Dynamics of Income Volatility in the US and in Europe, 1971-2007: The Increasing Lower Middle Class Instability

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Persistence in Poverty and the Longitudinal Dynamics of Income Distributions in the PSID and EU-SILC: Comparing Income Mobility in Poverty, Affluence and Middle Class Positions

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Abstract

In line with the recent studies, our aim is to compare short term income mobility (volatility) at different levels of the income distribution, and over time and space: Are the poor/rich particularly mobile? How has this changed over time? Are there cross-country differences in mobility patterns? Investigating changes in quantile ranking along the income scale, we test the dissymmetry hypothesis (mobility is different for the poor/rich) with the PSID 1970-2007 and the EU-SILC. Our empirical contribution is the European-American comparison as such studies are rare. We show that mobility in the US is the highest among the poorest, followed by the top group but is the lowest in the middle income classes. The comparison with Europe shows moreover that mobility patterns are diverse in Europe: Nordic countries and the Netherlands are characterized by lower income mobility specifically at the bottom whereas the UK and Portugal show strong instability of the poor.

Introduction: Understanding the heterogeneity of income volatility

A disquieting fact that initiated much new research in different directions is the growth in inequalities in many industrialized countries over the last decades. Inequality in the U.S. has increased faster than in other Western countries and is today one of the nations with the highest household income inequality in the Western developed countries (Atkinson et al. 1995, Gottschalk 1997, Gottschalk and Smeeding 1997, Danziger and Gottschalk 1995) although there is disagreement in the literature about the exact trajectory of this development (timing of surges and leveling off), which seems to reflect the different data and samples, observation periods and techniques applied. In view of this lack of consensus, Gottschalk (1997) appeals for differentiating three processes: inequality, income growth and mobility. Inequality refers to the variance of the marginal distribution of income while growth refers to the differences in means of the marginal distribution. We are, however, interested in volatility, which is typically defined as the short term (yearly) variability of personal earnings or income (Dynarsky and Gruber 1997, Dahl, DeLeire and Schwabish 2007, Dynan, Elmendorf and Sichel 2008). This terminology is close to its sense in finance and in the economics of assets variability (f.ex. Gabaix 2009). Research has shown that since the 1970s the US has also experienced a significant increase in (household) income and earnings instability, variability or volatility (Gottschalk and Moffit 1994, 2002, 2006, Haider 2001, Comin and Rabin 2006, Hacker 2006, Hertz 2006, Bollinger and Ziliak 2007, Bania and Leete 2007, Dahl, De Leire and Schwabish 2007, Winship 2007, Nichols 2010, Shin and Solon 2011, Dynan, Elmendorf and Sichel 2012). This household income instability completes the big picture of systemic instability that is spreading in economic life (Osberg 2013).

Investigating volatility requires a dynamic approach on social stratification. Recent economic scholarly work has shown the importance of the dynamic analyses of inequalities (Christiaensen & Shorrocks 2012, Hoy, Thompson and Zheng 2012, Bossert, Chakravarty and D'Ambrosio 2012). One of the main challenges of analyses observing income changes for particular income groups (such as the poor) is that the membership to groups can change over time as some members enter and some exit states (e.g. poverty). Therefore, analyses of changes in poverty/richness do neither provide information on moves of individuals in the income distribution nor on the disproportional increase between individuals' income over time (Mussini 2013). However, we use here a continuous measure of rank volatility in order to obtain more detail.

Volatility is often negatively associated, although volatility includes also upward mobility and may also imply that downward slips (into poverty) are "only" transitory. Unpredictable events may cause economic insecurity, while stability of incomes eases and improves planning of the future (Jenkins 2011). Hardy (2013), for instance, has shown that household incomes volatility has long-term implications as it is modestly negatively associated with children's educational attainment, but more so for low and middle-income households. Volatility of income can thus be seen as a proxy for risk of welfare losses (Jensen and Shore 2008).

Its degree of undesirability, however, depends on the individual risk preferences, risk pooling possibilities and the level of insurance against the risks of income losses. Social protection as well as transfers of income and labour supply within the household or family provides such income-smoothing insurance. Therefore, volatility based on household income is the more appropriate methodological choice compared to approaches based on individual earnings (Jenkins 2011: R34, Western et al 2013: 342). The family or household as a research unit has a long tradition in stratification research (compare Western et al 2013 for a review). While the importance of the family has also been underlined by many sociologists (Goldthorpe 1983, Sørensen 1994, DiPrete 2002, McLanahan 2004) referring to family dynamics and women's economic status, Esping-Andersen (1999) has pushed the notion of a threefold analysis of causes of social stratification: the (labour) market, the welfare state and the family. We are interested in how household income security has changed over the last decades and less in earnings volatility. Whereas the latter focuses on explanations related to the labour market, the first allows us to reflect on more general structural changes, not only in labour market and economy but also on the role of the welfare state and family dynamics in absorbing negative events (unemployment, sickness, etc.) and income shocks.

Decomposition methods differentiating structural inequality trends and income mobility have become more popular in recent years (Shorrocks 1999, Mussard and Pi Alperin 2011). Comparing the composition of income inequality in Belgium, Germany and the US, van Kerm (2004) reveals that despite the different levels of income inequality in the investigated countries, the major component is 'exchange mobility' (compare Fields and Ok 1996) accounting for 67-76%[1] of the income movements between 1985 and 1997. The so-called exchange mobility component refers to the "reranking of individuals over the positions

[1] Based on the hierarchical decomposition method (the Fields and Ok indices are additively decomposable by population subgroupds) compared to even 86-91% in the non-additive decomposition method (see van Kerm 2004:234f).

available in the economy" (van Kerm 2004: 224) or in other words the change of one's position in the income pecking order.[2] This relative importance and the fact that most of the studies in the field of income or earnings volatility look at earnings or income *per se* rather than looking at ranks (Gottschalk and Moffit 1994, 2006, Haider 2001, Hacker 2006, Ziliak et al 2010, Shin and Solon 2011, Hardy and Ziliak 2013) are the reasons for us to focus in this article on the ranking of individuals derived from their positions in the income distribution.

The concepts of status and rank in society have a long history in the social sciences (since the seminal study of Easterlin 1974) and its relevance has also been largely confirmed by recent research (Krueger 2008, Brown et al. 2008, Clark, Frijters and Shields 2008, Boes, Staub and Winkelmann 2010, Mujcic and Frijters 2012, Boyce, Brown and Moore (in press); modest support find, however, Stevenson and Wolfers 2008). Most of these studies refer to the positional goods framework or Easterlin's theory of relative utility. The latter explains the empirical discrepancy between happiness and income on an aggregate level with the notion that people compare themselves to others: Their utility depends in Easterlin's view on relative income rather than on the absolute level of income. This rationale is shared by the positional goods approach. Although a subjective rank does not necessarily coincide with one's objective position in a society, research has shown that higher positions in an income distribution rather than the absolute income or one's position compared to a reference wage leads to utility gains (Brown et al. 2008, Clark, Kristensen and Westergard-Nielsen 2009, Clark, Masclet and Villeval (in press), Hagerty 2000, Boyce, Brown and Moore (in press), Alpizar, Carlsson, and Johansson-Stenman 2005, Carlsson, Johansson-Stenman and Martinsson 2007).

