whereas most agents do not see their income change, or on the contrary whether the income of the majority vary in limited magnitude.[5]

To avoid confusion, the following terminology is used in the remainder of the paper. Individual (income) *gains* or *increases* refer to the signed change in log-income over time: $(\log(y) - \log(x))$. Individual (income) *changes* refer to the unsigned (absolute value) change in log-income over time: $|\log(y) - \log(x)|$. By looking jointly at the location and spread of these two measures across the populations, i.e. looking at the expected value and the quantile function of gains/changes in a country, I interpret results in terms of a 'lottery' faced by individuals. The prizes of the lottery are income gains (or income changes) experienced between two

[5] See Fields, Leary, and Ok (2002) for a stochastic dominance approach based on the cumulative distribution of the distance function.

interviews. The lottery therefore describes the short-term prospects of individuals. Depending on context, I describe one lottery for all individuals in a country, or consider the lottery faced by individuals conditionally on their rank in a base period income distribution.

2.2 Controlling for population structure in cross-national comparisons

As suggested in the Introduction, income is a composite measure and its variability may vary with individual or household characteristics (such as household size, age and gender attributes of household members) and may be triggered by events such as demographic changes and labour market attachment variations in the household. In comparing levels and patterns of income mobility across countries, I attempt to disentangle differences that are due to differences in the population structure and in the prevalence of demographic and labour market changes, from differences in individual income volatility conditional on these events and population attributes. Differences in cross-national aggregate mobility estimates due to the former factors are termed 'explained' differences, whereas the residual difference that is not merely explained by differences in population structures or frequency of 'trigger events' reflect genuine cross-national differences in individual income volatility.

The methods used to control for observable differences in population characteristics are inspired from the approach developed by DiNardo, Fortin, and Lemieux (1996) in the context of kernel density difference decompositions, and subsequently used, e.g., in Hyslop and Maré (2000), or Biewen (2001). First, note that all the aggregate income volatility measures defined above are direct functionals of f. Knowledge of f is all that is necessary to compute the desired quantities. Now, let $A_1, \ldots, A_k$ be sets of k individual attributes. (In the analysis, these will be the age of the household head, its gender, a household composition indicator, and the absence (or otherwise) of changes in household composition and labour market attachment.) Denote by $f(x, y|A_1 = a_1, \ldots, A_k = a_k)$ the joint distribution of X and Y for individuals living in households having particular attributes $a_1, \ldots, a_k$. The overall joint distribution f can be written as

$$f(x, y) = \int_{A_1} \ldots \int_{A_k} f(x, y|A_1 = a_1, \ldots, A_k = a_k) f_A(a_1, \ldots, a_k) da_1 \ldots da_k \qquad (5)$$

where f_A is the multivariate probability distribution of the k attributes (i.e. the probability of "drawing", in a given country, an individual living in a household with the given set of characteristics $a_1, \ldots, a_k$). This notation distinguishes the two factors of interest: the distribution of attributes in the population, that is f_A, and the joint distribution of X and Y conditional on the attributes. Differences in the f function of two countries, say f^r and f^c, can be related to differences in the distribution of attributes, f_A^r and f_A^c, or to differences in the joint distributions conditional on attributes, $f^r(x, y|A_1 = a_1, \ldots, A_k = a_k)$ and $f^c(x, y|A_1 = a_1, \ldots, A_k = a_k)$ for all combinations of attributes.

To assess the impact of differences in the distribution of attributes, I construct counterfactual f distributions for country c by replacing the f_A^c function in equation (5) by the distribution of attributes of the reference country, f_A^r. The constructed counterfactual is the distribution *that would be observed in country c if the population attributes were those of country r.* Counterfactual income volatility statistics can then be constructed by applying equations (1)-(4) to the counterfactual distributions. Any remaining difference from the measures computed for the reference country is the 'residual' that reflects genuine individual income volatility differences between country c and country r after controlling for cross-country differences in population attributes.

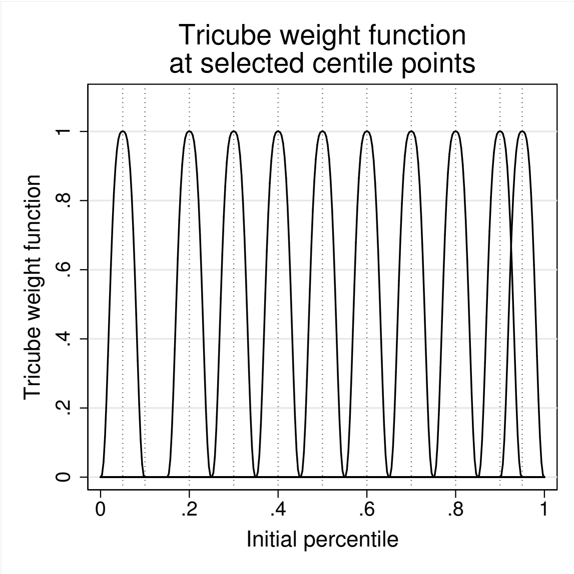
Rather than working directly with f_A, DiNardo, Fortin, and Lemieux (1996) express it as a chain of conditional distribution functions:

$$f_A(a_1, \ldots, a_k) = f_{A_k|A_1=a_1 \ldots A_{k-1}=a_{k-1}}(a_k) \ldots f_{A_2|A_1=a_1}(a_2) f_{A_1}(a_1) \tag{6}$$

where the $f_{.|.=.}$ denote obvious conditional distributions. This permits to construct finer counterfactual distributions by replacing only subsets of these conditional distributions for one country by the equivalent distributions for another country. This permits to identify the role of separate attibutes on differences in variability levels. Note however, that we now face a sequencing problem, since the order of the attributes in the chain can be arbitrarily chosen. In the analysis, I use the gender of the household head as a first attribute, then use the age of the household head conditionally on its gender as a second attribute, then use the household type (which is one of the four combinations of 1 or more child(ren) and 1 or more adult(s)) conditional on age and gender of the head, then finally condition on the experience of labour and demographic changes (which is one of the four combinations of experiencing a change in household structure or not, and experiencing a change in number of workers in the household or not) conditionally on the household attributes.

Direct non-parametric estimation of the multivariate distributions or of the conditional distributions in equations (5) and (6) is usually not tractable for large k and/or continuous at-

Figure 1: Weight function for locally weighted estimates



tributes. To overcome this difficulty, DiNardo, Fortin, and Lemieux (1996) construct the counterfactual statistics using a reweighting procedure similar to what is used for calibrating survey data. The objective is to reweight country c sample observations in order to make it representative of the country r population with regard to some, or all, of the k attributes.

An obvious estimator of $M(X,Y)$ is the sample mean: $\hat{M}(X,Y) = (\sum_i^n s_i)^{-1} \sum_i^n s_i d(x_i, y_i)$, where the (s_i, x_i, y_i) triple represents the sample data for individual i (x_i and y_i are base period and final period incomes, and s_i is the sample weight –or 1 for a simple random sample–). For the estimation of $M(X,Y|F_X(x) = p)$, I use a simple locally constant sample mean estimator (see e.g. Stone 1977): $\hat{M}(X,Y|F_X(x) = p) = (\sum_i^n \alpha_i)^{-1} \sum_i^n \alpha_i d(x_i, y_i)$, where $\alpha_i = s_i \times W(p_i - p)$, p_i being the value of the empirical cumulative distribution funtion of X at x_i, and W being a tricube weight function (see Cleveland 1979). The estimator of the conditional mean at p is obtained by reweighting locally all sample observations, by applying a weight function that decreases with the distance of the observations' p_i from p. In the implementation, the large number of observations available allows me to use a high speed of decrease for the weight function: only observations with p_i within $p - 0.05$ and $p + 0.05$ actually receive non-zero weights. This should maintain low the bias inherent to smoothing. The shape of the tricube function is shown in Figure 1 for various values for p.

