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Abstract

Nonresponse in surveys may result in a distortion of the distribution of interest. In a panel survey the participation behavior in later waves is different from the participation behavior at the start. With register data that cover also the information for non-respondents one can observe a fade away of the distributional differences between the distribution of the full sample, including nonresponders, and the respondent sample, without the nonrespondents.

The mechanics of this effect may be explained by a Markov chain model. Under suitable regularity conditions the distribution on the state space converges to the steady state distribution of the chain, which is independent from the starting distribution of the chain. Therefore the fade-away effect is considered here as the swing-in into the steady state distribution.

An essential condition for the fade-away effect assumes the same transition law for the responders and the nonresponders. Such a hypothesis is investigated here for the Finnish subsample of EU-SILC for the equivalized household net-income. The income is grouped into income brackets which divides the starting sample into quintiles. This analysis is based on register information. For this analysis the null-hypothesis of equal transition behavior between income quintiles for responders and nonresponders cannot be rejected. This finding restates a result for Finland for the ECHP (European Community Household Panel).

A second condition concerns the selectivity of panel attrition after wave one. Here panel attrition must not depend on the income state of the previous panel wave.

The velocity of the swing-in into the steady state distribution depends on the stability to stay in the same income state. The stability may vary among the European countries. Therefore we investigated the transition

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matrices for 25 EU-SILC countries. We simulated 6 different pattern of nonresponse bias and investigated the fade-away effect across the waves 2006 to 2009. We found remarkable differences between these 25 countries. Expressed by the relative bias, i.e. bias in 2009 divided by bias at start in 2006, we found a reduction down to 26 percent of the initial bias for Bulgaria (foremost reduction) up to 61 percent for Finland (least reduction). Our results vote for longer observation periods in rotation panels like EU-SILC.

Keywords: Panel surveys, nonresponse, panel attrition, Markov chains, income mobility, EU-SILC.

1 Introduction

Nonresponse reduces not only case numbers of a survey but it may also distort the results of survey analysis. It was a surprising finding of Sisto (2003) that these distortions diminish in later waves of a panel survey. Rendtel (2005) used a Markov chain approach to give a statistical explanation for this phenomenon. He coined the term "Fade-Away Effect". The core of this approach is the steady state distribution of a Markov chain. If the transition law of the Markov chain is stable over time, then (under regularity conditions) the distribution on the state space of the Markov chain converges to its steady state distribution. The convergence is independent from the starting distribution at wave 1 of the panel. However, the transition law between successive states must be the same for responders and nonresponders. Furthermore, panel attrition must not be selective after wave 1. In a recent paper Alho et al. (2015) present an extended methodological treatment of the fade-away effect, which does not need time-homogeneity of the transitions. They give also some theoretical results on the speed of the convergence. Also extensions for the treatment of longitudinal profiles are given there.

This article focusses on three aspects. First we want to replicate results which were delivered for the Finnish subsample of the European Community Household Panel (ECHP) for its subsequent survey, the European Statistics on Income and Living Conditions (EU-SILC). This concerns mainly the validity of the key assumption of this approach, namely the equality of the transition law for respondents and nonrespondents. This can only be done with the help of register information for the nonrespondents.

The second issue is an extended check of the selectivity of panel attrition in the Finnish subsample of EU-SILC. In the ideal case panel attrition must not be selective to guarantee a fade-away effect. As this condition is not exactly met we use some simulations to demonstate the stability of the fade-away effect in the presence of moderate deviations form the ideal conditions.

The third issue is the speed of convergence which is equivalent to the size of the fade-away effect. For empirical applications it is an important parameter. It makes a difference whether one has to wait 3 or 30 panel waves until a possible non-response bias has reduced. Here we will use six different bias scenarios to simulate the speed of the convergence in the 25 national subsamples of EU-SILC. We will also investigate regional pattern across the EU-member states.

The article is organized as follows: Section 2 displays shortly the methodological framework of the fade away effect. Section 3 checks the condition of the same transition law for responders and nonresponders. Section 4 investigates whether panel attrition can be ignored for the swing-in into the steady state distribution. Here also the effect of deviations from a strict non-selectivity of panel attrition is studied. Section 5 compares the speed of convergence to the steady state distribution over 25 national EU-SILC subsamples. Section 6 concludes.

2 Regularity conditions for the fade-away effect

We assume that the characteristic of interest $\{Y_t\}_{t\in\mathbb{N}}$ follows a Markov chain with state space $S = \{1, \ldots, I\}$:

$$\begin{aligned} P(Y_t = j|Y_{t-1} = i, Y_{t-2} = s_{t-2}, \ldots, Y_1 = s_1) &= P(Y_t = j|Y_{t-1} = i) \\ &= p_{i,j}(t) \end{aligned}$$

In order to avoid lengthy expressions we display here the results for a panel with 4 waves, which is the standard case in EU-SILC. From this case the results may be easily extrapolated to longer panels. We use the response indicators R_1, R_2, R_3, R_4, where $R_t = 1$ indicates response and $R_t = 0$ indicates nonresponse at wave t. The distribution on the state space at wave 4 in the observed sample, denoted by OBS, is $P(Y_4 = j_4|R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1)$.
Now by virtue of the Bayes theorem we have:

$$\begin{aligned} & P(Y_4 = j_4|R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) \\ = & \sum_{j_3} P(Y_4 = j_4|Y_3 = j_3, R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) \\ & \times P(Y_3 = j_3|R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) \qquad (1) \\ = & \sum_{j_3} P(Y_4 = j_4|Y_3 = j_3, R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) \\ & \times \frac{P(R_4 = 1|Y_3 = j_3, R_1 = 1, R_2 = 1, R_3 = 1)}{P(R_4 = 1|R_1 = 1, R_2 = 1, R_3 = 1)} \\ & \times P(Y_3 = j_3|R_1 = 1, R_2 = 1, R_3 = 1) \qquad (2) \end{aligned}$$

In order to proceed have to assume that the transition behavior must not depend on the participation behavior (**Assumption A**):

$$P(Y_4 = j_4|Y_3 = j_3, R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) = P(Y_4 = j_4|Y_3 = j_3) \quad (3)$$

Assumption A is equivalent to the missing at random (MAR)assumption, which states in our case that the probability law of interest, say the distribution of Y_1, Y_2, Y_3, Y_4, is the same for respondents and nonrespondents.
Furthermore we need **Assumption B** stating that the previous state does not have a direct effect on the participation in the present wave:

$$P(R_4 = 1|Y_3 = j_3, R_1 = 1, R_2 = 1, R_3 = 1) = P(R_4 = 1|R_1 = 1, R_2 = 1, R_3 = 1) \quad (4)$$

By using Assumptions **A** and **B** one gets:

$$
\begin{aligned}
& P(Y_4 = j_4 | R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) \\
= & \sum_{j_3} P(Y_4 = j_4 | Y_3 = j_3) P(Y_3 = j_3 | R_1 = 1, R_2 = 1, R_3 = 1) \qquad (5)
\end{aligned}
$$

Using the same kind of analysis for $P(Y_3 = j_3 | R_1 = 1, R_2 = 1, R_3 = 1)$ and inserting into eq. 5 one obtains:

$$
\begin{aligned}
& P(Y_4 = j_4 | R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) \qquad (6) \\
= & \sum_{j_3, j_2} P(Y_4 = i | Y_3 = j_3) P(Y_3 = j_3 | Y_2 = j_2) P(Y_2 = j_2 | R_1 = 1, R_2 = 1)
\end{aligned}
$$

Finally we arrive at:

$$
\begin{aligned}
& P(Y_4 = j_4 | R_1 = 1, R_2 = 1, R_3 = 1, R_4 = 1) \\
= & \sum_{j_3, j_2, j_1} P(Y_4 = i | Y_3 = j_3) P(Y_3 = j_3 | Y_2 = j_2) P(Y_2 = j_2 | Y_1 = j_1) \\
& \times P(Y_1 = j_1 | R_1 = 1) \qquad (7)
\end{aligned}
$$

where the last term $P(Y_1 = j_1 | R_1 = 1)$ in eq. (7) is the starting distribution for the respondents of wave 1 and the summation is done over 3 cycles of the Markov chain. Denote this distribution by π_{RESP}. If there would have been no initial nonresponse we would have used in equation (7) the distribution π_{FULL} based on the gross-sample of the panel. The contraction theorem in Juha et al. (2015) shows under suitable regularity conditions a uniform convergence of the distributions in equation (7) for any starting distribution. The regularity conditions of the contraction theorem refer to weak ergodicity and are not restrictive for our analyses.