Reasons for growing income disparities and volatility put forward by sociologists and economists are on the one hand linked to the welfare state reforms (social security benefits, tax schemes, etc.) and on the other hand to labour market developments such as technological change, deindustrialization, skill-based technological change (SBTC)[3] that

[22] The second most important factor is (economic) growth, which contributes with 20-31% to the income movements. With a clearer example, a simple doubling of all incomes, which would not change an individual's position in the pecking order, would, however, lead to an increase in inequality in that population.

[3] A challenge to the SBTC is, however, that technological change has similarly impacted Europe and the US while inequalities have been developing differently in these countries.

shifted the demand for high-skilled workers upward relative to low-skilled labour (DiPrete 2007). Against the general trend of increasing income volatility in the US, Jensen and Shore (2008) reveal that a systematic rise in volatility of incomes over time for the population at large cannot be found when decomposing the average volatility. Their argument is that the average volatility has largely been driven by a sharp rise by very volatile incomes and that research has ignored individual heterogeneity in this trend. These reasons call for decomposing income volatility, and in particular along the income distribution. Most studies investigating differences in income volatility across different population groups measure instability in terms of income rather than ranks.

Among previous studies that give insights into mobility for different positions in the income distribution and trends in mobility patterns, Gottschalk (1997) for instance finds for US males aged 20-59 that the probability of staying in the lowest quintile between 1974 and 1975 was 69% compared to 80% of stayers in the top quintile. He observed a similar pattern when looking at the long-run: 42% of the individuals in the lowest quintile in 1974 were still in the same quintile 17 years later compared to 54% of stayers in the top quintile indicating overall that there seems to be more mobility at the bottom than at the top of the income distribution. Given the shift from stable public assistance to earnings, Bania and Leete (2009) find that income volatility is highest for lower income households and that the instability has even more increased between 1992 and 2003 for this group than for others. Dynan, Elmendorf and Sichel (2012), who – unlike many other studies – include also zero or close to zero incomes as well as earnings, find that income volatility rose in the early 1970s as well as in the late 2000s specifying that this widening of the income distribution is a phenomenon that is related to the changes in the tails of the distribution. In view of the comparably high volatility of family incomes at the extremes of the income distribution, Hardy and Ziliak (2013) allude even to a “wild ride” at the top and at the bottom.

Given the impact of demographic changes on risk pooling (more single person households and single parent households), the trends of income inequality and volatility also vary according to the household composition. Married individuals and those with children are less likely to experience changes in their incomes (Jensen and Shore 2008). As single person households have fewer possibilities to share or compensate income changes, their incomes are more fluctuating. Regarding age groups, volatility of incomes was found high among older persons in the US (Jensen and Shore 2008) but lower in the UK (Jenkins 2011). In contrast, women and men under age 30 are the most volatile, likely due to frequent transitions between education, paid work, unemployment and switching from parent's to one's own income (Jenkins 2011 for the UK).

Following these arguments and thus complementing other studies, we argue that volatility is not symmetrically distributed over income levels and other characteristics such as household type, education. We expect that income instability is different along the income distribution and can locate the most extreme magnitudes and trends. The heterogeneity of volatility has only been shown in terms of income (e.g. Jensen and Shore 2008, Bania and Leete 2009, Dynan, Elmendorf and Sichel 2012, Hardy and Ziliak 2013), but – to our knowledge – not in terms of ranking in the income distribution. Research questions we tackle here relate to income volatility (as changes in ranking along the income scale) over time and how these trends differ over the income distribution: Are the poor particularly volatile? How has the picture changed over the last decades? Is there evidence for a growing polarization in terms of income mobility or poverty traps? Our paper contributes to the understanding where in the income distribution changes in volatility have occurred to better be able to disentangle the causes of persistent (dis)advantages. In sum, the added value of this study is (1) that we are able to observe volatility trends net of structural changes, (2) the use of a continuous measure of volatility (logit of income ranks) and (3) modeling the effects of different background characteristics.

Methods

The logics of income ranks

Relatively new in the research on inequalities is the focus on top earners in addition to the traditional treads of poverty research. We investigate (changes in) income volatility along the income distribution and adopt a method based on the percentile ranks of individuals in the distribution rather than income as such (compare Jäntti and Jenkins (2014) for an overview).[4] Studies on income or earnings volatility using ranks often examine quintile or

[44] This implies moreover objective, not subjective, ranks.

decile transitions over varying time periods (Burkhauser, Holtz-Eakin and Rhody 1997, Gottschalk 1997). The shortcoming of using larger income rank categories such as quintiles is that intra-group income volatility is ignored. Moreover, this method cannot differentiate the magnitude of the change in income ranks (Daly and Valletta 2004): it treats, for instance, changes from the 19th to the 21st percentile in the same way as transitions from the 1st to the 39th percentile. In order to be able to account for such more detailed results, we use a continuum of ranks. While such an approach has also been (partly) followed by a number of studies (Daly and Valletta 2004), these studies using ranks based on income or earnings have, however, not looked at the differences of volatility along the income distribution.

We define income rank following Frank (1985), Becker et al. (2005) and Mujcic and Frijters (2012) as inverse of the cumulative density function of income R(Y) with $R(Y_i) \in [0, 1]$, and is thus, with a sample of size N, proportion of people with an income less than Y (i-1): $R_i = \frac{i-(\frac{1}{2})}{N}$. These individuals are defined at time t by their continuous relative position (percentile rank) between 0 and 1, 0 referring to the poorest and 1 to the richest. Subsequently, we calculate the logit of the percentile. This allows us to normalize our variable of interest and use it for regression analysis and moreover approximates the Champernowne-Fisk distribution so that log(medianised income)=alpha*logit(p) where alpha equals the Gini coefficient (Dagum 2006, Fisk 1961). In a 212 samples comparison (Chauvel, 2014), this relation approximates more than roughly the empirical distributions in terms of level of living (post-tax and transfer income per consumption unit). In other words, the logit of the percentile is proportional and thus an equivalent measure to the log of the medianised income, which can be decomposed by population subgroups (compare Jäntti and Jenkins 2014).