The counterfactual counterparts of $\hat{M}(X,Y)$ and $\hat{M}(X,Y|F_X(x) = p)$ for country c that measure aggregate income volatility when applying the reference country distribution of characteristics f_A^r, are estimated as follows: $\hat{M}^C(X,Y) = (\sum_i^n \psi_i s_i)^{-1} \sum_i^n \psi_i s_i d(x_i, y_i)$, and $\hat{M}^C(X,Y|F_X(x)=p) = (\sum_i^n \psi_i \alpha_i)^{-1} \sum_i^n \psi_i \alpha_i d(x_i, y_i)$, where $\psi_i = \hat{f}_A^r(\tilde{a}_i)/\hat{f}_A^c(\tilde{a}_i)$, $\tilde{a}_i$ being the vector of attributes of the sample observation i. The ψ_i are the reweighting factors that modify the weights of sample observations in country c so that the reweighted sample is representative of the distribution of attributes in country r. Individuals with a relatively idiosyncratic set of attributes in country r (as compared to its frequency in country c) are downweighted, whereas individuals with a relatively common set of attributes are upweighted.

The only missing element is $\hat{f}_A^r(\tilde{a}_i)$, the estimator of $f_A(\tilde{a}_i)$, for all i's in both countries. This multivariate distribution is expressed as a chain of univariate conditional distribution as in equation (6), and these are obtained using a parametric, yet flexible, specification which allows tractable estimation of the required densities without imposing much linearity and/or additivity constraints on the shape of the estimates. The conditional distribution functions are estimated as follows:

- by simple histogram counts for the gender distribution, f_{gender};
- by simple histogram counts for the age distribution, $f_{age|gender}$, separately for male headed households and female headed households, where the age distribution was discretised into 13 bins defined as 15-24, 25-29, 30-34,..., 75-79, 80-99;
- by multinomial logit regression for the household type distribution, $f_{type|age,gender}$, separately for male headed households and female headed households, where the age of the household head enters as an independent variable in cubic form;
- by bivariate probit regression for the 'events' distribution, $f_{events|type,age,gender}$, separately for male headed households and female headed households, where the age of the household head enters as an independent variable in cubic form, and the household type is entered as a set of dummy variables with all interaction effects with the age variables.

These models are estimated for all countries, and the estimates are used to predict the 'likelihood' of all sample individuals given their household attributes, that is $\hat{f}_A^r(\tilde{a}_i)$, in all countries. Predicting the 'likelihood' of an individual from country c given the distributions of country r simply collapses to making out of sample predictions derived from the estimated models for country r. The ψ_i term is computed as the ratio of the predicted 'likelihood' of observation i derived from models estimated in countries r and c.[6]

[6]For some observations, it is possible that the reweighting factor ψ_i goes to zero (if their 'likelihood' is zero

3 The CHER dataset

This paper is made possible by the efforts of the Consortium of Household Panels for European Socio-Economic Research (CHER) to generate a cross-nationally comparative dataset from a series of independent longitudinal household surveys. The database contains a set of comparable variables derived from the original surveys according to a common plan and set of definitions (*ex post* harmonisation). The topics covered include family and household composition, housing and living conditions, health, income and employment.

The CHER database currently holds longitudinal micro-data from 17 countries covering 1990 to 2000 (14 European Union member states –only Swedish data are not available–, plus Hungary, Poland and Switzerland). The number of waves of panel data available for each country varies from 2 (for Switzerland) up to 11 (for Germany). The data availability and the names of the underlying surveys are given in Table 1. More details on the project are available on the CHER website (`http://cher.ceps.lu/`).[7]

One of the attractive features of the CHER database lies in the availability of data from both EU countries and Central European countries (Poland and Hungary). Next to the Hungarian (1992-1997) and Polish (1994-1996 and 1997-2000) surveys, information on citizens from the former German Democratic Republic is available in the German panel which includes a sample drawn from the East German population since 1990. This allows comparison between 'mature' market economies and economies that recently switched from socialist central planning to market economic systems.

The measure of individual income adopted is real annual net household disposable income expressed as 'single adult equivalent' using the 'modified OECD scale'.[8] Disposable household

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in the reference sample), or goes to a large number (if their 'likelihood' is small relative to what is observed in the reference sample). Observations whose weight goes to zero pose no problem. They are eliminated. However, observations whose weight shoots up may exert excessive leverage on the counterfactual estimates, and thence increase its variability. For this reason, weights are top-coded at 15 (i.e. no observation is allowed to 'stand for' more than 15 individuals). Only a few observations were affected.

[7]The CHER dataset holds converted data from independent national surveys, and from Eurostat's European Community Household Panel (ECHP). Data derived from the ECHP are not allowed for distribution. The CHER group only distributes ECHP-to-CHER conversion programs that enable ECHP owners to create a full CHER dataset by themselves.

[8]Total household income is divided by an adjusted household size where the first adult counts for one person, other adults count for 0.5 and children count for 0.3 (see e.g. Atkinson, Cantillon, Marlier, and Nolan 2002).

Table 1: The CHER database

	Survey years										
Country (survey):	90	91	92	93	94	95	96	97	98	99	00
Austria (ECHP)						x	x	x	x	x	
Belgium (PSBH)			x	x	x	x	x	x	x		
Denmark (ECHP)					x	x	x	x	x	x	
Finland (ECHP)							x	x	x	x	
France (ECHP)					x	x	x	x	x	x	
Germany (GSOEP)	x	x	x	x	x	x	x	x	x	x	x
Greece (ECHP)					x	x	x	x	x	x	
Hungary (HHP)			x	x	x	x	x	x			
Ireland (ECHP)					x	x	x	x	x	x	
Italy (ECHP)					x	x	x	x	x	x	
Luxembourg (PSELL)						x	x	x	x	x	x
Netherlands (ECHP)					x	x	x	x	x	x	
Poland I (PHP-HBS)					x	x	x				
Poland II (PHP-HBS)								x	x	x	x
Portugal (ECHP)					x	x	x	x	x	x	
Spain (ECHP)					x	x	x	x	x	x	
Switzerland (SHP)										x	x
United Kingdom (BHPS)		x	x	x	x	x	x	x	x	x	x

Note: The surveys used by CHER are the European Community Household Panel User database (ECHP), the Panel Study on Belgian Households (PSBH), the German Socio-Economic Panel (GSOEP), the Hungarian Household Panel (HHP), the Panel Socio-Economique 'Liewen zu Lëtzebuerg' (PSELL), two consecutive samples of the Polish Household Panel derived from the Household Budget Survey (PHP-HBS), the Swiss Household Panel (SHP), and the Brisith Households Panel Survey (BHPS).

income is the pooled income of all family members, including employment income, private and public transfers, minus total household taxes and social security contributions. Incomes are deflated to January 1997 prices using country-specific consumer price indices.

The annual income recorded in survey year t is the annual income received in calendar year $t-1$. The other variables, such as household size and composition, refer to individual or household status at the time of the interview. Therefore, to construct the 'single adult equivalent' income variables, the income reported in survey year t is divided by the household needs 'index' derived from household composition variables recorded in survey year $t-1$.[9] The minimum number of waves required to estimate mobility measures is therefore three, thence no results have been derived for Switzerland.

Only positive incomes are retained, and to prevent outlying observations from driving the results, the top and bottom one percent of income observations for each country and wave of data are set to missing. Only valid or partly imputed income observations have been used: Income observations containing non-imputed missing information have not been used in the analysis. The sample weights provided with the data, which correct for unequal sampling probability in the initial wave and subsequent survey attrition, are used.

In order to construct the household attributes variables, identification of the household head is required. The household head is identified as the main breadwinner in the household, or if this is not available in the data, as the person with the largest number of months of employment in the last calendar year, and if this is not available, or in case of ties, as the person identified as reference person in the survey.

Four household types are considered: (i) single adult households without children, (ii) multiple adults households without children, (iii) single adult households with children, and (iv) multiple adult households with children, where children refer to persons under 16 years of age.