In the case of time-homogeneity we have $p_{i,j}(t) = p_{i,j}$ for all $t = 1,2,\ldots$. This defines the transition matrix $P = (p_{i,j})_{(i,j=1,\ldots,I)}$. The t-fold transition matrix $P^{(t)}$ will be denoted by $P^{(t)} = (p^{(t)}_{i,j})_{(i,j=1,\ldots,I)}$. A transition matrix is called ergodic if there exists a $t_0 \in \mathbb{N}$ such that all $p^{(t_0)}_{i,j} > 0$ for all $i, j = 1, \ldots, I$. In all our applications we will have $t_0 = 1$. Then there exists a steady state distribution $\pi^* = (\pi^*_1, \ldots, \pi^*_I)'$ with:

$$
P'\pi^* = \pi^* \qquad (8)
$$

The speed of convergence to the steady state distribution follows a geometrical pattern and is given by:

$$
|p^{(t)}_{ij} - \pi^*_j| = O(|\lambda_2|^t) \text{ for all } i, j \in S, t \in \mathbb{N} \qquad (9)
$$

where λ_2 is the second largest eigenvalue of P', see Juha et al. (2015) for details.

3 A comparison of the Markovian law for respondents and non-respondents

The fade-away effect bases on the same transition law for respondents and non-respondents. In order to replicate the findings of Rendtel (2005) for the ECHP we repeated a similar analysis for EU-SILC.

Junes (2012) investigated the 2006 rotation quarter of the Finnish subsample of EU-SILC. This rotation group remained in EU-SILC until wave 2009[1]. Of these 2353 persons 584 persons, about 25 percent, did refuse to participate in the first wave of SILC. It is possible to compute the disposable household income for the gross sample from the Finnish national register files. In order to make comparisons across time and across persons with a different household composition the disposable household income is divided by the sum of the OECD weights, which are 1 for the head of the household, 0.5 for every additional adult and 0.3 for every child under 14 years. This results in the equivalized disposable income.

We use the framework of a discrete Markov chain between income brackets which create five income states. The income brackets are chosen such that the $FULL$- or gross-sample with 2353 persons is separated into 5 income quintiles[2] Finally, we we had to correct the bracket limits for inflation to avoid a trend in the distribution on the income states. Here we used the increase factor of the median, which was 1.16 from wave 2006 to wave 2009. All income bracket boundaries are multiplied by the reciprocal of the corresponding inflation factor[3].

Table 1 compares the distribution on the income brackets for the $FULL$-sample and on the $RESP$-sample, the respondent part of the sample that participated in wave one of the ECHP (1996) or SILC (2006). By construction the distribution for the $FULL$-sample is identical for both surveys. While we have a virulent under-representation of high incomes in the ECHP, there is virtually no bias in the SILC survey. The reason for this different behavior will be probably due to a different organisation of the field–work: while the ECHP questionnaire was run as a separate survey meaning some extra respondent burden, the SILC questionnaire was completely integrated into the general Finnish income survey, which is a well established survey, see Junes (2012)for details.

Table 2 displays the transition rates between the income states. For each of the two groups the transitions are pooled over the panel waves. A likelihood ratio test[4] on differences of the transition matrices between the two groups resulted in 2*(-12189.03 + 12197.07)=16.06 with $5 * 4 = 20$ degrees of freedom.

[1]As the register income is based on taxation records they refer to the previous year. For this reason Junes (2012) refers to the income years 2005 to 2008.

[2]There were two alternatives here: the first alternative is to choose the income brackets according to a design-based analysis. In this case the income brackets refer to the population quintiles. Or, we may refer to the level of the $FULL$-sample without using the design weights. In this case we refer to the pure biasing effect of the nonresponse at the start of the panel. As the design weights use calibration techniques that try to compensate for a nonresponse bias, the use of the survey weights might obscure the biasing effect of nonresponse, which is the issue here. For that reason we did use the unweighted results in our analysis.

[3]There are different methods of deflation, for example, one might use a consumer price index. However, deflation is not the main topic of this paper and we simply want to avoid trends in the distribution of the income states.

[4]The computations were done with the $l$em package of Vermunt (1997)

	FULL	ECHP	SILC
Quintile	Sample	RESPONDENT Sample	RESPONDENT Sample
$\mathbf{Q_1}$	20.0	21.8	19.3
$\mathbf{Q_2}$	20.0	20.7	20.1
$\mathbf{Q_3}$	20.0	21.8	20.0
$\mathbf{Q_4}$	20.0	20.1	20.5
$\mathbf{Q_5}$	20.0	15.6	20.1
Results from Junes (2012) and Rendtel (2005)			

Table 1: Comparison of the initial bias for income quintiles in the ECHP and SILC

	Responders				
Quintile	$\mathbf{Q_1}$	$\mathbf{Q_2}$	$\mathbf{Q_3}$	$\mathbf{Q_4}$	$\mathbf{Q_5}$
$\mathbf{Q_1}$	76.5	16.2	4.4	2.1	0.7
$\mathbf{Q_2}$	15.7	57.6	19.1	5.7	1.8
$\mathbf{Q_3}$	4.6	17.2	51.4	22.9	3.9
$\mathbf{Q_4}$	3.0	5.9	16.1	58.9	16.1
$\mathbf{Q_5}$	2.8	1.2	3.3	14.0	78.6
	Non-responders				
Quintile	$\mathbf{Q_1}$	$\mathbf{Q_2}$	$\mathbf{Q_3}$	$\mathbf{Q_4}$	$\mathbf{Q_5}$
$\mathbf{Q_1}$	73.9	17.9	5.0	2.1	1.0
$\mathbf{Q_2}$	16.8	58.4	17.1	5.8	1.7
$\mathbf{Q_3}$	4.2	16.7	55.9	18.5	4.6
$\mathbf{Q_4}$	1.2	5.5	15.7	63.9	13.7
$\mathbf{Q_5}$	3.7	2.0	3.9	10.1	79.4

Table 2: Transition rates in percent between income states for EU-SILC. Upper panel: transitions for wave 1 respondents, lower panel: transitions for wave 1 non-respondents

This results in a p-value of 0.72. Hence the null-hypothesis of equal transition matrices cannot be rejected for the Finnish subsample of EU SILC.

A similar result was obtained for the ECHP. Such empirical findings do not hold only for Finland. Juha et al. (2015) report for the German register based panel on Labour Market and Social Security (PASS = Panel Arbeitsmarkt und Soziale Sicherung) equal transition laws between the states "unemployment benefits (Type II)" (UBII) and "not UBII".

For the above comparison we used the time-homogeneity of the Markov chain. A formal test, which checks the equality of the three transition matrices, gives a likelihood ratio of 2*(-12169.7 + 12197.1)=54.8 with $2 * 20 = 40$ degrees of freedom. The corresponding p-value is 0.06. The separate estimates of the transition probabilities, however, don't exhibit a meaningful trend over time, see the Appendix. Therefore we will not reject the hypothesis of time-homogeneous transition matrices. Furthermore, time-homogeneity is not necessary to establish a fade-away effect, see Juha et al. (2015).