The interest for the “logit rank” metrics is relatively new in social science but we can find former conceptualizations, notably in epidemiology: “Logit rank” (O’Brien, 1978; Copas, 1999) or “logistic quantile” (Orsini and Bottai, 2011) or other names for logit rescaling of]0,1[proportions exist in the literature but have not received the attention they deserve. Among others, Clementi and colleagues (2012) log-transform the value of rank, even if quantile, as a]0,1[intervalled variable, requires a symmetric treatment that logit transformation does perform. Similarly, in the sociology of stratification, Tony Tam (2007) introduced the Positional Status Index (PSI), $p_i/(1-p_i)$ that we log here. The same scripture can thus receive different names: logit-rank, log-PSI, or logged odd of the percentile. The latest expression makes it more familiar in the domain of social mobility analysis where the field of intergenerational fluidity (net relative mobility between occupational classes) is precisely focused on odds ratios based models like in log-linear modelling strategies (Blanden 2013 for a review of this domain).

In addition to the theoretical arguments made above, there are also methodological advantages of conceptualizing volatility in terms of ranks rather that income. Most importantly, this approach allows us to give meaningful comparisons over time and countries as income changes may result from exchange mobility *and* from structural mobility (Jäntti and Jenkins 2014). The "logit-rank" for each year transforms income distributions having variable Gini coefficients and distributional characteristics in a single invariable type of distributional shape (a logistic one). When income-based volatility captures a mix of structural mobility (due to distributional transformations) and of exchange one (the degree to which individuals are affected in their relative position on the income scale), the logit-rank-based volatility is independent of structural changes in the distributional characteristics and focus on the sole exchange mobility. If the conventional approach on income-based volatility is sensitive to modifications in the Gini, inter-quantile ratios, and distributional shape transformations, our logit-rank approach offers a net-of-distribution measure. When using log of income, results of the log of income can moreover easily be dominated by small changes in the level of income near zero (e.g. unemployed) leading to huge or infinite changes in the log income.

On top of that, the logit-rank approach facilitates the analysis of changes along the income scale: in the conventional income-based volatility, the percentage of individuals below 50% of the median, for instance, changes over time due to structural changes in the distributions. In this new proposal, we have invariably 11.9% of the population below logit(p)= -2 (Table 1). Thus, we dispose of a fixed scale allowing comparison of exchange mobility for different income groups.

An additional argument in favour of ranks when working with the PSID is that changes in income can also be driven by the changes in the top-code (Jensen and Shore 2008, Dynan, Elmendorf and Sichel 2012). Using ranks avoids this issue.

Measuring volatility of income ranks

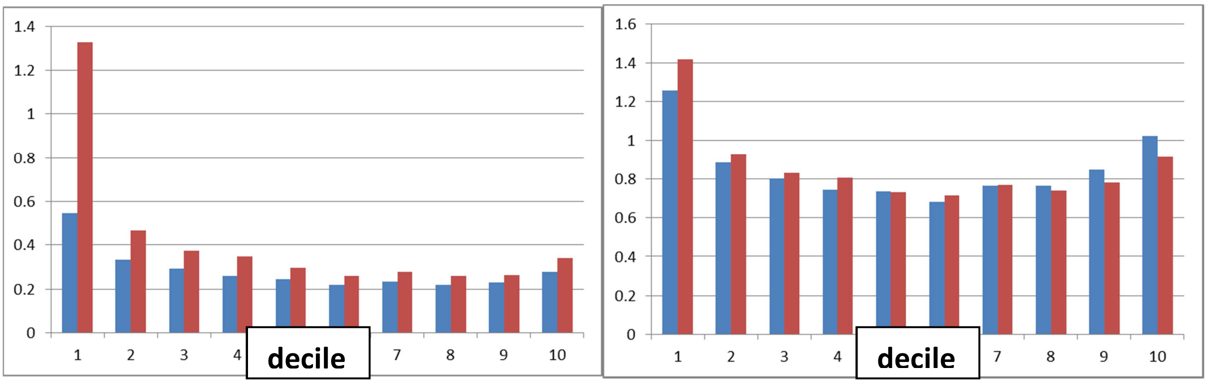
For looking at *trends* in volatility or mobility many years of longitudinal data are necessary. The Panel Survey of Income Dynamics (PSID) combines this with other advantages such as detailed household information. We test the dissymmetry hypothesis (mobility is different at the top and the bottom of the distribution) with the PSID on several decades (PSID 1970-2007, biannual intervals). To construct the dependent variable, we use the (medianized) equivalized post-governmental household income Y, which includes total family income from labor earnings, asset flows, the imputed rental value of owner occupied housing, private transfers, public transfers, and social security pensions minus total household taxes. The equivalised income is defined as the household income Y divided by the square root of the number of household members. Thus, all members of the household have the same equivalent income, regardless of age, status in the household, etc.

In their seminal study on labour earnings volatility, Gottschalk and Moffit (1994) estimate transitory earnings using two different concepts: volatility defined as (1) earnings minus a moving average of earnings and (2) as derived from time-series decompositions of earnings. Our aim, however, is to measure volatility based the magnitude of *total* changes in household income rather than to depict the transitory component of volatility. We agree thus with Dynan, Elmendorf and Sichel (2012) that this procedure usefully complements Gottschalk and Moffit's method as on the one hand there is no consensus in the literature to date on how to measure household income volatility and its development over time, and that results are sensitive to underlying assumptions of these approaches. This had lead prominent scholars to plead for simpler and least processing approaches (Shin and Solon 2011).

We calculate the income ranks for households with head of households between 25 and 59 years old. We restrict our sample to Black and White Americans and exclude other ancestries such as Asians and Hispanics. We look at short-term income rank volatility understood as changes in the logit of the percentile ranks in two-year intervals or the the log of the odds ratio of x: $\text{logit}(x) = \ln[x/(1-x)]$. For a conversion between the logit of the percentile rank and the percentile rank, please see Table 1.

The first question to ask here is the intrinsic added value of the logit-rank volatility compared to the conventional approach in terms of income-based volatility. With the PSID, we can compare both approaches. To provide a simple comparison we simply analyze by income decile the average absolute difference in log-incomes, like in the paper of Hardy and Ziliak (2013), from year t0 to year t2 (two years changes), and compare them to the most similar results based on the average absolute difference in logit-ranks. We report on figure o the transformation of these average values in the years 1970s and 2000s.