The demographic change variable is binary and takes a value of one if the 'needs' of the household to which the individual belongs changed by more than 10 per cent. The 'needs' are as measured by the adjusted household size using the modified OECD equivalence scale (see *infra*). Note that with this definition, most family changes count (a birth in a small to medium sized family, an adult leaving the household, etc.). Only in large households may a demographic event change the needs by less than 10 per cent.

[9] See Atkinson, Cantillon, Marlier, and Nolan (2002, pp.105-108) for a discussion of the difficulties implied by the inconsistency in the observation period for annual income and household characteristics.

Finally, the labour market attachment change is also binary and takes a value of one if the number of workers in the household to which individual belongs at the time of the interview changed relative to previous year.[10]

The analysis is based on the pooled sample of all available pairs of consecutive 'single adult equivalent' income observations in each country. This results in very different sample sizes for the different countries. The largest sample size is for Germany which has eleven waves of data available, with about 119 500 income pairs,. The smallest sample size is for Hungary with about 10 800 observations (Switzerland being excluded from the analysis with only two waves of data available). Note that I have separated Eastern Germany from Western Germany, in order to identify specificities of each region. Finally, Belgium has been excluded from the analysis because a large amount of annual income values appeared to be excessively volatile, at least well above any reasonable standard.

4 Income volatility comparisons

This section first reports raw income volatility statistics for the different countries available in the CHER dataset. The behaviour of the statistics when estimated conditionally on individual base period income rank is presented in a second step. For clarity, most of the results are reported graphically. Tables with detailed figures are available from the author on request.

Figure 2 reports aggregate statistics on the distribution of signed and unsigned income variations. The top panel shows the expected income gains, as well as the value of the 10th and 90th percentiles of its distribution. The bottom panel shows the expected income change along with five percentile points. These pictures provide insights on the distribution of year-to-year income changes, both in terms of central tendency or levels of change, and in terms of spread or 'certainty' of the variations.

The higher average log-income changes were observed in Ireland, at slightly above 0.05. Then follow the southern European countries (Portugal, Spain, Greece and Italy) and Poland.

[10]A respondent is identified as being a worker if he works normally more than 15 hours per week at the time of the interview. The change identifies change between two separate dates, but ignore possible variations within the year. A potentially better indicator of labour market attachment of a household, like the change in the total number of employment-months in the household in the calendar year is not available for several countries (among which, crucially, Poland) and has therefore not been used.

Interestingly, the three former planned economies fared very differently. Poland is among the high income gains countries, whereas Hungary shows up as an outlier at the very bottom of the group with substantially negative average income changes (*circa* -0.07). East Germany appears between these two polar cases, between Denmark and the United Kingdom in the ranking.

The contrast between Hungary and Poland is surprising, as these countries adopted similar reform and policies in the 1990s. A potential explanation for this difference lies in the period at which the surveys were carried out. The data pertain to pooled surveys from 1992 to 1997 in Hungary, and a later period, 1994 to 2000, in Poland. Data are thus closer to the years of early transition from planned to market systems in Hungary than in Poland, during which real GDP tended to decrease before the trends reversed in the second half of the nineties.[11]

A striking feature of the top panel of Figure 2 is that, although cross-national differences in expected income increases are not very large, the cross-national variation in the (inter-personal) dispersion of the income gains is substantial. The range between the 10th and 90th percentile of log-income increases is the widest in the southern European countries and Poland, followed by Hungary and the United Kingdom. The dispersion is strikingly smaller in Luxembourg, Finland and the Netherlands. The 10th percentile of the gains distribution is about -0.21 in Luxembourg, but it reaches -0.45 in Greece or Hungary. Inversely, the 90th percentile is only about 0.25 against more than 0.50 in Greece or Spain. Notice that the 90th percentile of the Hungarian distribution of gains is also among the lowest at about 0.30. The Hungarian distribution of gains is clearly shifted to the left of most other countries.

It seems that countries with higher income inequality, also experience larger dispersion of income gains, and usually higher expected gains. The United Kingdom being the most notable exception, with relatively high inequality and dispersion of gains, but comparatively low average gains. However the reverse relationship does not seem to hold since three low inequality countries (Finland, Luxembourg, and the Netherlands) directly follow the southern European countries in terms of average gains although they have a concentrated distribution of gains.

Looking at the absolute value of log-income changes draws a different picture. Mean income increase are close to zero in most countries, but, as suggested by the P10 and P90 statistics discussed above, this hides a lot of different individual experiences. On average, gains of some

[11] See, e.g., Milanovic (1998) or Förster (2003) on the change in the income distribution in Hungary and Poland.

offset losses of others. The average of the absolute value of log-income changes ranges between 0.16 (Luxembourg) and more than 0.30 (Greece, Spain). The median is expectedly lower than the mean given the skewness of the absolute value of the changes, and ranges between 0.09 (Luxembourg, Finland) and 0.20 (Greece, Poland).

Differences across countries are more noticeable with this unsigned change measure. The main cross-country differences are not in levels of the lottery faced by agents, but in its risk (the spread of the gains). Largest volatility levels are observed in the southern and central European countries (except East Germany), followed by the two anglo-saxon countries.

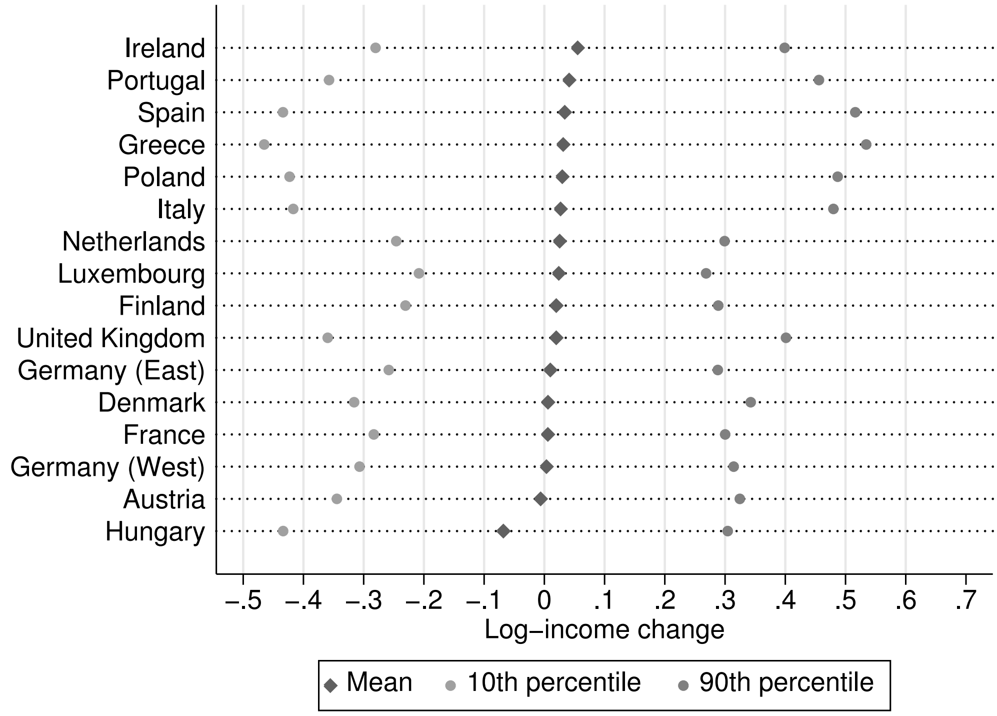
Upon closer inspection, the three ‘new’ market economies appear to deviate from all the other countries in the inter-personal distribution of the income changes. Mobility tends to affect a larger number of people than in countries with otherwise similar average level of fluctuation: the mean is similar, but the P10, P25 and P50 statistics are larger in the three former socialist economies. The largest changes are smaller, but the smallest gains are larger.

