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**Working Paper — Digitized Version**

## The estimation of poverty-dynamics using different household income measures

DIW Discussion Papers, No. 56a

**Provided in Cooperation with:**

German Institute for Economic Research (DIW Berlin)

*Suggested Citation:* Rendtel, Ulrich; Langeheine, Rolf; Berntsen, Roland (1992) : The estimation of poverty-dynamics using different household income measures, DIW Discussion Papers, No. 56a, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin

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**Discussion Paper No. 56a**

**The Estimation of Poverty-Dynamics Using  
Different Household Income Measures**

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This paper was presented at the Social-Science-Methodology Conference  
in Trento, Italy. The authors wish to thank Greg Duncan for helpful comments.

**Berlin, December 1992**

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### **Abstract**

Household income and composition are the basis for the assessment of income poverty. Panel surveys often provide two possibilities to measure income: The self-assessed reported total household income and the income computed by adding all components at the individual level. While the reported income is easy to obtain from the questionnaire the computed household income needs a lot of data management and imputation of missing components. On the other hand the self-assessed income is under suspicion to underreport the total income.

It is investigated whether these income measures yield different estimates of poverty dynamics. Latent Markov models are used to analyze the two indicators separately as well as jointly. Results for the German socio-economic panel indicate a high sensitivity of estimated poverty stability to measurement error.

# 1 Introduction

At its beginnings poverty research encountered a lot of normative problems: namely when is a person or household regarded as "poor". Since panel surveys - besides other reasons - have been designed to measure the dynamics of poverty, additional questions like characterizing transitory and permanent poverty arise. Generally results on the amount and stability of poverty are very sensitive to their definitorial basis; see for example Kapteyn et al. (1988) and Ringen (1988) for different concepts of poverty definitions and Ashworth et al. (1982), Bane/Ellwood (1986), Berntsen (1992), Berntsen/Rendtel (1991), Duncan (1984) and Hill (1981) for dynamic aspects.

Once one has decided what is meant by saying that a "household is poor" with respect to income, there still remains a problem to be solved: In many panel surveys it is possible to get two measures for the household income: first by asking a household to self-assess the total household income and secondly by adding all components at the individual level to a computed household income. While the first indicator, the reported household income, is easy to obtain from the questionnaire, the second indicator, the computed household income, needs a lot of data management and imputation of missing components.

The data quality of the reported and computed income may be judged with respect to the level of poverty and/or its dynamic behaviour. With respect to the level of poverty it is usually referred to that the reported income underestimates the total household income because the respondents forget to add some components, for example transfers from social aid or from other persons. In the German Income and Consumption Survey (1978) a check of reported and computed incomes revealed that in 50% of the households the reported income was lower than the sum of all components (Euler 1983). Other German surveys produced similar results (Engel 1988). It has to be noted that an underestimate of household income may be irrelevant if poverty concepts are used that are based on a relative definition of poverty, for example a household income less than 50% of the average household income. If the distribution of reported and computed income has — besides a translation — roughly the same shape, then the percentage of (relative) poor households will be the same, regardless what income measure is used.

With respect to poverty dynamics up to now no results were reported that compare these two measurements of household income. Besides the different

measurement also different definitorial concepts come into play: One may ask for the income at the last month or for the average income over the last year.<sup>1</sup> The implications of these different concepts for poverty dynamics are not obvious. Income at the month before the interview ignores income mobility during the rest of the year while average income downweights income differences between single months. Although not necessary, panel questionnaires often link the reported income with the last month, while the individual components of the household income are combined with a monthly, retrospective calendarium of individual activities. Here, in order to avoid lengthy questioning for each activity, only the averaged amount is asked for. In these cases the computed income from the calendarium is more or less an average income. It is not clear to what extent respondents return averages if the questionnaire asks for the last month income. Nor is it obvious in what way the respondents compute averages if the questionnaire asks them to do so in the calendarium.<sup>2</sup> Thus there are good reasons to assume that both incomes inhibit a good deal of measurement error.<sup>3</sup>