Figure o: Log-income based (left) and logit-rank volatility (right) on two years by decile (1970-1979 = blue ; 2000-2007 = red ;)(X=logit-rank year 0 and Y = logit-rank year 2)



On the side of income based volatility, the indicator increased in each decile, systematically, from the 1970s to the 2000s, and even massively at the lower decile, where logged incomes can provide almost null values. By comparison, the logit-based volatility measure give more stable results. First the average values are higher: if the gini is .30, the log-income based volatility will be only 30% of the logit-rank one. Second, the log-income volatility is sensitive to distributional transformations: the average Gini in the 1970s was 29.9% and 38.9 in the 2000s. The conventional view does not capture a change in the way volatility intrinsically works, but simply the increases of the sizes in the income brackets potential moves: when the income distribution is stretched between the bottom and the top, income instability mechanically increases in terms of changes of income percentages. This is due to a kind of big-elastic-band theory of income distribution (different to the Jenkins' rubber-band theory[5]): when the elastic band is stretched, the distance between individuals and between potential relative positions increase as well. In terms of income, volatility increases with

[5] https://www.iser.essex.ac.uk/files/in-praise-of-panel-surveys.pdf

higher Gini indexes. It is not the case for the logit-rank based volatility that is independent of the stretches on the distribution. There, in terms of logit-ranks, volatility increased at the bottom and reduced at the top. This means that the upper middle class positions are more stable today (in terms of relative ranks) than yesterday, even if the lower middle class face more instability. The changes in the US are first increasing inequality, and second a change in the distribution of volatility where the lower middle class has more risky positions, and the upper middle class benefit from more stable income ranks (or statuses). Most of the job is done now, but we would like to deepen even more the new method.

The problem here is that decile based analysis is not satisfying since the upper decile (and symmetrically the lower one as well) aggregates very different income categories: in 2007, decile 10 mixes relatively comfortable yearly family incomes above 200.000 dollars a year (not equalized by consumption units), and multimillion incomes a year: households aggregated in deciles are too diverse to make sense. So the method we propose here is based on logit-ranks for both the vertical axis (volatility defined by moves on the scale), and the horizontal axis (the definition of relative income position).

The method applied here allows us to describe and visualise changes in income ranks and volatility over time, net of distributional transformations. Plotting the logit of the percentile ranks of all individuals at t0 and t2, we rely on contour plots using kernel density estimation as illustrated in Figure 1 in addition to simple scatterplots, which ignore the bivariate Kernel density.

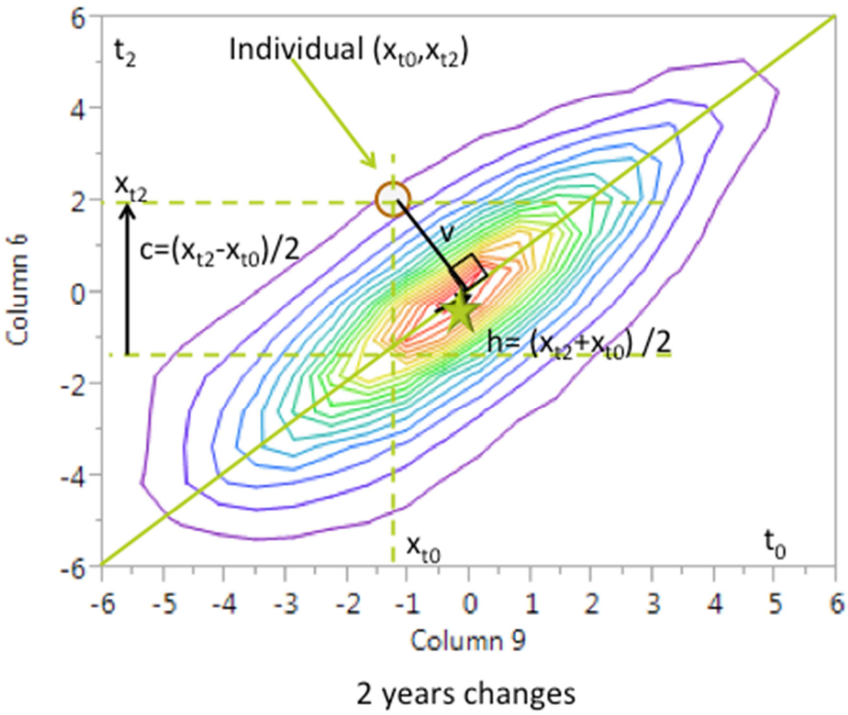
Table 1 : Magnitudes of logit(percentile) and percentile rank

logit(quantile rank); log(medianised income)	-5	-4	-3	-2	-1	0	1	2	3	4	5
Quantile rank	0.007	0.018	0.047	0.119	0.269	0.500	0.731	0.881	0.953	0.982	0.993

Note: on axe X, a magnitude of -2 relates to quantile .119, then close to the first decile; on axe 2, a magnitude of 2 relates to an income 2.7 times higher than the median.

The case of complete stability or immobility would be if every individual had the same rank in t0 and t2, i.e. placed on the diagonal in Figure 1 (compare also Jäntti and Jenkins 2014). We test dissymmetry based on three concepts. First, we investigate the change c defined as the difference in logit-ranks between two time points divided by the number of time points: $c=(x_{t2}-x_{t0})/2$. Thus, the higher c, the stronger the increase in logit-ranks. Second, we refer to hierarchy h, which is a measure of the inter-temporal position in the income distribution or "average" between the two time points: $h= (x_{t2}+x_{t0}) /2$. Hierarchy h or level l points to individuals with same average of logit of the percentile over the two time points (but not necessarily the same ranking at one of these time points). The higher h, the higher the inter-temporal income rank. Third, the volatility v is defined as the standard deviation of logitx0 and logitx2, which is a measure of how widely values are dispersed from the average value (the mean) and reflects thus the intensity/magnitude of moves and measures thus the instability of a position: $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2}$.

Figure 1: Income-rank volatility measured across two time points (X=logit-rank year 0 and Y = logit-rank year 2)



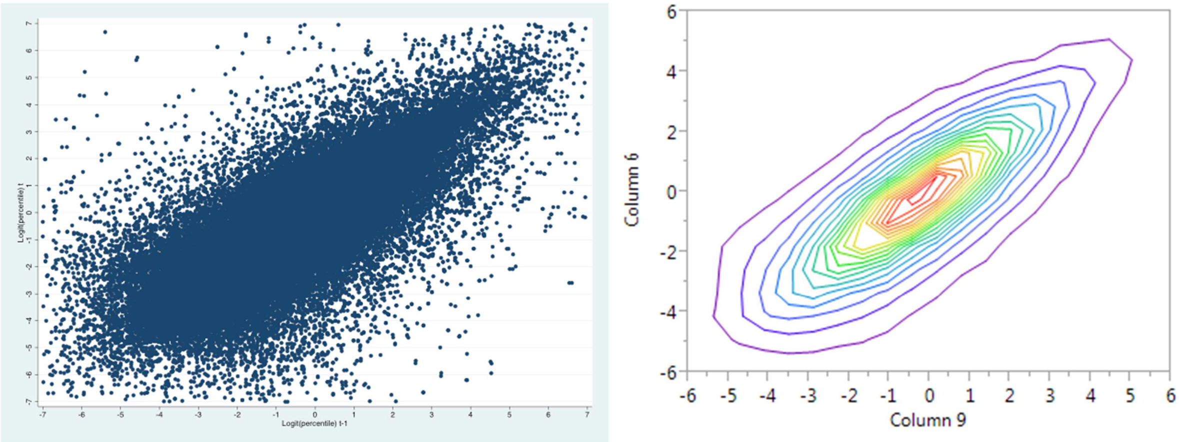
Note: The contours refer to density isoquants.