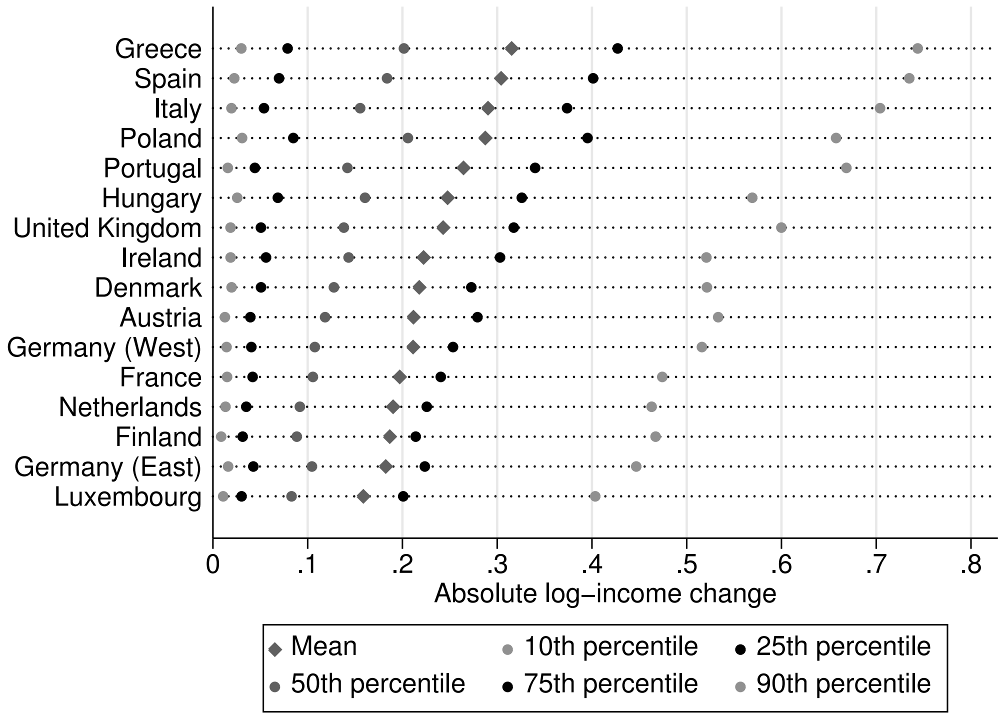
Income mobility is often perceived as a favourable phenomenon because it is expected to reduce inequality of the long term flows of income, and to allow poor people to escape from their position. However these consequences only hold if the poorest have larger than average income gains. The social judgement of whether volatility is good should depend on how volatility varies along the income line. To appraise this, the volatility measures are estimated conditionally on the normalised rank of individuals in the base period income distribution. Figures 3 and 4 report income volatility statistics (mean, P25, P50, P75) estimated locally at selected centile points. These statistics describe the distribution of income changes conditional on a centile position in the base period income distribution. These figures help assessing whether most of the gains are obtained by the poor or the richer individuals.

The most obvious result is that the location of the mean income increases is indeed decreasing with the initial position. Mean income change is largely positive up to about the 30th percentile of the base period distribution, but is negative for the richest 20 percent in the base period. This holds for almost all countries, with only moderate variations. Some countries have rather flat profiles (like Finland, Luxembourg or the Netherlands), whereas others have steeper profiles with marked difference of the lottery faced by the rich, the middle class and the poor (Poland, Italy, Greece or Spain).

Particularly high expected gains at the lowest 5th and 10th percentiles are observed in the southern and central European countries, but also, perhaps more surprisingly, in the Nether-

Figure 2: Income volatility comparisons: mean and selected percentile values of log-income change (top) and absolute log-income change (bottom)





lands, the UK and Western Germany.

It is important to note however that the P25 line is negative for almost all base period centile points and all countries: a quarter of individuals lose ground, irrespectively of their base period income. (The only exceptions are slightly positive values at the lowest 5th percentile point in Spain and Poland.)

Hungary is an extreme case exhibiting the grimest instance: even the mean and median income gain are negative at all estimated centile points but the 5th.

In most countries (except Poland and Hungary), the mean gain is below the median at the top of the base period distribution. This suggests that the negative mean at the top is driven downward by a number of large income losses rather than widespread moderate losses.

The location of the lottery varies with the base period rank, but its spread tends to be fairly constant. Substantially wider spread is observed only at the very bottom positions (below 10th percentile) in most countries.

Again, the most signficiant cross-country difference lies in the uncertainty of the lotteries faced by individuals. Substantial uncertainty is observed in Poland and in the southern European countries. But this higher uncertainty is associated with larger expected gains at the bottom of the base period distribution (though not necessarily at the top).

Figure 4 shows results for the absolute log-income change. The general pattern tends to be a flat base U-shape, with larger volatility at both extremes of the base period distribution than in middle range positions. This is unsurprising given the results depicted in Figure 3. In most cases however, volatility is higher at the bottom end. The poorest tend to experience larger income fluctuations.

The southern European countries have the highest level for volatility at the bottom of the distribution, but the highest volatility for higher positions is found in the two central European countries, Poland and Hungary.

Interestingly, the Netherlands tend to have a rather low level of volatility (in line with levels of France or Finland), except for the poorest positions for which income fluctuations are high (at levels of the Polish sample). The gradient of the curve connecting the estimates at the different centiles is particularly high at the bottom of the distribution. The same remark holds for West Germany.

Figure 3: Income mobility estimates conditional on selected initial centile points (log-income change)