4 Attrition behaviour

4.1 Empirical results for the Finnish SILC subsample

Table 3 compares the nonresponse rate of wave 1 (2005) and the attrition rates in waves 2, 3 and 4 (2008). It is a typical feature of panel surveys that the attrition rate sharply decreases after wave 1. This also happens here. However, a look to the case numbers indicates a cumulation of losses which reduces the response rate at wave 4 to only 61 % of the gross-sample size at the start of the panel.

	Number of interviewees	**Respon-dents**	**Response rate (Basis 2005)**	**Nonres-pondents**	**Attrition-rate**
2005	2 353	1 769	75 %	584	25 %
2006	1 769	1 634	69 %	135	8 %
2007	1 634	1 522	65 %	112	7 %
2008	1 522	1 448	61 %	74	5 %

Table 3: Response and attrition rates in the Finnish subsample of EU-SILC

Behr et al (2005) have examined the panel attrition in the national subsamples of the ECHP. They argue that attrition is mainly related to field-work. In an interviewer-based panel like the ECHP the change of an interviewer has negative consequences on participation. Residential mobility is also related to increased attrition as the effort to re-contact the interviewees at the new address is higher. Often these para-data that describe the field work are unrelated with the variable of interest, which is the income quintile position here.

A comparison of the income distribution of those who participated in wave 1 (sample RESP) and those who participated in the last wave (sample OBS) may reveal a possible attrition effect. Table 4 compares the two distributions for the ECHP (last wave =wave 5) and EU SILC (last wave= wave 4). While for the ECHP we see only minor discrepancies between the two distributions, the findings for SILC might indicate an attrition effect with an over-representation

Quintile	ECHP Sample FULL 14616	ECHP Sample RESP 7809	ECHP Sample OBS 5192	EU-SILC Sample FULL 2353	EU-SILC Sample RESP 1769	EU-SILC Sample OBS 1448
$\mathbf{Q_1}$	23.9	22.2	22.4	20.4	20.5	18.9
$\mathbf{Q_2}$	16.9	16.6	17.4	19.8	19.3	18.7
$\mathbf{Q_3}$	18.3	17.9	17.6	18.7	18.2	18.1
$\mathbf{Q_4}$	20.6	21.4	21.8	21.1	21.7	22.2
$\mathbf{Q_5}$	20.4	22.0	20.9	20.1	20.4	22.1
Results from Junes (2012) and Rendtel (2005)						

Table 4: Comparison of the distribution on income states for the three samples FULL (All selected persons wave 1), RESP (All respondents wave 1) and OBS (All observed persons in last wave)

Quintile in previous wave	Response probabilities wave 2	wave 3	wave 4
$\mathbf{Q_1}$	0.918	0.868	0.951
$\mathbf{Q_2}$	0.901	0.916	0.947
$\mathbf{Q_3}$	0.901	0.954	0.948
$\mathbf{Q_4}$	0.934	0.953	0.956
$\mathbf{Q_5}$	0.964	0.965	0.954

Table 5: Comparison of the impact of the income quintile position in previous panel wave on the attrition probability

of the above median incomes and under-representation of low incomes, see Junes (2012).

A direct check of Assumption B is given in Table 5. It displays the estimated response probabilities according to the income state in the previous panel wave. At waves 2 and 3 persons with low income states have a significantly lower response probability than persons in the upmost income state. The differences are about 5 percent points. However, this tendency has completely disappeared in wave 4 where there are virtually no differences with respect to income states. Thus there is no indication of a constant fixed link between income position and attrition that is established by some kind of habit.

In order to get a deeper insight about the impact of income on attrition we used a local regression approach (Loader 1999) to demonstrate the impact of the unclassified income on the probability to respond. Figure 1 displays the estimated probabilities and their confidence intervals. For the computation the R-Package $locfit$ was used, see Loader (2013).

The results from Figure 1 re-state the findings from Table 5. For waves 2 and 3 persons with lower incomes in the previous wave have the tendency to respond with lower probability. However, there is not a global trend over the whole range of incomes.

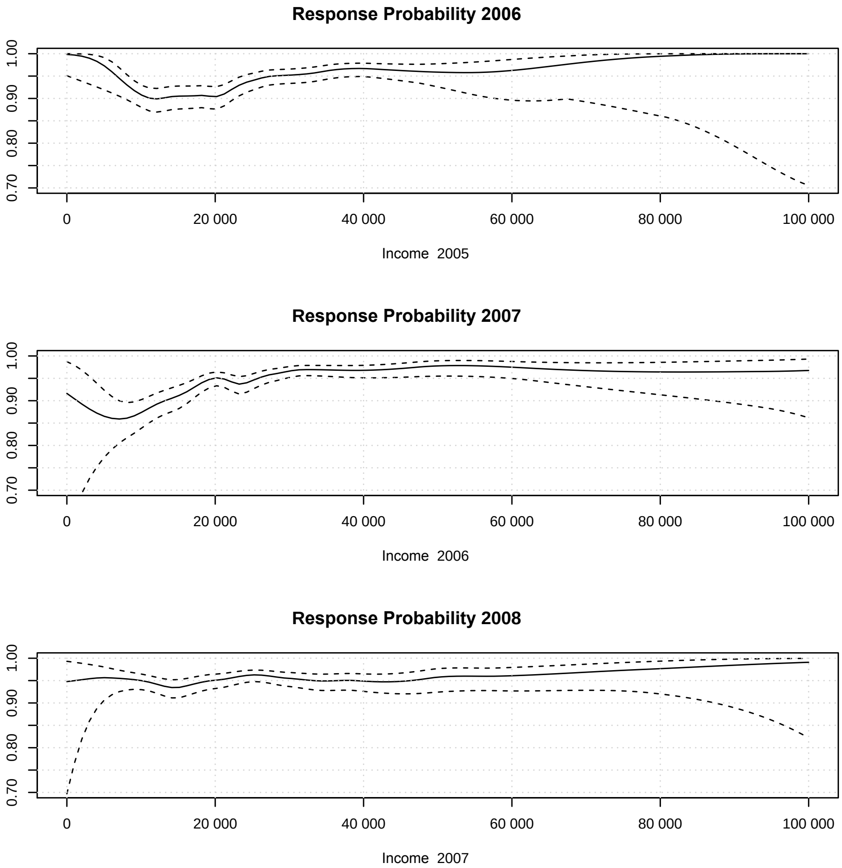

Figure 1: Local regression of the impact of the income in previous wave on panel attrition

4.2 Simulations of initial nonresponse and panel attrition

The results on attrition may be somewhat misleading as there is almost no initial nonresponse bias for SILC. With a substantial initial nonresponse bias there are also larger effects of the swing-in into the steady state distribution that have to be balanced against an attrition effect. Therefore we simulate a substantial initial nonresponse bias and investigate the effect of deviations from Assumption B.

For the simulation runs we used a joint transition matrix $\mathbf{P}$ that is estimated from the respondents and non-respondents. It is a mixture of the transition matrices displayed in Table 2. The values can be found in the appendix in Table 11. We use 6 different starting distributions of the Markov chain as an artificial $RESP$ sample, which are displayed in Table 6.