The shape of the density distribution of income percentile transitions is, as we will show later (Figure 6), different from the normal distribution and can be described by a Lévy alpha-stable distribution. Although this type of distribution has been detected in other studies (Daly and Valletta 2004), it has not been connected to the alpha-stable distribution.

Results in the U.S. (PSID)

Our main interest here lays in the *individual* period-to-period mobility on the scale of (logit of) percentiles. Plotting the period-to-period volatility in terms of logit of the percentile rank on a continuous scale (Figure 2a and b), the cloud of observations is anisotropic rather than a bi-normally distributed cloud. The plots suggest that there is less variation in ranks over the two time points at the top of the income distribution (upper right corner) as the observations are clustered closer to the diagonal than at other parts of the income distribution.

Figures 2a and b. Distribution of income rank mobility (year to year+2) in the U.S. 1971-2007



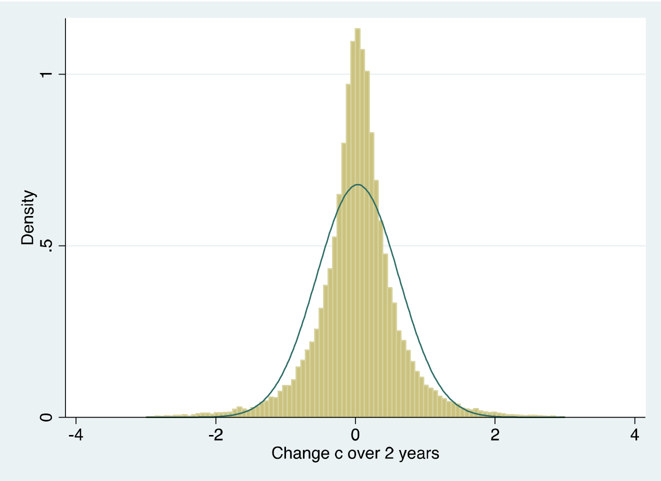
Notes: x-axis logit percentile of year t-1, y-axis logit quantile of two years later (t).
Source: PSID. Our computations.

This year to year+2 phenomenon is very far from a normal distribution phenomenon (Figure 6) since the change c in logit-rank of income present much more extreme moves (and almost-still) individuals than in the normal hypothesis. We detect here a typical Lévy alpha-stable distribution (Nolan 2009; Umarov et al 2010) where α is close to 1.3. A general stable distribution can be described by four parameters: an index of stability or characteristic exponent $\alpha > 0$ ($\alpha = 2$ for a normal distribution[6] and becomes leptokurtic for a<2), a skewness

[6] According to the Central Limit Theorem, a normalized sum of a set of variables with finite variance will be normally distributed as the number of variables increases. Refraining from the finite variance assumption, the limit may be a stable distribution.

parameter $\beta \in$ [-1;1], a scale parameter $\gamma > 0$ and a location parameter $\delta \in$ R (Nolan 2009). Leptokurtic non-normal stable distributions are also known as stable Paretian distributions. These heavy-tailed distributions are common in the statistics of finance and assets volatility analysis.

Figure 6. Change c year to year +2 in the U.S. 1970s and 2000s

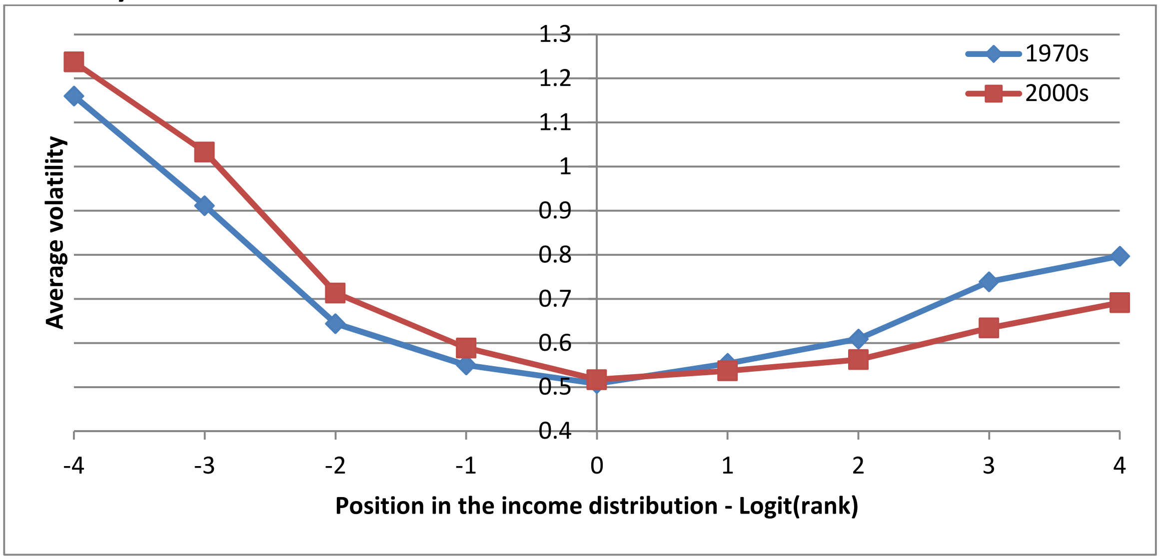


Source: PSID. Our computations.

The comparison of period-to-period differences in income position (Figure 3) elaborates this phenomenon. The U curves show that the middle income classes have been and are more stable and that the top income classes have been and are still less stable than the bottom but more fluid (or unstable) than the middle. While income volatility around the median income (x=0 in Figure 3) has not changed in the last thirty years, the curve of the two-year difference in logit percentile rank has decreased for the upper 5% (x>=3, compare table 1 in annex for a conversion). The curve of the two-year difference in logit percentile rank has increased for the lower part of the income distribution between the 1970s and the 2000s. In other words, this translates into a change in the profile: the upper ranks of incomes gain in stability while the poorer become more unstable over time.

We precise this U curve (Figure 3) is not to be expected as a natural result of our method. In Champernowne-Fisk distributions, a constant change (equal wherever along the income scale) of x% in the income means a constant volatility. A U curve means the average percentage of change is higher at the bottom and the top than at the middle of the distribution.