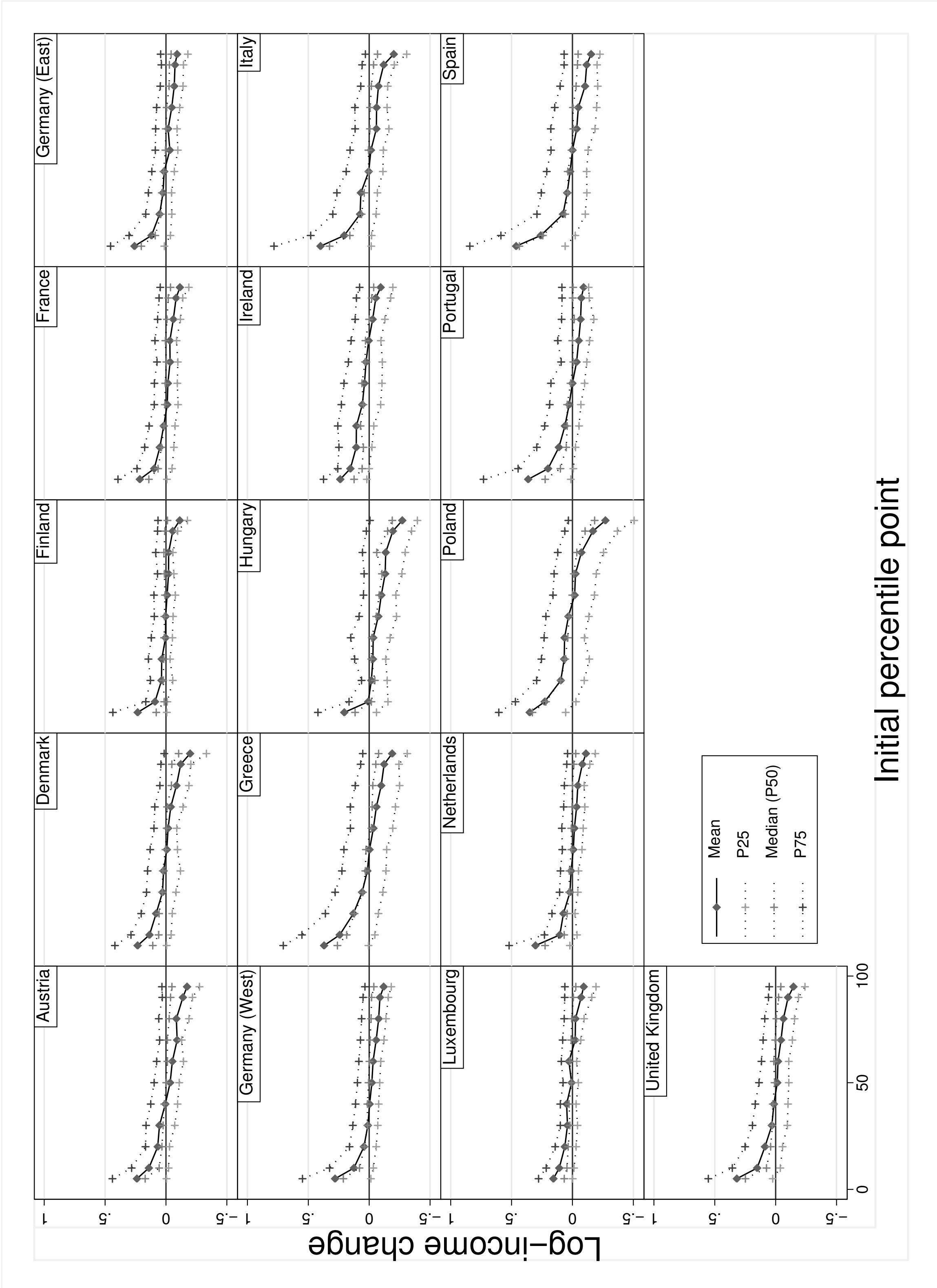
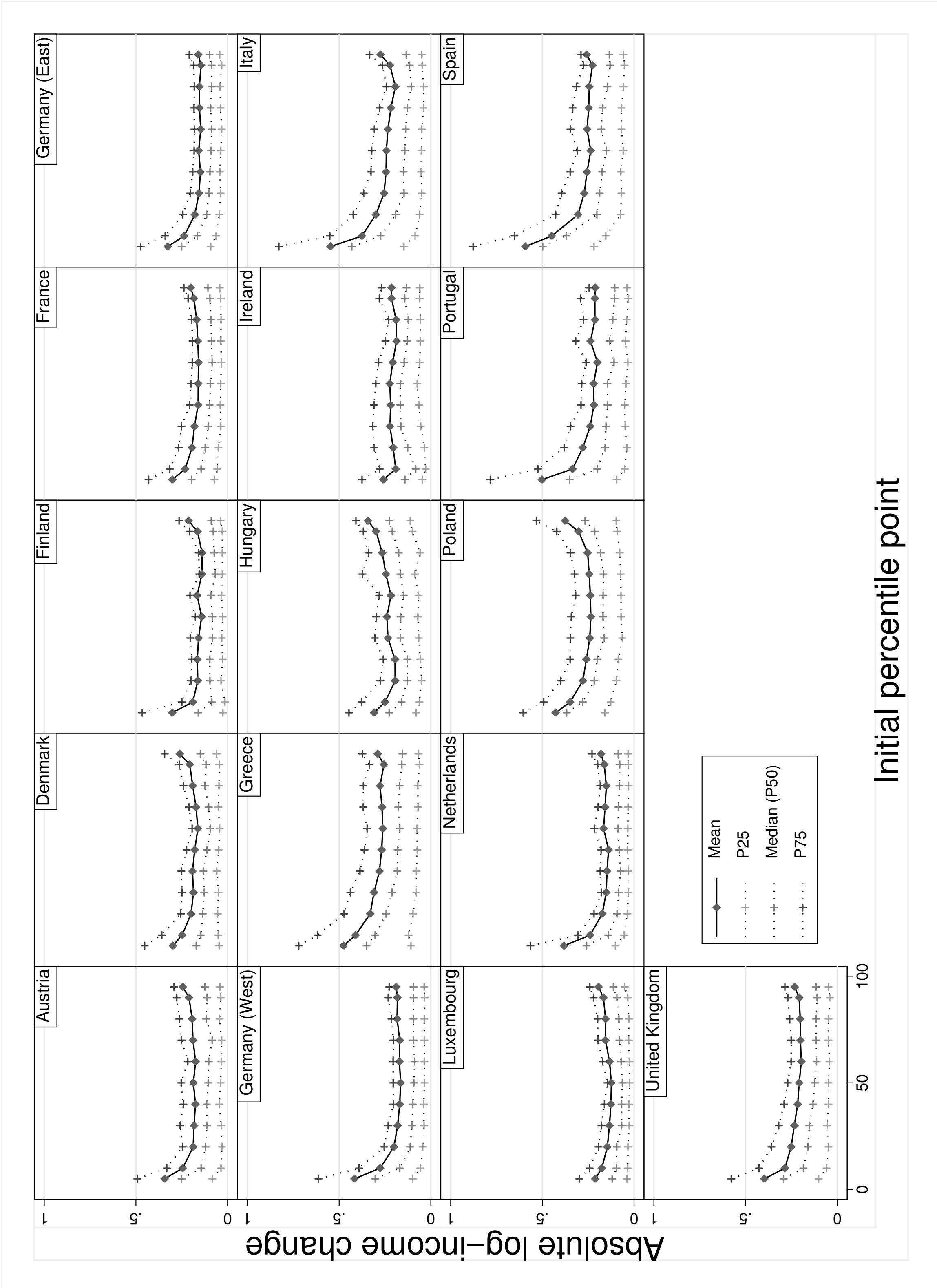


Figure 4: Income mobility estimates conditional on selected initial centile points (absolute log-income change)



5 Accounting for cross-national differences

This section explores now the factors that may explain cross-national differences in income volatility.

Cross-national differences in income volatility patterns can arise for two reasons. First, the composition of the population may vary. A high level of overall variability may be due to the fact that a country has a larger fraction of its population having a 'high volatility profile' (in terms of household structure and labour market attachement and their change over time). Second, the degree of volatility, for individuals with similar characteristics, may be different because of country-specific factors (such as social security generosity, redistribution level, labour market and wage structure and regulations, etc.).

In this section, levels of income volatility are compared after neutralisation of the 'different population characteristics' effect. This is done by selecting a reference country and assigning the population characteristics of the reference country to all other countries. The remaining differences in volatility levels are due to the second of the two factors described above.

The reference country selected for the analysis is the United Kingdom. The main reason for this choice is that the country has a large number of observations and thence relatively little sample uncertainty in its estimates. This is important for the baseline estimates. However, the choice of the reference country in this paper is largely arbitrary. (Results for other reference countries are available from the author on request.)

Figure 5 plots the difference in expected log-income changes between the various countries for which data are available and the UK. Countries are ordered from high to low with regard to income volatility. The graphs also show the residual difference to the UK (i) after controlling for cross-national differences in population demographic characteristics (age and gender of household heads, and household types) marked by crosses, and (ii) after controlling for cross-national differences in population demographic characteristics and in labour market and household formation dynamics, marked as small diamonds. The distance from the small diamonds to the vertical line is the level of volatility that remains after neutralising differences in population attributes.

More detailed results are reported in Tables 2 and 3. The tables show the proportion of the difference to the UK that is explained by the different factors, separating the effects of household head gender, household head age, household sizes, and demographic and labour market changes. The columns report the remaining difference to the UK after controlling for the cumulation of the left hand factors, as well as the marginal effect of adding a new factor (expressed as percentage reduction in the remaining difference to the UK). Note that the percentage reduction (and the marginal effects) need not be bounded between 0 and 100. A negative value indicates that the factor(s) already mitigate(s) the observed difference: normalising the population structure exacerbates the difference rather than explains it. It is also possible that normalising the population structure accounts for more than 100 percent of the difference: the countries with more volatility becomes the country with less volatility after normalisation.