	Starting Distribution					
	1	**2**	**3**	**4**	**5**	**6**
$\mathbf{Q_1}$	0.218	0.235	0.320	0.135	0.150	0.300
$\mathbf{Q_2}$	0.207	0.200	0.250	0.165	0.225	0.160
$\mathbf{Q_3}$	0.218	0.225	0.190	0.215	0.240	0.100
$\mathbf{Q_4}$	0.201	0.210	0.150	0.225	0.225	0.150
$\mathbf{Q_5}$	0.156	0.130	0.090	0.260	0.160	0.290

Table 6: Starting distributions of the RESP-sample on the quintile positions $\mathbf{Q_1}$ to $\mathbf{Q_5}$ in 6 different simulation scenarios

Scenario **1** is the situation of the Finnish ECHP at it's start with an under-representation of the persons in the upmost quintile. In Scenario **2** the situation is even somewhat more skew with an additional moderate over-representation of the lowest quintile. Scenario **3** is even more extreme with a substantial over-representation of the lowest quintile and a substantial under-representation of the upmost quintile. Scenario **4** is in the opposite direction. Here the poor people are under-represented while the rich persons are over-represented. In Scenario **5** we have an over-representation of the mid-quintile positions. And finally scenario **6** displays a situation where the extreme categories are over-represented.

If we measure the initial nonresponse bias by the Euclidian distance to the distribution of the $FULL$-Sample, which is (0.2,0.2,0.2,0.2,0.2), we get the values displayed in Table 7

Scenario	**1**	**2**	**3**	**4**	**5**	**6**
	0.0513	0.0828	0.1778	0.0995	0.0834	0.1794

Table 7: Initial Nonresponse bias the 6 scenarios of the simulation runs

These 6 nonresponse scenarios are combined with 6 attrition scenarios which are displayed in Table 9. Each row represents a different attrition scenario. The first 5 columns display the response probabilities with respect to the previous income position. The last column under symbol $|\cdot|$ measures the maximum difference between the response probabilities, which is a measure of selective attrition.

Table 8: Six attrition scenarios with differential response probabilities in each panel wave

Attrition scenario	$\mathbf{p(Q_1)}$	$\mathbf{p(Q_2)}$	$\mathbf{p(Q_3)}$	$\mathbf{p(Q_4)}$	$\mathbf{p(Q_5)}$	$\mid\cdot\mid$
A	0.9120	0.9242	0.9364	0.9485	0.9607	0.05
B	0.8570	0.8935	0.9164	0.9475	0.9718	0.11
C	0.8000	0.8532	0.9365	0.9607	0.9807	0.18
D	0.9720	0.9443	0.9274	0.9185	0.8790	0.10
E	0.9020	0.9242	0.9663	0.9424	0.9020	0.06
F	0.9720	0.9242	0.8564	0.9085	0.9420	0.12

Table 9: Six attrition scenarios with differential response probabilities in each panel wave

Attrition scenario **A** reflects a linear trend in the probability to respond. The maximum difference in the response rates is 5 percentage points which is regarded as a mild violation of Assumption B. Scenario **B** increases this difference to 11 percentage points and generates a clear differential attrition between low and high income people. Scenario **C** is even more dramatic in the same direction. Scenario **D** reverses Scenario **B**. Now the rich ones are not so willing to cooperate. A two sided approach is displayed in Scenario **E**. Here the extreme categories have a lower tendency to stay in the panel. Finally, Scenario **F** reflects a situation where the extreme categories are more cooperative than the middle income groups.

These response probabilities are applied for the 3 transitions to waves 2, 3 and 4. They are combined with the 6 initial bias scenarios. We compare at each wave t = 1,2,3,4 the simulated distribution on the state space for the $FULL$-sample, the $RESP$-sample and finally the OBS-sample, the net-sample at wave t, which resulted from attrition. Denote the Euclidian distance between the distributions in $FULL$ and the $RESP$ sample in wave t by $\mathbf{B_t^{FR}}$. Similarly, $\mathbf{B_t^{FO}}B$ denotes the distance between the $FULL$ and the OBS sample in wave t. These distances are used here as measures for the absolute bias of the nonresponse.

Figure 2 compares the decline of $\mathbf{B_t^{FR}}$ (solid line) and $\mathbf{B_t^{FO}}$ (one line for each of the 6 attrition scenarios). All 6 scenarios demonstrate a substantial convergence of the distribution of $RESP$-sample to the distribution of the $FULL$-sample within 3 successive panel waves. This is a consequence of the second eigenvalue of the transition matric P, which is λ_2=0.816. Because of $(\lambda_2)^3$= 0.54 we can expect the bias to decrease by a factor of about 0.54. The violation of Assumption B (no selective attrition) leads in most cases to a variation of the decrease around the $RESP$-sample line. However, the monotone decrease pattern is preserved in 28 out of 36 cases. There are 7 cases with a non-monotone pattern where the bias re-increases in wave 3 or 4. This happens in the scenarios **1B** , **1C** ,**1D** ,**2C** , **4C** and **5C**. Attrition scenario **C** represents the most severe violation of Assumption **B** with a response differential of 18 percentage points, that is applied repeatedly. Such a stable, highly selective drift seems to be rare for real panels. In most cases moderate violations of assumption **B** will dampen or accelerate the fade-away effect. So the combination of the scenarios **1**, **2**, **3** with over-representation of the high incomes with the attrition scenarios **D**, **E** and **F** dampen the fade-away effect. However, the monotone pattern persists! Response pattern **A** and **E** with a response differential of about 5 percentage points have almost no effect on the fade-away effect.

In order judge the attrition effect on the speed of the fade-away effect we compute the relative bias, i.e. $\mathbf{B_4^{FR}}/\mathbf{B_1^{FR}}$ or $\mathbf{B_4^{FO}}/\mathbf{B_1^{FO}}$. Table 10 compares the relative bias for the 6 attrition scenarios with the $RESP$-sample. Here small values indicate a high fade-away effect. If the relative bias is 15 % above the corresponding $RESP$-value we mark the combination of the start and the attrition scenario with red color. In case of a relative bias less than 15 % of the corresponding $RESP$-value we use a green mark. Table 10 reveals 27 (out of 36) fields which are uncoloured. 12 red fields have to be balanced against 7 green fields.

	Scenario attrition						
Scenario at start	**A**	**B**	**C**	**D**	**E**	**F**	**RESP**
1	0.20	0.38	0.90	1.00	0.59	0.75	0.47
2	0.28	0.20	0.47	0.77	0.49	0.62	0.45
3	0.46	0.34	0.21	0.69	0.51	0.66	0.55
4	0.71	0.92	1.14	0.25	0.55	0.53	0.54
5	0.34	0.55	0.83	0.40	0.46	0.09	0.28
6	0.30	0.38	0.49	0.36	0.20	0.40	0.28

Table 10: Relative bias for RESP und OBS after four waves (Red areas: relative bias 15 % above RESP-value. Green areas: relative bias 15 % less RESP-value.

The results of this section refer to Finnish data. Misselbeck (2014) analysed also a transition matrix gained from the Iceland subsample of SILC under the same framework. The results were quite similar to the ones reported here despite substantial differences in the transition behavior in Iceland. Therefore we resume that selective attrition does not contradict the fade-away effect per se. The critical point is a strong selective attrition process which lasts permanently over all panel waves.

5 A comparison of the fade-away effect in 25 EU-SILC subsamples

The distribution of income states is one of the core variables of EU-SILC. Here we use the equivalized household income which establishes comparability over households with different composition. In order to establish comparability over time we have also to use some deflation of the income brackets that define the income classes. The results of this section are taken from Dietz (2012), who used the consumer price index for deflation[5] In order to facilitate the comparison across countries we used here the cross-sectional design weights to establish

[5]This differs from the approach in the previous section where we used the ratio of the medians of the equivalence income. To our knowledge the effect of different deflations factors is small.