Figure 3. Average two-year volatility in the U.S. 1970s and 2000s, by position in the income hierarchy

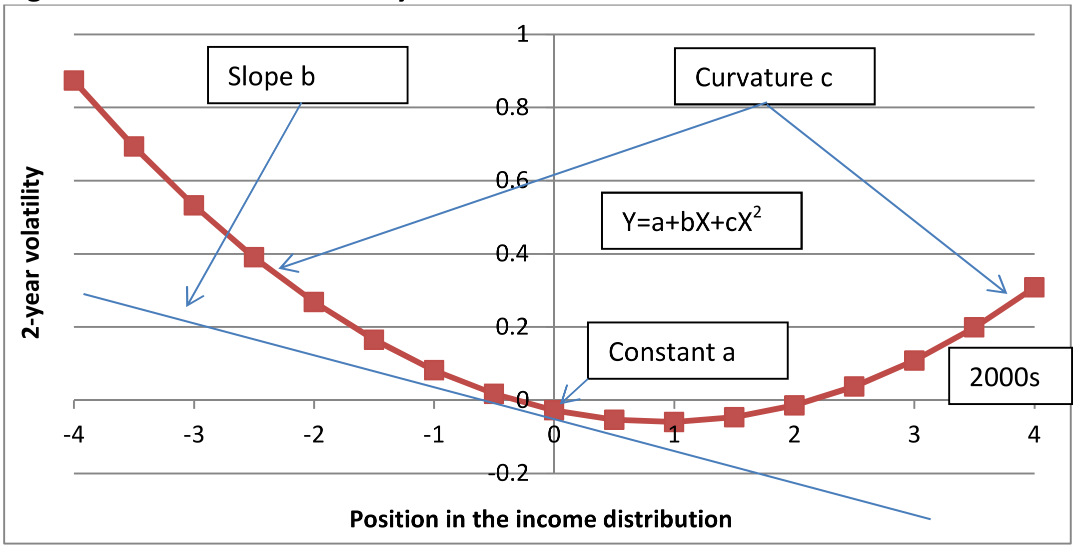


Source: PSID. Our computations.

The quadratic model of the curve controlling for age (Figure 4, see model T1 in Table 2) resembles very much the previous one with the difference in magnitudes of changes over the last decades and the exact location of the changes in volatility. We call "profile of volatility" (Figue 3bis) the quadratic fit of Y the measure of volatility by X axis, hierarchy in terms of logit-rank $Y = a + bX + cX^2$. In this "profile of volatility", we detect a constant a that catches volatility near to the median, b the slope that denotes de degree to which volatility is higher (or lower if b<0) at the top, and c that expresses the degree of increase of volatility t the extremes of the distribution (c>0 provides a U shaped curve of volatility). Then, the variation of the three parameters gives interpretable information on where volatility increases or decreases. Positive change in a means increasing volatility for all, increase in the values of b means more volatility at the top, and higher values of c mean more volatility for extreme values (and relatively higher stability at the median level). Then we can understand where instability is increasing more in the distribution.

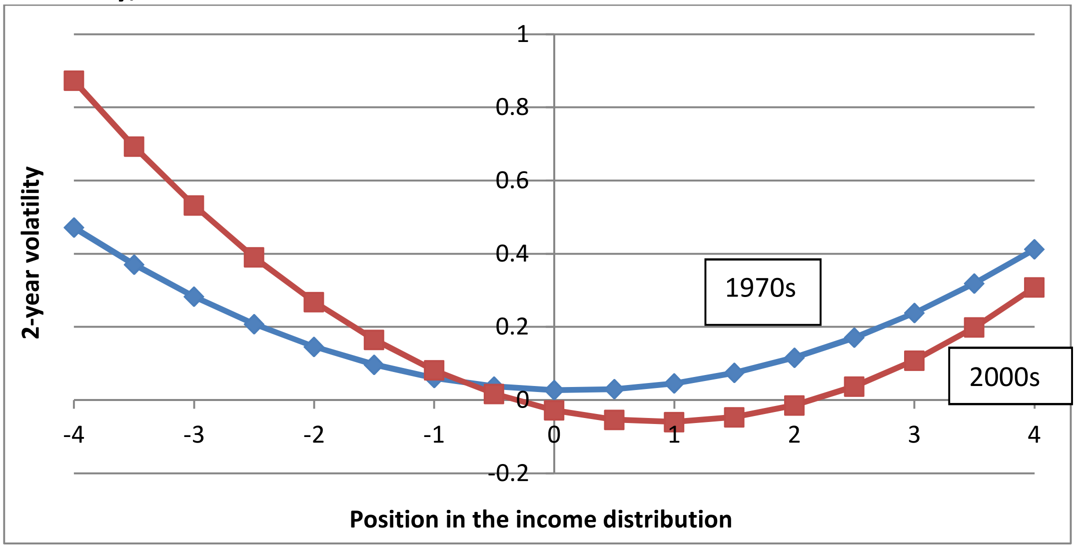
Now, empirically in the PSID, it seems that the most stable group – given the differences in the characteristics – is the quartile just below the median (0>x>=-1).

Figure 3bis. Profile of volatility



Note: Predictions based on model T1 in Table 2 controlling for hierarchy, hierarchy squared and both interactions with time, time, age and age squared. Source: PSID. Our computations.

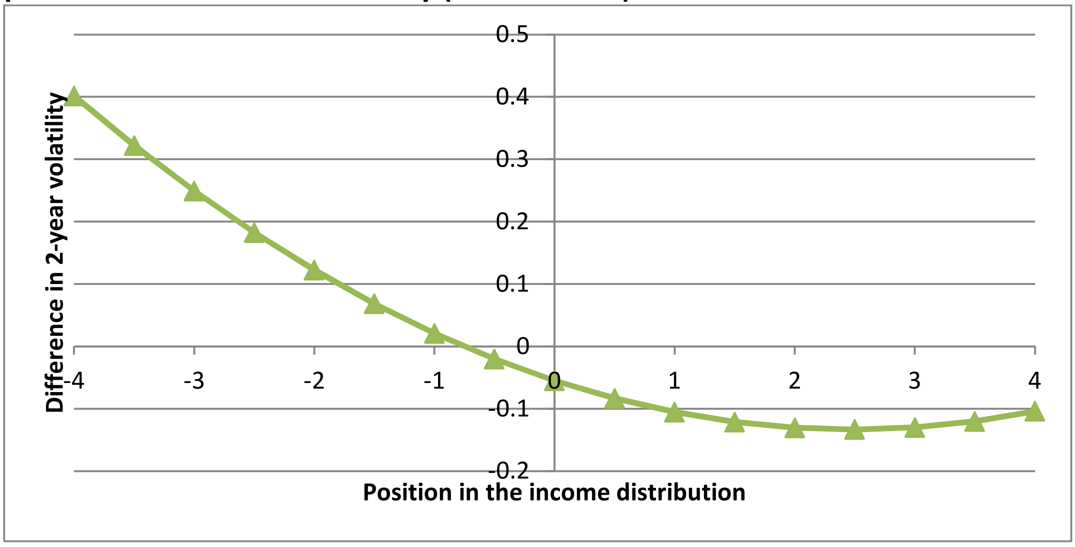
Figure 4. Average two-year volatility in the U.S. 1970s and 2000s, by position in the income hierarchy, incl. controls



Note: Predictions based on model T1 in Table 2 controlling for hierarchy, hierarchy squared and both interactions with time, time, age and age squared. Source: PSID. Our computations.