The degree of explanation of the differences to the UK varies considerably across countries. If we consider the signed change in log-income, substantial explanations are obtained for Poland (101 percent), Ireland (44 percent), Spain or the Netherlands (both 41 percent). The difference between Poland and the UK (the expected increase in log-income is about 50 percent larger than in the UK) is completely due to differences in population attributes and labour market/demographic dynamics! At the other extreme, the normalisation accounts for less than 5 percent of the difference between the UK and Italy or Western Germany. The normalisation gives a negative explanation for the difference to Denmark.

Controlling for gender differences in household heads frequently has a substantially negative contribution: it tends to increase the gap between the UK and countries like the Netherlands, Italy, Spain and Poland, or plays a limited role. Controlling for the age of household heads also plays only a modereate role, except for the positive contributions for explaining the UK difference with Finland, Luxembourg or the Netherlands. The most influential factor appears to be the difference in household composition. Controlling for this factor accounts for more than 50 percent of the difference with Poland, Italy, the Netherlands. However, the contribution is negative for the two German regions, Luxembourg and France. Finally controlling for the frequency of demographic and labour market changes also plays a significant role, albeit lower than household composition differences. Contribution is particularly marked for Poland, Luxembourg and Finland.

The degree of explanation obtained in the absolute change in log-income framework is lower. The largest percentage explanations are for Hungary (83 percent), the Netherlands (27 percent), Austria and Poland (23 percent) and Spain (22 percent). The explanation is now negative for Greece, Italy, Ireland, and Finland. These countries would thus have an even larger level of mobility compared to the UK if not compensated by population characteristics.

Figure 5: Total and unexplained mean income volatility difference with the UK: log-income change (top) and absolute log-income change (bottom)

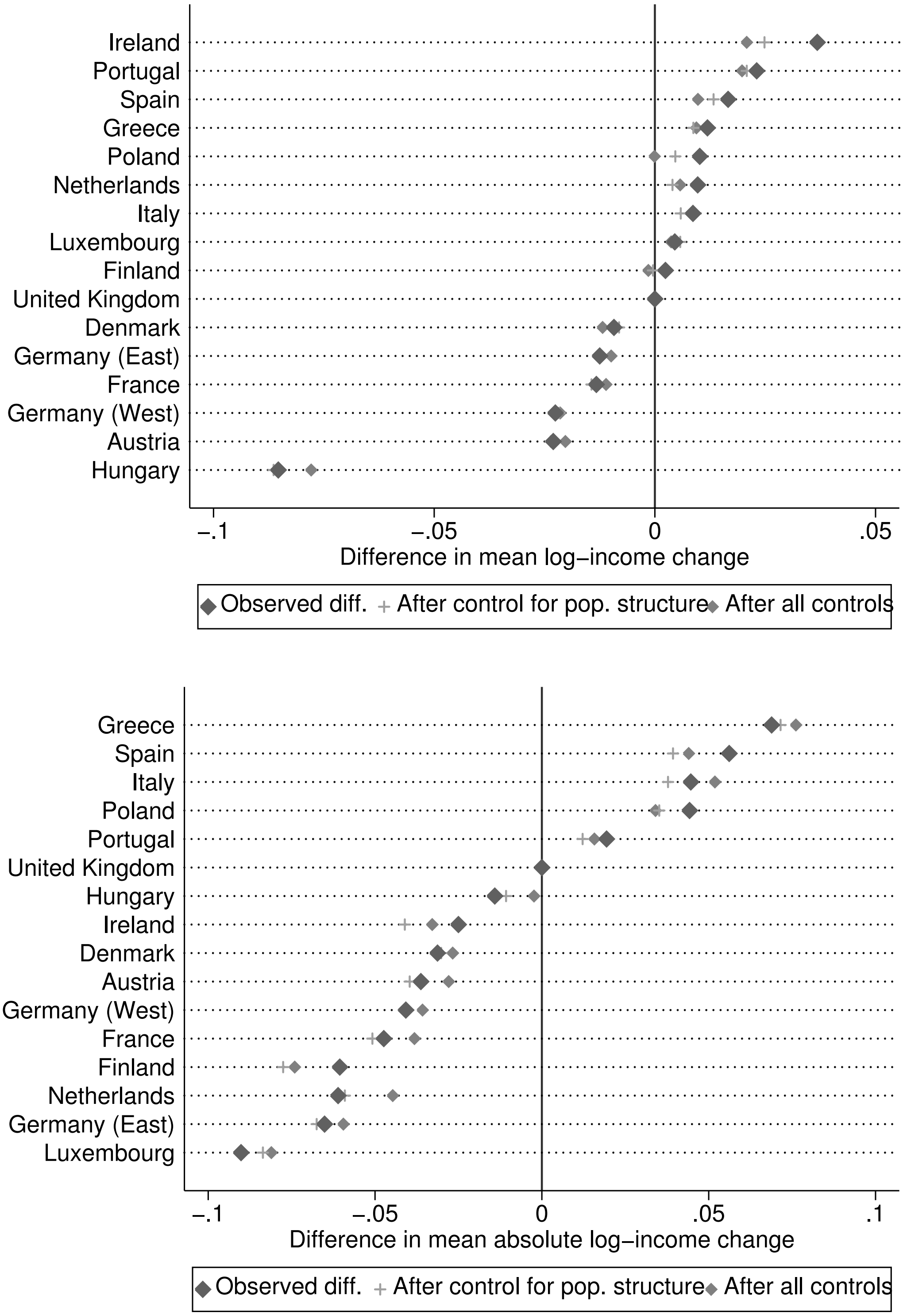


Table 2: Difference to the UK mean income variability level (change in log-income)

Country	Actual diff.	Count. I: Gender control diff.	perc. reduc.	marg. effect	Count. II: + Age control diff.	perc. reduc.	marg. effect	Count. III: + Hh.type control diff.	perc. reduc.	marg. effect	Count. IV: + Events control diff.	perc. reduc.	marg. effect
1. Ireland	0.037	0.037	-0.1	-0.1	0.035	5.3	5.5	0.025	32.5	27.2	0.021	43.5	11.0
2. Portugal	0.023	0.023	1.3	1.3	0.024	-5.2	-6.6	0.021	9.7	15.0	0.020	14.4	4.6
3. Spain	0.017	0.020	-21.2	-21.2	0.020	-18.1	3.0	0.013	19.9	38.0	0.010	41.2	21.3
4. Greece	0.012	0.013	-8.4	-8.4	0.013	-9.9	-1.4	0.009	26.8	36.7	0.009	21.0	-5.8
5. Poland	0.010	0.012	-17.7	-17.7	0.010	-2.1	15.6	0.005	54.4	56.5	-0.000	100.9	46.5
6. Netherlands	0.010	0.014	-42.2	-42.2	0.012	-20.0	22.2	0.004	58.9	78.9	0.006	40.9	-18.0
7. Italy	0.009	0.011	-26.8	-26.8	0.011	-24.6	2.3	0.006	32.0	56.6	0.009	1.0	-31.0
8. Luxembourg	0.005	0.005	-6.4	-6.4	0.003	25.3	31.7	0.006	-27.3	-52.6	0.004	18.2	45.5
9. Finland	0.002	0.002	-0.8	-0.8	0.000	99.7	100.4	-0.000	118.0	18.4	-0.001	161.7	43.6
10. United Kingdom	0.000	-	-	-	-	-	-	-	-	-	-	-	-
11. Denmark	-0.009	-0.009	0.1	0.1	-0.010	-12.7	-12.7	-0.008	12.5	25.1	-0.012	-27.8	-40.3
12. Germany (East)	-0.012	-0.012	0.4	0.4	-0.012	5.3	4.9	-0.013	-0.9	-6.2	-0.010	20.8	21.7
13. France	-0.013	-0.013	0.8	0.8	-0.013	1.0	0.3	-0.014	-8.3	-9.4	-0.011	16.5	24.9
14. Germany (West)	-0.023	-0.021	5.9	5.9	-0.021	7.7	1.7	-0.022	3.8	-3.9	-0.021	4.9	1.1
15. Austria	-0.023	-0.021	7.5	7.5	-0.021	7.1	-0.4	-0.024	-2.5	-9.6	-0.020	11.9	14.4
16. Hungary	-0.085	-0.085	0.4	0.4	-0.088	-2.8	-3.2	-0.086	-1.3	1.5	-0.078	8.7	10.0
Total (abs.) difference	0.290	0.299	-3.2	-3.2	0.293	-1.2	1.9	0.255	11.9	13.2	0.232	20.0	8.1

Notes: The *diff.* column shows the remaining difference to the UK after controlling for all the factors already introduced. The *perc. reduc.* column show the corresponding percentage reduction achieved. The *marg. effect* column isolates the marginal effect on the percentage reduction obtained by adding a new factor.