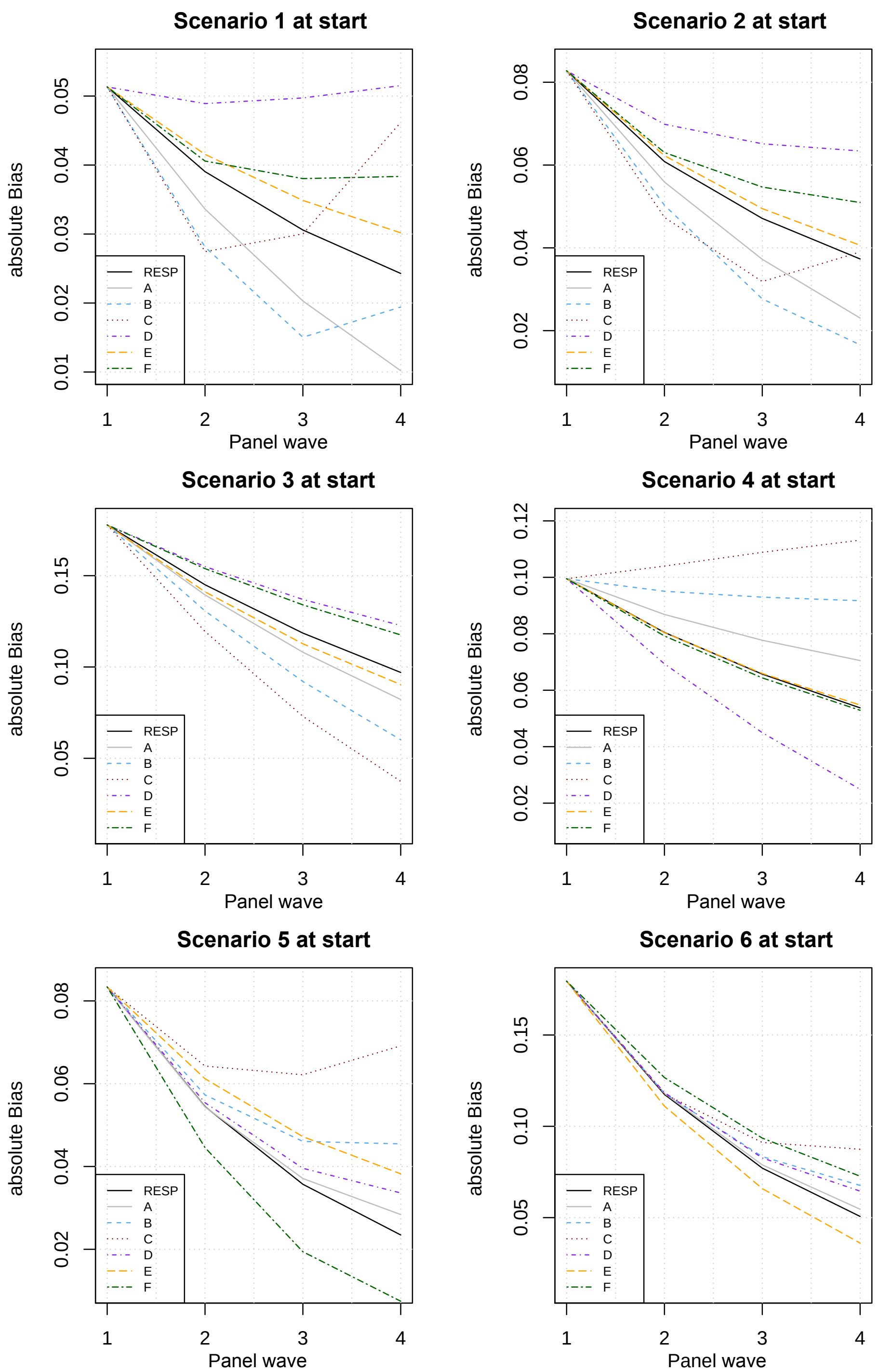

Figure 2: Absolute bias for 6 different starting scenarios (1 to 6) and 6 different attrition scenarios (A to F)

national quintile intervals. For the longitudinal analysis we used the longitudinal SILC weights[6].

The following analysis uses 25 sub-samples based on the EU-SILC User Data Base, taking into account 23 EU Member States[7] plus Norway and Iceland. Figure 3 displays some characteristics of these 25 states included in this analysis. The case numbers refer to the longitudinal cohorts that participate over 4 waves (2006 – 2009). There is an apparent variation of the median income and the Gini-coefficient.

Cntry	N	Median	Min	Max	Gini
SE	4 173	19 857	1	268 782	21.49
DK	3 714	25 347	614	284 042	22.49
SI	9 410	9 237	128	43 413	23.89
NL	5 572	17 958	166	155 200	24.62
CZ	8 646	4 743	269	93 068	25.46
AT	4 964	17 273	11	114 750	25.60
FI	4 825	18 008	154	422 234	26.43
NO	9 124	27 488	1	3 679 263	26.87
BE	4 916	16 867	67	308 000	27.00
FR	18 175	16 250	20	193 690	27.39
MT	3 374	9 239	155	113 006	27.40
IS	1 772	28 458	1 323	529 424	27.75
LU	10 403	29 433	7	1 118 114	27.77
ES	10 047	11 101	3	116 807	29.86
BG	3 038	1 391	160	16 478	30.18
CY	2 853	14 575	4 929	297 977	30.42
HU	6 522	3 794	106	63 370	30.99
IT	15 304	14 727	50	218 733	31.80
UK	7 591	19 735	59	325 666	32.27
LT	4 173	2 574	25	23 376	33.44
PL	12 305	3 154	44	30 640	33.86
EE	4 615	3 655	137	35 285	34.12
GR	4 702	9 174	367	133 800	35.36
PT	3 035	7 153	193	123 899	36.76
LV	3 598	2 637	37	51 025	38.04

Figure 3: Number of Observations, Median, Minimum and Maximum in Euros and Gini coefficient of net-equivalence income (2006), (Source: EU-SILC, Calculations taken from Dietz (2012))

Figures 4 and 5 display the estimated transition matrices between the successive income quintiles. The time period covers the years 2006 to 2009. There are remarkable differences between the transitions matrices within the EU. For example, the probability to stay in the lowest quintile ranges from 0.39 for Latvia (LV) to 0.84 for Cyprus (CY). With respect to the highest income quintile Slovenia (SI) is the most stable country with a probability of 0.90 while Island (IS) has become the most risky country for high incomes with a probability of 0.57. Island is also a country where transitions to the next lower quintile are more frequent than transitions to the next higher quintile position. Just the opposite pattern can be found in Norway (NO). Here the risk to reach the next higher quintile is always higher than the risk to fall down one position.

[6] These methodological differences may explain the different values for Finland, where the results of the previous section will differ from the transition matrix displayed in Figure 4 below.

[7] Some EU Member states, for example Germany, are missing as they do not provide longitudinal data for this data base.

AT				
58.84	23.97	8.84	4.59	3.76
17.52	45.47	21.91	11.20	3.90
4.58	19.10	38.98	26.90	10.44
3.00	8.29	18.11	41.31	29.29
2.62	3.02	5.59	20.21	68.57

BE				
66.89	21.73	6.62	2.65	2.12
13.92	53.27	23.87	5.78	3.16
4.24	15.68	51.24	22.22	6.61
1.62	4.71	18.15	55.90	19.62
1.49	3.12	3.62	15.70	76.08

BG				
47.27	25.88	11.88	8.25	6.72
15.86	36.74	25.69	13.80	7.92
5.84	12.33	30.34	25.08	26.41
3.10	7.29	14.13	33.03	42.45
2.44	2.44	3.33	12.37	79.42

CY				
84.23	11.72	3.37	0.53	0.15
32.96	37.95	25.99	2.80	0.30
23.9	20.73	35.27	17.65	2.45
3.06	20.16	19.35	45.11	12.32
1.34	2.66	9.32	18.4	68.27

CZ				
46.00	28.29	15.35	6.87	3.49
7.81	28.37	39.34	17.98	6.50
2.07	7.32	32.58	43.28	14.75
0.59	1.75	7.82	40.10	49.75
0.14	1.06	2.04	7.42	89.34