The difference between the two-years volatility and thus the curves above is given in Figure 5. The lower the position in the income distribution, the larger the increase in two-year volatility. Again, the most stable group over the last decades is the quartile just below the median (0>x>=-1) where the difference in volatility between the 1970s and the years 2000 equals zero. Volatility decrease generally for the upper part of the distribution with the largest gain in income rank stability for the upper 12-5% of the income distribution.

Figure 5. Difference in two-year volatility in the U.S. between the 1970s and the 2000s, by position in the income hierarchy (incl. controls)



Source: PSID. Our computations.

Next, we regress two-years change in logit of the income ranks on several characteristics in order to find out which households experience highest levels of volatility. We control for linear and quadratic age effects in all models to account for income gains in the life cycle. In addition we add stepwise household characteristics that might have changed considerably over this period, such household composition (more single-parent families, etc.). The discussion of the results focuses on our main interest here – the impact of changes in household composition and status as well as work-related changes.

Table 2: OLS results predicting logit(income ranks)

Variable	t1	t2	t3	t4	t5	t6
Hierarchy h	-0.0389***	-0.0395***	-0.0540***	-0.0549***	-0.0468***	-0.0378***
Hierarchy h squared	0.0322***	0.0323***	0.0322***	0.0320***	0.0290***	0.0282***
Time (years)	-0.0139*	-0.0137*	-0.0326***	-0.0319***	-0.0272***	-0.0319***
h*time	-0.0157***	-0.0157***	-0.0122***	-0.0094**	-0.0090**	-0.0081*
h squared*time	0.0032**	0.0032**	0.0039**	0.0037**	0.0034**	0.0029*
Age (std.)	-0.0429***	-0.0428***	-0.0726***	-0.0365***	-0.0406***	-0.0328***
Age square	0.0412***	0.0411***	0.0142*	0.0050	0.0000	-0.0015
Ancestry of head of household: White						
Black		-0.0126	-0.0133	-0.0354*	-0.0183	-0.0204
Sex of head of household: Male						
Female		0.0021	-0.0036	-0.0001	-0.0204	-0.0179
Years of education of head of hh<17						
17-19 (high school)			0.0328	0.0467**	0.0467**	0.0397*
20-21 (undergrad. college)			0.0984***	0.1102***	0.1108***	0.0992***
22 (graduate college)			0.0729***	0.0862***	0.0919***	0.0849***
Marital status of head of hh: single						
Married			-0.0875***	-0.0257	-0.0038	-0.0026
Separated/other			0.1361***	0.0082	0.0235	0.0222
Children in hh: none						
1 child			-0.0602***	-0.0822***	-0.0817***	-0.0801***
2 children			-0.1898***	-0.1712***	-0.1756***	-0.1636***
3 and more			-0.2954***	-0.2975***	-0.3100***	-0.2951***
Change marital status				0.4514***	0.4577***	0.4407***
Change number of children				0.0613***	0.0545***	0.0554***
Change number of person in hh				0.3004***	0.2991***	0.2943***
Yearly hours worked of head of hh: <1000h						
<2000h					-0.1946***	-0.1500***
<3000h					-0.1717***	-0.1149***
3000h and more					0.1036***	0.0530*
Change in hours worked						0.4497***
Constant	-1.2685***	-1.2683***	-1.2054***	-1.3427***	-1.2019***	-1.2945***
N	120275	120275	118076	118076	116470	116470
BIC	401713.1	401735.3	393281	389856.7	383535.9	381764.3

Notes: * p<.05; ** p<.01; *** p<.001. For more detailed model statistics please consult Table 3 in Annex. Source: PSID. Our computations.

The interaction of hierarchy h (average logit rank between two time points) and time models the shape of the change in volatility along the income scale in the US between 1973 and 2007. The negative linear effect suggests that there is a tendency that higher incomes experience lower degrees of volatility (compare Gottschalk 1997, Bania and Leete 2009, Alvaredo et al 2013). Theories refer to better levels of insurance against income losses among the better-off households (Jenkins 2011). The positive quadratic effect, however, implies that there is a turning point around the third quartile where income rank volatility increases again confirming the hypothesis of a “wild ride” at the top and at the bottom postulated by Hardy and Ziliak (2013). The shape of this curve remains rather stable when including additional variables.

Regarding age, the negative linear and the positive quadratic effect confirm the results of existing studies. Households with younger heads of households have more instable incomes, in old-age volatility increases again. This is certainly due to life events, as the quadratic effect disappears when introducing variables depicting change in household composition such as change marital status, in the number of children and the number of person in the household (model t4).

Moving from model t3 to t4 uncovers another relationship between volatility and household composition. Namely, higher volatility is not associated to marital status *per se* but to *changes* in marital status or household composition, which may change risk pooling options and family transfers (Jenkins 2011, Western et al 2013). On the other hand, the impact of children remains fairly stable – not only the change to more or less children in the household is pivotal for the magnitude of volatility in household income rank but also the number of children in the household as such. Household with children are less volatile, which is in line with previous studies. This may be attributed to risk preferences.

Regarding job-related characteristics, the impact of hours worked is a crucial factor for volatility. Household with heads in full-time contracts are considerably less volatile than households where the head works fewer than 1000 hours per year. Most volatile are those households where the head works more than 3000 hours, which is perhaps often a temporary situation. However, including change in working hours in model t6, it can be seen that volatility in household income is largely but not only related to the change, but also to the working hours *per se*. To sum up, the change in working hours, in marital status and in number of persons in the household is the biggest trigger of volatility in household income rank.

Preliminary results: U.S. (PSID) versus Europe (EU-SILC)

The methodology developed on the U.S. can be applied in a more general context. We dispose of 14 country samples of the EU-SILC surveys where it is possible to follow income mobility on a 2 years base in the outgoing sample of 2010 where the level of living (after tax incomes per consumption unit) of 2008 and 2010 are measured. This allows the comparison of the profiles of volatility in 14 European countries (table 4), in comparison with US in the 1970s US70 and the 2000s US00 (PSID source above). For each European country we compute the logit-rank position in 2008 and 2010 and, its average h. This provides a magnitude of income X for each country, and we dispose of Y, the volatility of income between 2008 and 2010.

We have the same type of information for US70 and US00 that will be retained as a reference category.