Table 3: Difference to the UK mean income variability level (absolute change in log-income)

Country	Actual diff.	Count. I: Gender control diff.	perc. reduc.	marg. effect	Count. II: + Age control diff.	perc. reduc.	marg. effect	Count. III: + Hh.type control diff.	perc. reduc.	marg. effect	Count. IV: + Events control diff.	perc. reduc.	marg. effect
1. Greece	0.069	0.069	-0.9	-0.9	0.069	-0.1	0.8	0.072	-3.9	-3.8	0.076	-10.6	-6.7
2. Spain	0.056	0.058	-3.0	-3.0	0.054	3.1	6.1	0.039	30.0	26.9	0.044	21.6	-8.4
3. Italy	0.045	0.047	-4.5	-4.5	0.046	-3.5	1.0	0.038	15.3	18.8	0.052	-16.2	-31.5
4. Poland	0.044	0.044	-0.3	-0.3	0.039	11.4	11.8	0.035	20.5	9.1	0.034	23.0	2.5
5. Portugal	0.019	0.021	-8.2	-8.2	0.017	12.2	20.4	0.012	37.0	24.8	0.016	18.8	-18.2
6. United Kingdom	0.000	-	-	-	-	-	-	-	-	-	-	-	-
7. Hungary	-0.014	-0.014	0.7	0.7	-0.011	24.7	24.0	-0.011	24.0	-0.7	-0.002	83.3	59.3
8. Ireland	-0.025	-0.026	-3.3	-3.3	-0.030	-21.4	-18.1	-0.041	-64.3	-42.8	-0.033	-31.4	32.9
9. Denmark	-0.031	-0.031	-0.5	-0.5	-0.036	-15.0	-14.5	-0.030	3.6	18.6	-0.027	14.6	11.0
10. Austria	-0.036	-0.032	11.0	11.0	-0.038	-5.5	-16.6	-0.040	-9.3	-3.7	-0.028	23.0	32.2
11. Germany (West)	-0.041	-0.037	8.7	8.7	-0.041	0.1	-8.6	-0.041	-1.5	-1.6	-0.036	12.2	13.8
12. France	-0.047	-0.046	2.6	2.6	-0.046	2.7	0.0	-0.051	-7.2	-9.9	-0.038	19.4	26.6
13. Finland	-0.061	-0.060	0.4	0.4	-0.067	-10.1	-10.5	-0.078	-28.0	-18.0	-0.074	-22.3	5.7
14. Netherlands	-0.061	-0.052	14.7	14.7	-0.054	11.9	-2.8	-0.059	3.3	-8.5	-0.045	26.8	23.5
15. Germany (East)	-0.065	-0.065	-0.1	-0.1	-0.069	-6.1	-6.0	-0.067	-3.6	2.5	-0.059	8.6	12.3
16. Luxembourg	-0.090	-0.090	0.0	0.0	-0.090	0.4	0.4	-0.084	7.3	6.8	-0.081	10.1	2.8
Total (abs.) difference	0.705	0.694	1.6	1.6	0.707	-0.3	-1.9	0.697	1.1	1.4	0.645	8.5	7.4

Notes: The *diff.* column shows the remaining difference to the UK after controlling for all the factors already introduced. The *perc. reduc.* column show the corresponding percentage reduction achieved. The *marg. effect* column isolates the marginal effect on the percentage reduction obtained by adding a new factor.

In this framework, it is now the demographic/labour market dynamics differences that have the most prominant impact.

Finally, Figures 6 and 7 are the local equivalent to Figure 5. They show actual and ‘unexplained’ differences to the UK estimated locally at selected centile points in the base period income distribution.[12] It is hard to identify general patterns in these pictures. In the change of log-income framework, the extent of explanation is sometimes higher at the bottom of the distribution, e.g. in Ireland or Portugal, and sometimes higher at the top of the distribution, e.g. in France, Luxembourg or Spain. A similar variety of results appears in the in the absolute log-income change framework.

6 Concluding comments

This paper presents the first set of results for an anatomy of income volatility in European countries in the 1990s using the CHER dataset. The paper also presents fairly general methods that can be used to account for cross-national differences in volatility levels.

Two different frameworks are used to assess income volatility. First, the most natural choice is the change in the natural logarithm of the disposable income of the household to which individuals belong (income is adjusted for family-size differences). In this framework, income volatility is favourable since it is associated with income increases. However when aggregating individual experiences, gains offset losses and this hides substantial variations. Therefore, a second framework is used in which attention is put on the absolute value of the change in log-income.

The empirical analysis done so far points to a number of preliminary results summarised as follows:

- Cross-national differences in expected income increases are moderate. Ireland and southern European countries fared best, while Hungary is lagging behind the other countries.

- Most cross-national differences are found in the overall lottery faced by individuals: if expected gains are similar in levels, the dispersion around the mean increases varies

[12] The estimates reported in Figures 6 and 7 are based on a broader local weight function with a bandwidth of 0.20 rather than 0.10 as in Figures 3 and 4. The counterfactual statistics are based on a smaller sample for which it was possible to estimate the reweighting function, and thence it was necessary to enlarge the bandwidth to reduce the variability of the estimates.

Figure 6: Total and unexplained income volatility difference with the UK at selected centile points (log-income change)