DK				
68.16	23.51	4.73	2.14	1.45
10.10	60.36	23.47	4.35	1.72
2.51	14.96	42.37	33.26	6.90
2.71	2.39	18.93	43.25	32.72
1.22	0.81	3.77	13.25	80.95

EE				
53.21	29.41	12.20	3.74	1.44
9.71	43.71	31.25	12.71	2.62
3.17	13.03	39.35	38.30	6.16
1.22	4.83	12.24	53.79	27.92
0.95	0.61	2.05	19.51	76.88

ES				
54.01	25.18	13.56	4.44	2.82
20.53	35.66	27.11	12.41	4.29
8.69	18.93	36.26	25.57	10.55
3.30	7.31	18.01	41.61	29.77
1.48	2.22	4.46	15.05	76.80

FI				
66.37	25.66	4.11	3.03	0.84
10.14	53.69	25.04	9.71	1.42
1.010	13.08	53.37	28.98	3.56
1.65	2.13	11.74	56.43	28.05
0.91	0.70	0.91	7.37	90.11

FR				
54.76	29.75	7.77	3.85	3.86
13.00	47.88	25.81	9.87	3.45
3.67	12.28	46.03	30.03	7.99
1.98	3.37	12.58	54.34	27.72
1.34	1.09	3.07	11.40	83.10

GR				
57.72	25.81	10.85	4.43	1.19
15.49	53.36	25.56	5.10	0.49
5.08	13.19	54.99	23.85	2.89
1.72	2.65	15.98	61.52	18.14
1.23	1.26	3.93	16.79	76.79

HU				
55.74	27.77	10.00	5.53	0.96
12.32	41.75	33.36	9.8	2.77
4.16	18.01	40.73	30.02	7.08
2.12	5.00	17.45	48.93	26.50
1.65	3.51	6.87	16.07	71.90

Figure 4: Transition matrix between income quintiles for 12 EU-Member states (Source: EU-SILC, values taken from Dietz (2012))

IS				
79.04	10.60	6.93	1.38	2.05
40.87	33.79	16.72	6.05	2.57
25.73	22.58	29.85	17.15	4.69
13.05	17.16	22.25	29.75	17.78
5.52	5.29	11.31	20.53	57.35

IT				
68.35	21.98	6.72	1.96	0.99
13.03	55.91	23.40	4.79	2.87
5.06	14.10	51.93	22.83	6.08
1.59	4.05	13.85	53.27	27.24
0.85	1.92	5.37	16.37	75.48

LT				
43.76	32.77	14.23	6.89	2.35
6.82	38.73	36.96	14.69	2.80
3.61	9.26	42.08	37.74	7.31
0.69	2.52	13.02	47.82	35.94
0.09	0.86	3.02	9.22	86.80

LU				
77.4	17.49	3.04	0.99	1.07
20.07	53.26	21.07	4.14	1.45
4.43	15.94	53.47	20.00	6.16
1.41	4.02	19.65	53.59	21.33
1.07	1.84	3.78	16.44	76.87

LV				
39.11	32.00	15.37	12.05	1.46
3.50	37.91	34.01	17.67	6.91
1.53	7.52	34.51	39.66	16.79
1.01	4.94	7.30	31.13	55.62
0.37	1.25	4.26	7.15	86.98

MT				
61.18	25.85	9.44	2.41	1.11
21.34	44.98	25.67	5.27	2.74
6.54	18.83	49.77	19.45	5.41
3.19	8.34	14.83	52.85	20.79
0.76	2.23	6.92	20.9	69.2

NL				
66.26	24.17	5.62	2.68	1.27
9.09	57.83	25.03	4.36	3.70
3.35	6.70	58.88	27.96	3.11
1.35	1.22	10.84	60.14	26.44
0.55	0.91	2.28	8.63	87.63

NO				
63.21	23.08	7.62	4.26	1.83
9.67	47.99	29.56	8.10	4.68
3.18	9.19	47.21	34.87	5.54
2.48	3.03	9.97	53.32	31.20
1.98	1.28	2.75	8.83	85.16

PL				
50.54	33.66	9.97	3.95	1.89
9.62	46.11	30.77	10.55	2.95
1.99	10.42	40.53	36.17	10.89
1.02	2.77	11.72	49.67	34.81
0.69	0.79	2.70	9.54	86.28

PT				
65.38	24.54	6.54	2.78	0.76
13.07	45.92	29.72	9.91	1.39
5.34	16.56	46.85	27.77	3.48
1.37	4.53	11.41	66.4	16.29
0.18	0.97	1.42	9.94	87.49

SE				
70.37	15.26	7.58	4.52	2.28
13.82	56.3	22.87	4.31	2.71
2.67	13.6	48.77	30.14	4.83
0.97	5.34	13.15	54.5	26.04
1.08	0.69	3.2	10.81	84.22

SI				
64.47	25.98	6.83	2.23	0.50
9.55	45.55	33.6	9.53	1.78
1.13	9.61	46.08	35.49	7.69
1.22	1.86	8.96	53.96	34.00
0.35	0.59	0.82	7.87	90.37

UK				
59.1	27.72	7.40	3.33	2.45
25.56	47.11	19.04	5.83	2.45
9.03	27.19	44.06	16.11	3.61
3.58	9.21	28.19	45.25	13.77
3.38	3.47	10.48	20.14	62.53

Figure 5: Transition matrix between income quintiles for 11 EU-Member states plus NO and IS (Source: EU-SILC, values taken from Dietz (2012))

With the SILC user data base (UDB), the initial non-response bias can not be observed, therefore we decided to run a simulation experiment to demonstrate how fast the distribution on the quintiles swings back into the steady state distribution. For the transitions between the quintiles we assume the Assumptions A and B.

The nonresponse bias is simulated by using the six initial distributions, we used for our analysis with Finland. As the main focus is here on the different speed of the fade-away effect we did not analyse possible effects of selective attrition.

In the following tables we will use a global measure over all income states. For this purpose we use the absolute bias B, which is $B = \sqrt{\sum_q b_q^2}$ where b_q is the bias for quintile q. Therefore, the absolute bias is equal for all countries is in the base year 2006 in each of the 6 scenarios. The value differs between the scenarios. It's value is respectively 0.0513, 0.0828, 0.1778, 0.0995 0.0834 and 0.1794. Figure 6 displays the decrease of absolute bias with each panel wave. Until wave 4 in 2009 we observe for all subsamples substantial decreases of this absolute bias. However , the speed of the fade-away process varies substantially between the different scenarios. For the Scenarios 3 and 6 we also see substantial differences across the different SILC sub-samples. Scenario 3 refers to a monotonic over-representation of the low incomes, while Scenario 6 refers to the under-representation of the middle income classes.

The speed of the convergence can be best displayed by the ratio of the absolute bias in two subsequent waves.. Therefore we compare the relative bias B_{2009}/B_{2006}. Figure 7 orders the countries according to their relative bias in Scenario 1. Here, Bulgaria is the country with the largest reduction of the absolute bias (factor 0.26), while Finland turned out to be the country with the least bias reduction (factor 0.61). The ranking of the countries with respect to this reduction factor is quite stable across the different scenarios. Figure 7 displays also for Bulgaria and Finland the absolute bias in 2009 B_{2009}. For the other countries an absolute bias less 2.24 % are displayed with a grey field.