Table 4 Sample sizes by country/sample

Sample	N	Country
AT	12,264	Austria
BE	11,180	Belgium
DK	6,632	Denmark
ES	24,160	Spain
FI	10,832	Finland
FR	24,152	France
HU	18,308	Hungary
IT	36,928	Italy
LU	10,954	Luxembourg
NL	20,862	Netherlands
NO	8,024	Norway
PT	8,762	Portugal
SE	11,736	Sweden
UK	18,512	United Kingdom
US70	29,658	United States 1970s
US00	33,745	United States 2000s

Source: PSID & EuSilc . Our computations.

Regressions of volatility help us in comparing profiles of volatility of these different countries in gross (no control) terms. We consider a hierarchical model where block 0 expresses Y by a, b and c; block 1 adds the interaction between a and countries (=general volatility is different in terms of level); block 2 adds the interaction between b and country (=the contrast between the top and the bottom of the distribution differ); block 3 (=the shape of the U curve differs from one country to another).

Table 5 Modelization of the profiles of volatility

Var	block 0	+ block 1	+ block 2	+ block 3
a	-1.236***	-1.230***	-1.230***	-1.234***
b	-0.0434***	-0.0422***	-0.0609***	-0.0614***
c	0.0325***	0.0357***	0.0358***	0.0375***
a interaction country (ref cat US 2000)				
AT		0.176***	0.175***	0.185***
BE		-0.0606*	-0.0619*	-0.0801**
DK		-0.213***	-0.215***	-0.218***
ES		0.130***	0.132***	0.125***
FI		-0.199***	-0.198***	-0.162***
FR		-0.0000715	-0.000145	-0.0132
HU		0.0581**	0.0578**	0.0803***
IT		-0.205***	-0.204***	-0.206***
LU		-0.115***	-0.116***	-0.176***
NL		-0.314***	-0.315***	-0.295***
NO		-0.134***	-0.135***	-0.120***
PT		-0.203***	-0.204***	-0.203***
SE		-0.113***	-0.112***	-0.0807**
UK		0.183***	0.185***	0.187***
US70		0.0494**	0.0485**	0.0599**
b interaction country (ref cat US 2000)				
AT			0.0147	0.0157
BE			0.0380*	0.0363*
DK			0.0740***	0.0739***
ES			-0.0340**	-0.0357***
FI			-0.0109	-0.00699
FR			0.0145	0.013
HU			0.00832	0.00955
IT			0.0618***	0.0618***
LU			0.0402**	0.0343**
NL			0.0463***	0.0480***
NO			0.0496***	0.0512***
PT			-0.0803***	-0.0800***
SE			-0.005	-0.000558
UK			-0.00802	-0.00799
US70			0.0459***	0.0467***
c interaction country (ref cat US 2000)				
AT				-0.00378
BE				0.00682
DK				0.00116
ES				0.00271
FI				-0.0124**
FR				0.0049
HU				-0.00812
IT				0.000543
LU				0.0217***
NL				-0.00723
NO				-0.0055
PT				-0.000343
SE				-0.0112*
UK				-0.001
US70				-0.00405

Source: PSID & EuSilc . Our computations.

In this comparison (Tab 5), the main preliminary results are:

1- General volatility (a coefficient) is significantly lower in Nordic countries, Portugal and Italy (compared to the US 2000s), higher in the UK, Austria and Spain.

2- When we contrast volatility at the top and the bottom (b coefficient), the Portuguese specificity becomes clearer since volatility is much smaller at the top and stronger at the bottom, with very volatile poor and stable income elite. Conversely, Denmark and Italy present an opposite model where the rich are more unstable relatibvely to the poor. If we keep in mind the US2000 is the reference category with b= -0.0609, this means the value of b for Italy and Denmark are close to null, so there is no contrast between the poor and the rich in terms of volatility.

3- In terms of quadratic term, the U shape relatively similar everywhere, even if the c parameter is higher in Luxembourg, with a very less-volatile middle class of incomes and more shaky extremes.

The F tests (table 6) of the models show the lower importance of the c coefficients, a having a stronger role in terms of F, b in terms of r^2.

Table 6 Statistics of the blocks of models of the profiles of volatility

Block	F	Block df	Residual df	Pr > F	R2	Change in R2
0	240.84	2	138035	0.0000	0.0176	
1	80.23	15	138020	0.0000	0.0180	0.0004
2	13.43	15	138005	0.0000	0.0188	0.0009
3	3.84	15	137990	0.0000	0.0189	0.0000

Source: PSID & EuSilc . Our computations.

Conclusion

In a nutshell, we showed in this article that the US have and are experiencing an increase in instability notably at the bottom over the last decades - in addition to the increase in income mobility disclosed in the literature. Reasons for changes in income inequality over the last decades put forward in the literature (Gottschalk 1994, Alvaredo et al 2013), are related to the work and the labour market situation (e.g. increase in real wages paid to skilled workers, sharp decline in absoluate real wages at the bottom, bargaining power and greater individualization of pay in top-income professions), capital income, public welfare and tax policy (e.g. cuts in the marginal tax rates in 1986 and 2001, tax improvements for families with children in 1997), and demographic and life-style changes (female labour market participation, marital behavior, household composition, etc.).

The analysis based on the PSID over the period 1973-2007 has shown that the poor have been more volatile but are becoming even less and less sure about their position in the income distribution. The upper middle class households, on the contrary, have been and are getting more stable with respect to their income rank.

Our study is based on household income rather than on earnings which has been promoted as more appropriate concept for investigating volatility (Jenkins 2011, Western et al 2013) as it is able to reflect not only on work and labour market related changes but also on changes in family structure and welfare state provisions. In addition, we apply a continuous measure of income rank and contributes thus to the literature as it qualify results of other studies based on a discrete approach (quintile or deciles), which has the disadvantage of overlooking intra-group mobility.

The methodology developed here is appropriate for providing comparative analyses. The preliminary results on Europe show significant contrasts: intensity and profiles of volatility differ from one country to another. Nordic European countries show lower volatility and the UK higher ones. The profiles could be clearly different with the case of Portugal, specific of our hypothesis of dissymmetry: there we have very volatile poor and more stable rich. This dissymmetric model is interesting since there the poor are not only deprived from resources, their incomes are more unstable. The U.S. are closer to this model (stable upper middle class and unstable poor) today than in the 1970. But an obvious question remains: is instability of income a set of challenges or a source of opportunity? The answer could be different at the top and at the bottom.

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Annex

Table 3: Model summary statistics

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
t1	120275	-201801.8	-200809.8	8	401635.5	401713.1
t2	120275	-201801.8	-200809.2	10	401638.3	401735.3
t3	118076	-197998.4	-196535.4	18	393106.8	393281
t4	118076	-197998.4	-194805.7	21	389653.4	389856.7
t5	116470	-195112.9	-191628	24	383303.9	383535.9