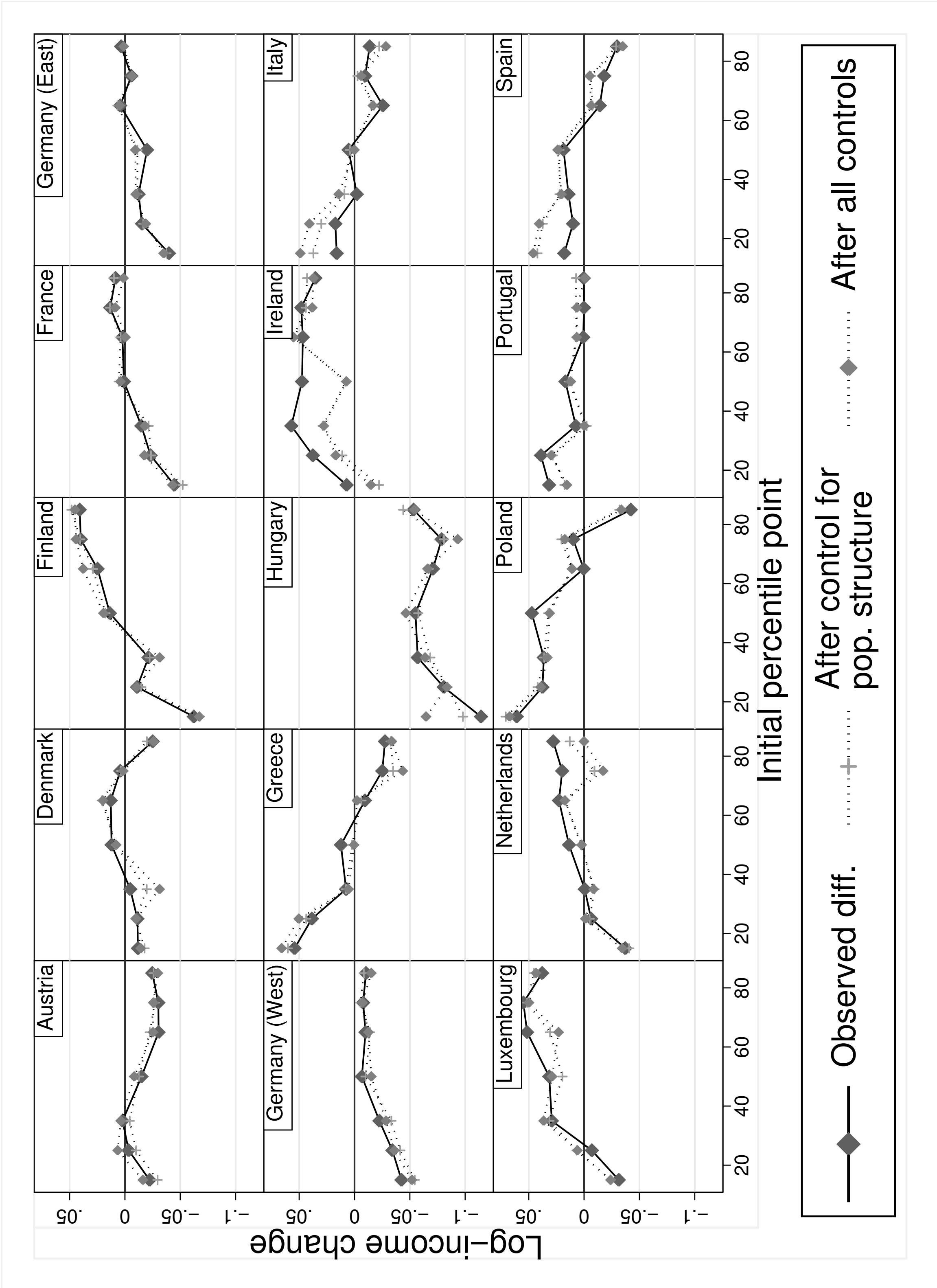
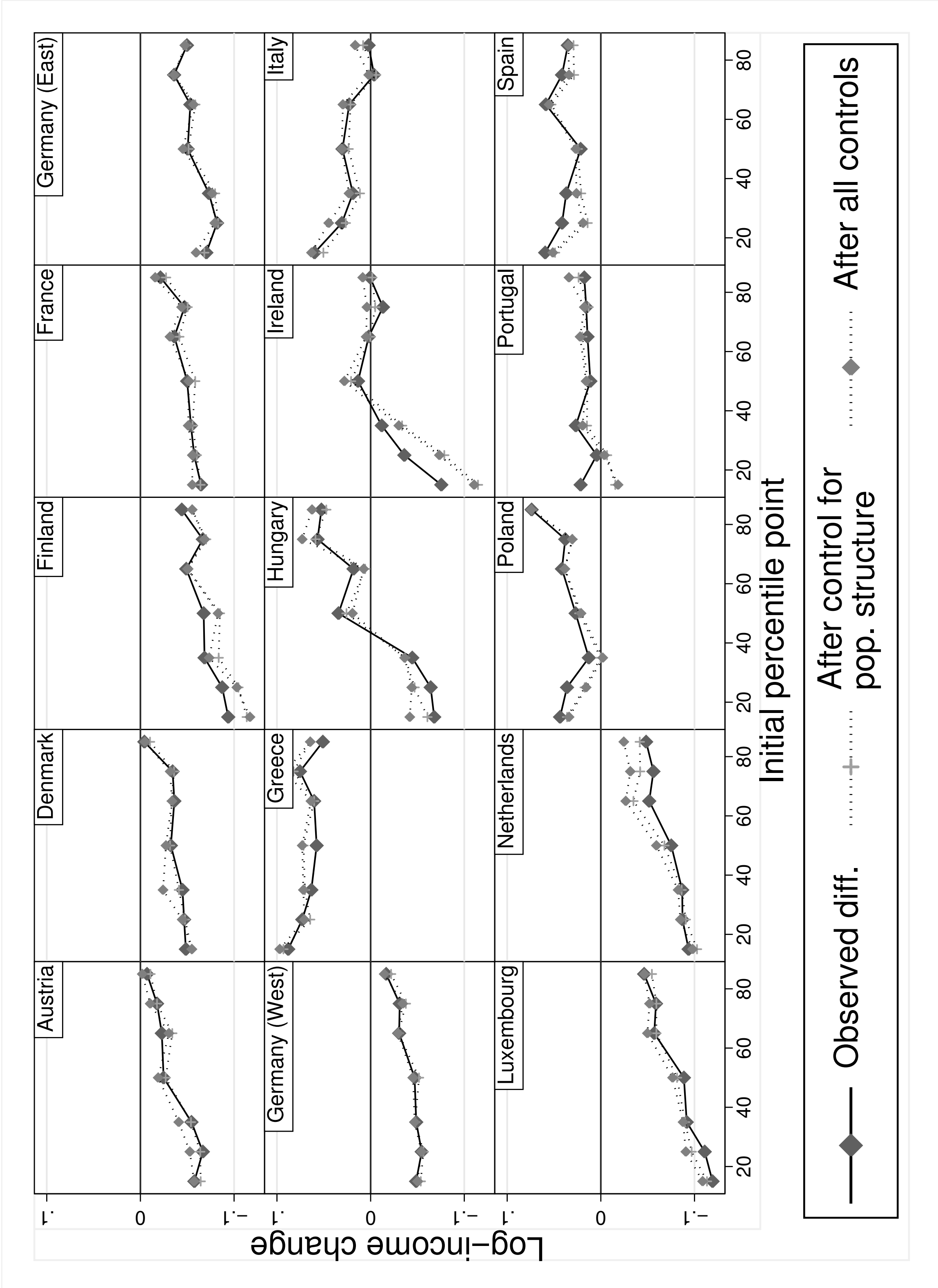


Figure 7: Total and unexplained income volatility difference with the UK at selected centile points (absolute log-income change)



substantially across countries. This result is confirmed by looking at absolute income changes that varies more widely across countries than the signed change.

- Patterns of income volatility in Poland and Hungary (and in East Germany in smaller extent) tended to differ from the other countries in that more people experienced small to moderate income changes but less people experienced large changes, compared to countries with similar average level of income change.

- When conditioning the estimation upon the rank of individuals in the base period income distribution, I observe a catching up of individuals at the bottom of the distribution over the richer individuals: their lottery is more favourable than the lottery for the middle class or the richest. The general impression, at least in short run I focus on, is a regression to the mean rather than low income traps as some theories of cumulative (dis-) advantage may predict. It would however be worthwile to consider a longer time period for testing this, but this requires longer panels than available in most countries in the CHER database.

- Controlling for population characteristics tends to reduce cross-national differences in expected log-income increases and changes. The sum of the differences to the UK for all countries is reduced by about 20 percent for expected income increases, but only 9 percent for expected income changes. However the degree of accounting varies widely across countries. Controlling for differences in household composition patterns appears to be the most important factor when looking at expected income increases. Controlling for differences in labour market attachment and household demographic dynamics is also important, especially when looking at the dispersion of individual income changes. However, even after controlling for the latter factors, a great deal of 'unexplained' cross-national differences remain.

The analysis is still incomplete. In particular, although the aim of the analysis is descriptive and exploratory, more attention still needs to be devoted to interpreting the results obtained in light of differences in labour market institutions or welfare regime, and relating it to analyses that have considered more sophisticated measures of income mobility. The issue of measurement error also deserves more attention. The robustness of the results should be checked against various assumptions regarding the extent of measurement error in the data. In particular, it is on the agenda to assess to the role of measurement error in driving the 'regression to the mean' results (Fields, Cichello, Freije, Menéndez, and Newhouse (2003) could be a starting point for this). The degree of harmonisation of the data used should also be a concern. But only cumulating research and experience on the CHER database will help identifying the degree of harmonisation in the data.

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