Finally Figure 8 compares the relative bias of column 1 (Scenario 1) of Figure 7 according to their geographical distribution. While there seems to be a pattern of countries with a slow fade-away effect in Northern Europe there is no clear geographical pattern with respect to medium or fast fade-away effect. However, the speed of the swing-in into the steady state distribution depends on the diagonal of the transition matrix, i.e. the probability to stay in the same income quintile. Figure 9 classifies the SILC countries according to their average stability figures which are computed by the mean of the diagonal of the transition matrix. This classification resembles the fade-away effect of Figure 8 quite well. Thus we have arrived at an economic interpretation of the fade-away effect: If the regularity assumption for fade-away apply, the effect will be largest in countries with the lowest stability in income positions.

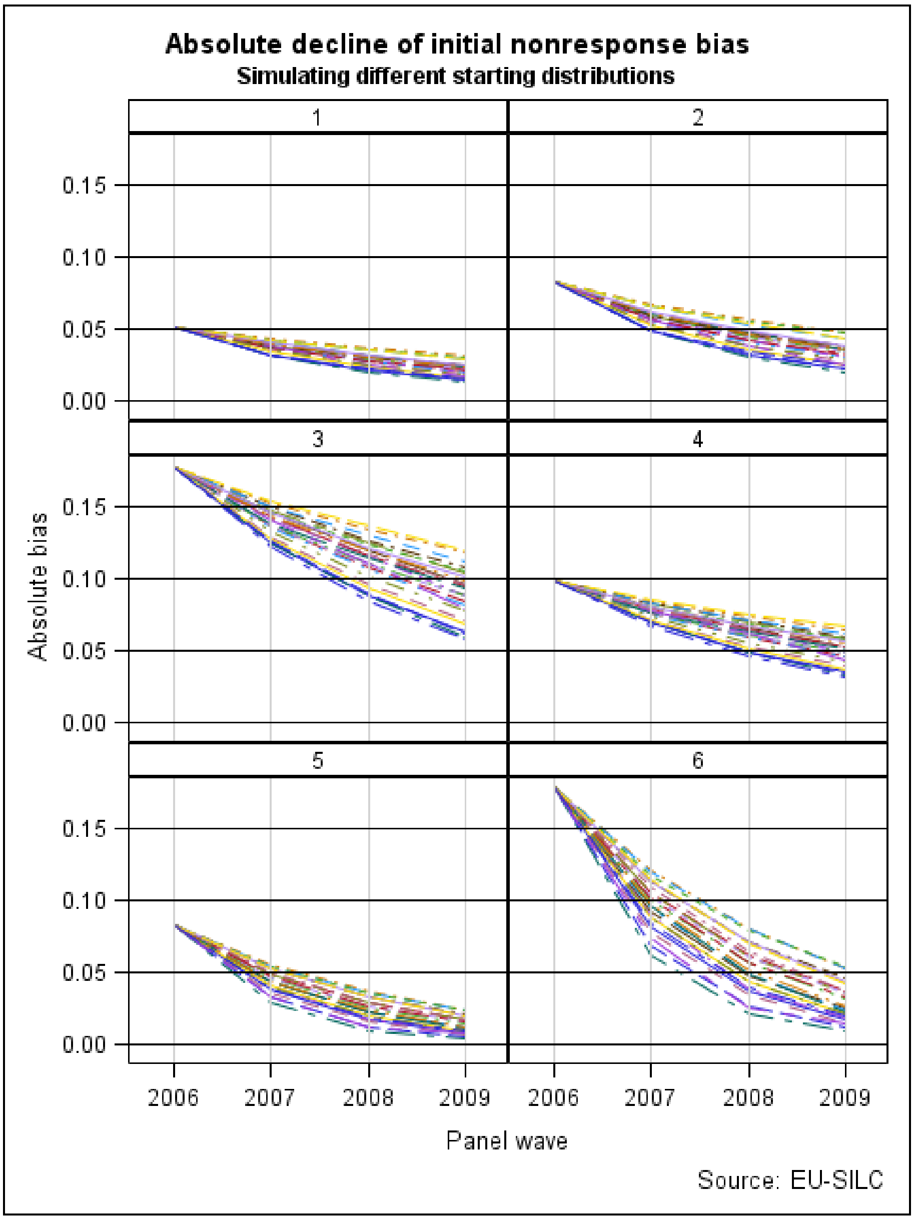

Figure 6: Decline of the absolute bias in the national sub-samples under six different scenarios for initial distribution at wave one (2006). Each country is displayed by a different color (Source:EU-SILC, Calculations taken from Dietz (2012))

No.	Country	Bias in 2009 in percent of bias in 2006 by country and scenario					
		1	2	3	4	5	6
	B(2006)	*(0.0513)*	*(0.0828)*	*(0.1778)*	*(0.0995)*	*(0.0834)*	*(0.1794)*
1	BG	0.26	0.24	0.34	0.34	0.05	0.05
	B(2009)	*(0.0132)*	*(0.0201)*	*(0.0600)*	*(0.0337)*	*(0.0044)*	*(0.0090)*
2	AT	0.28	0.27	0.35	0.35	0.10	0.10
3	UK	0.29	0.28	0.33	0.32	0.11	0.11
4	IS	0.31	0.30	0.35	0.34	0.06	0.06
5	HU	0.32	0.30	0.38	0.38	0.12	0.12
6	LV	0.33	0.31	0.44	0.44	0.09	0.08
7	ES	0.36	0.34	0.40	0.40	0.08	0.08
8	MT	0.37	0.35	0.44	0.43	0.12	0.12
9	CZ	0.38	0.36	0.50	0.50	0.11	0.10
10	EE	0.39	0.37	0.46	0.46	0.14	0.14
11	BE	0.40	0.38	0.47	0.47	0.21	0.21
12	IT	0.43	0.40	0.53	0.53	0.18	0.18
13	FR	0.44	0.41	0.50	0.49	0.17	0.17
14	GR	0.45	0.42	0.50	0.49	0.19	0.20
15	LT	0.46	0.43	0.52	0.52	0.12	0.13
16	PL	0.46	0.43	0.56	0.55	0.15	0.15
17	DK	0.47	0.44	0.59	0.59	0.20	0.20
18	NO	0.47	0.44	0.54	0.53	0.21	0.21
19	LU	0.48	0.45	0.61	0.60	0.26	0.26
20	CY	0.49	0.47	0.54	0.53	0.14	0.14
21	SE	0.50	0.47	0.57	0.57	0.24	0.25
22	NL	0.57	0.53	0.63	0.63	0.28	0.29
23	SI	0.57	0.53	0.68	0.67	0.24	0.23
24	PT	0.59	0.57	0.60	0.59	0.29	0.30
25	FI	0.61	0.57	0.67	0.66	0.29	0.29
	B(2009)	*(0.0315)*	*(0.0475)*	*(0.1187)*	*(0.0653)*	*(0.0238)*	*(0.0525)*

Figure 7: Bias in 2009 as ratio of the bias in 2006 by country and scenario (Source:EU-SILC, Calculations taken from Dietz 2012)

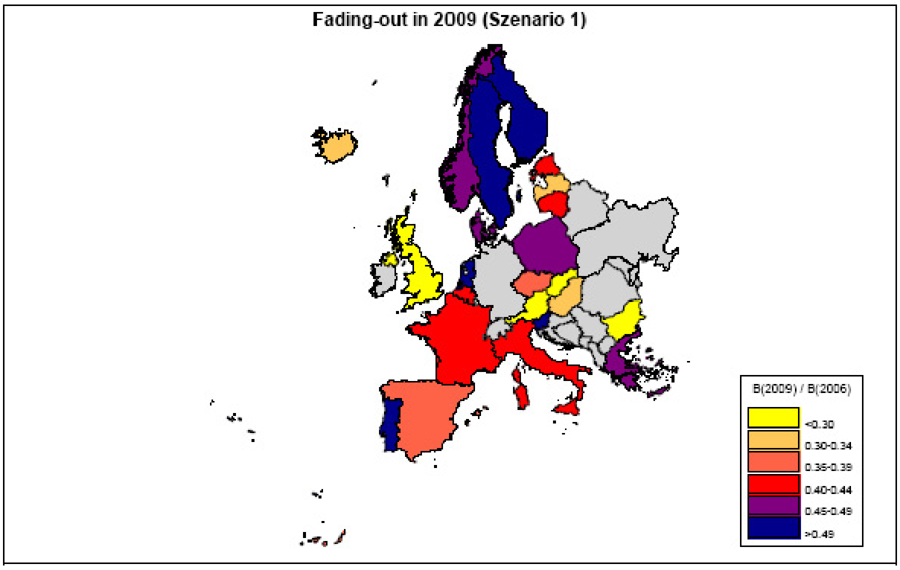

Figure 8: The stability of the relative of the relative initial bias (2006) in 2009 (Source:EU-SILC, Calculations taken from Dietz(2012))

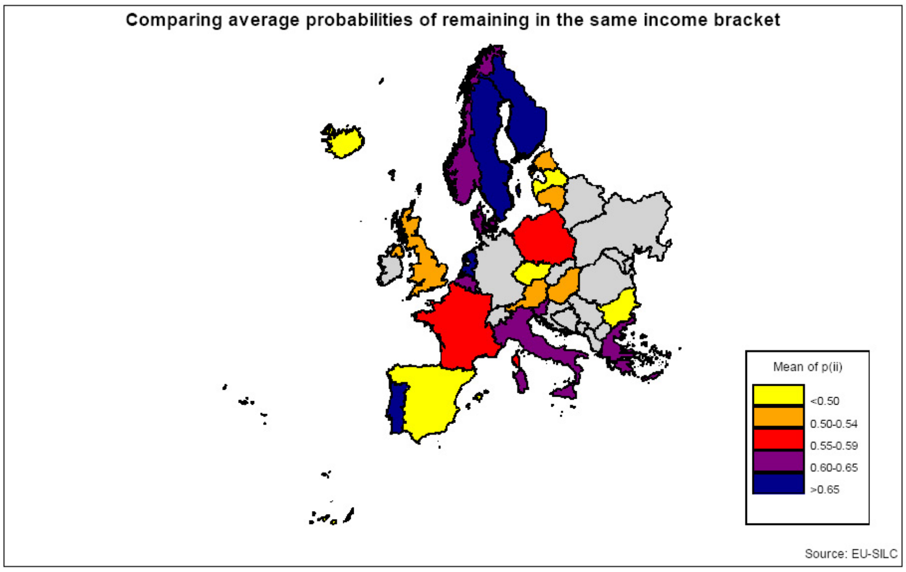

Figure 9: Classification of SILC countries according to their average stability to stay in the same income quintile. (Source:EU-SILC, Calculations taken from Dietz(2012))

6 Conclusions

The size of the fade-away effect depends on the specific convergence properties of the characteristic of interest. Income transitions between income states are a central issue of EU-SILC. Our results display remarkable differences in the speed of the convergence to the steady state distribution between the EU-member states, depending on the stability of the income position.

Even if the regularity conditions for the fade away effect are not perfectly met an initial nonresponse bias will decline rapidly within 4 panel waves. Furthermore, it is not necessary for the $FULL$-sample distribution is near the steady state distribution. As shown by Juha et al. (2015) differences between the FULL-sample and the RESP-sample fade-away in a similar geometric decrease pattern. Even if there exists no steady state distribution, like in the case of a time-inhomogeneous Markov chain, the differences between between the $FULL$- and the $RESP$-sample decline as long as they both follow the same transition law, see Juha et al. (2015). Thus Assumption A turns out to be essential, while mild violations of Assumption B will not turn down the fade-away effect in principle. Only stable attrition differentials larger than 10 percentage points have the potential to counteract the transition laws of income mobility in a substantive way.

In the case that the population is near a steady state distribution large cross-sectional surveys, like a micro-census, should resemble the steady state distribution in the population. Therefore long running panels should converge to this distribution. Fitzgerald et al. (1998) state in their evaluation of the Panel Study of Income Dynamics (PSID) after 30 years a decrease of the distributional differences of the design-weighted PSID results and US micro-census counts. Calibration to micro-census counts is a standard routine to compensate for nonresponse, see for example Estevao/Särndal (2006) and Särndal (2007). However, we can estimate a steady state distribution also from a panel. Therefore Juha et al. (2015) propose to use the steady state distribution for calibration purposes. This approach has the advantage that we can calibrate to the steady state of the variable of interest, which is in most cases not delivered by a micro-census.

The national subsamples of EU-SILC are mostly rotation panels where the respondents stay for four waves in the survey and are then dismissed. The period of four waves was motivated to record longitudinal measures of poverty, for example being at least two times out four subsequent measurements regarded as poor, see for example Atkinson/Marlier(2010). However, panels with longer observation periods are possible and offer increased opportunities for longitudinal research, for example the PSID since 1968, the SOEP since 1984 or the BHPS since 1991, to name only a few.

A short rotation period may be motivated by case number arguments as panel attrition has the tendency to melt down the sample size. Also the coverage of immigrants with the new rotation groups might be regarded as an argument for shorter and therefore larger rotation groups. The fade-away effect argues for longer rotation periods as every "refreshment"-sample by a new rotation group is under the risk to incur a fresh initial wave nonresponse bias. The alternative is a longer observation period with more reliable data. Low case numbers can be anticipated by a first wave sample, that is high enough to guarantee reasonable case numbers also in later panel waves. The coverage of immigrants can be realized with specialized immigrant samples. Therefore our results support the recommendation to prolongate the panel rotation interval from four to six years. Such a change is discussed by Eurostat and the national statistical institutes of the EU member states.

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Appendix

For the simulation runs the transition matrix of Table 11 was used.

Quintile	1	2	3	4	5
1	75.9	16.6	4.5	2.1	0.8
2	16.0	57.8	18.6	5.7	1.8
3	4.5	17.1	52.5	21.8	4.0
4	2.6	5.8	16.0	60.1	16.5
5	3.0	1.4	3.5	13.3	78.8

Table 11: Transition rates in percent between income quintiles. Estimated from transitions for respondents and non-respondents, pooled over waves 2 to 4.

A separate estimation of transition probabilities between for panel waves 2, 3 and 4 is displayed in Table 12 :

State at		State at End				
Start	Transition	1	2	3	4	5
1	$Y_2\|Y_1$	75.1	18.1	3.8	1.9	1.0
1	$Y_3\|Y_2$	77.8	14.1	4.4	2.7	1.0
1	$Y_4\|Y_3$	74.7	17.7	5.4	1.8	0.4
2	$Y_2\|Y_1$	16.7	56.7	18.8	5.7	1.9
2	$Y_3\|Y_2$	17.6	57.2	16.7	7.3	1.1
2	$Y_4\|Y_3$	13.6	59.5	20.4	4.1	2.5
3	$Y_2\|Y_1$	4.5	15.5	50.6	24.7	4.7
3	$Y_3\|Y_2$	4.4	19.9	53.6	18.3	3.7
3	$Y_4\|Y_3$	4.6	16.2	53.6	22.2	3.7
4	$Y_2\|Y_1$	2.7	5.7	14.0	59.5	18.0
4	$Y_3\|Y_2$	2.1	3.7	19.8	59.8	14.6
4	$Y_4\|Y_3$	2.9	7.9	14.1	61.1	13.9
5	$Y_2\|Y_1$	3.4	1.5	3.4	10.2	81.5
5	$Y_3\|Y_2$	3.4	1.6	3.0	13.7	76.4
5	$Y_4\|Y_3$	2.2	1.0	4.0	15.9	76.8

Table 12: Transition rates in percent between income quintiles for EU-SILC: The values in each cell refer to transition 1/2, transition 2/3 and transition 3/4.

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