At this moment our analytical interest comes into play. The measurement error for high incomes may be quite big. If we are interested in whether the household is poor or not the answer to this question is not effected by moderate measurement error if the true income is far away from the poverty line. On the other hand if income is low, measurement error may play an important part. Measurement error is treated here by latent Markov chain models with one or two manifest indicators, cf. Langeheine/v. d. Pol (1990a, 1990b, 1992a, 1992b). These models generalize turnover tables which compare transitions between poverty states from time  $t$  to time  $t + 1$ . These turnover tables, which are frequently used to describe the dynamics of poverty (cf. Duncan 1984), exhibit a high mobility from poverty to non-poverty and vice versa. The use of these turnover tables is equivalent to the assumption that

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<sup>1</sup>The averaging over different time spans is closely connected with notions about long-term/short-term poverty and the intensity of poverty, i.e. the extent of lack of income, cf. Ashwood et al. (1992) and Headey et al. (1991).

<sup>2</sup>Even the questionnaire may lack precision by simply asking for the "average". If two amounts occur one may either compute the arithmetic mean or the mean weighted by the time intervals the amounts were received.

<sup>3</sup>Besides the reasons mentioned above also rounding of amounts is apparent, cf. Rohwer (1991), Rendtel/Schwarze (1991) for empirical experience with the German Socio-Economic Panel.

transitions between poverty states are Markovian and no measurement error is present. As soon as we deal with the possibility that due to measurement error a poverty state is incorrectly indicated a sequence like poor/non-poor/poor may appear to be an imprecise measurement of “always poor” . Hence the introduction of measurement error will divide the manifest mobility into true mobility (at the latent state) and measurement error. One expects that true mobility is somewhat lower than manifest mobility. With respect to reported and computed income one may ask whether these two measures give the same true mobility and which one of these indicators is the more reliable in measuring the latent poverty position.

Our empirical data base is the German Socio-economic Panel (SOEP) which is a household panel that started in 1984, cf. Hanefeld (1984) , Projektgruppe (1990, 1991) and Wagner et al. (1991).

The article is organized as follows: Section 2 specifies the reported and the computed household income in the SOEP. Section 3 discusses differences in level of poverty which result from the two income measures. In section 4 manifest and latent transitions are computed for the reported and computed income. Section 5 shows a simultaneous analysis of reported and manifest income which serve as two indicators for latent income. Section 6 discusses different reliabilities of the manifest income position in a Mover-Stayer model assuming no measurement error for stayers. Section 7 concludes.

## 2 Reported and Computed Income in the SOEP

### 2.1 The Reported Income

In each wave of the SOEP the main respondent of a household is asked: “If you add all: What is the total monthly amount of the household net income of all household members today? Please report the monthly net amount, i.e. the amount after tax and social insurance. Regular payments like aid for dwelling and children, student loans, alimony payments, etc. add to the amount! In the case of “I don’t know”, please estimate the amount”.

There are three points to note: First it was asked to add the regular income of **all** household members. But there may be situations where the respondent is not well informed about the income of all household members or

some incomes may be not regarded as part of the household pool, for example the income of persons that don't belong to the family of the respondent <sup>4</sup> or the income of children.

Second, it was asked to include **regular** transfers which is somewhat vague, although it seems that annual gratifications, like a 13th salary, are excluded.

Third, the net income in a certain month was asked for. In case the household belongs to a selfemployed person only a rough guess for the net is possible since the annual net is only known after the taxation which is done a year after the interview. There also is no obvious rule to recalculate the actual monthly net from the annual net.

## 2.2 The Computed Income

The SOEP questionnaire asks all adult members of a sampled household for their individual income in a retrospective calendarium.<sup>5</sup> For each activity of the preceeding year it is asked for the **average gross** income. The reasons for this design were twofold: Although it is desirable to have information about the individual income for each month, this was considered to be a too hard burden for the repondent. One has to admit that "average" (for the individual income) is as vague as "regular" (for the household income).<sup>6</sup> The gross income was asked for since in many cases the taxation was not known for the previous year.<sup>7</sup> Since all tax-relevant information (household and family composition) was known from the panel, it was decided to estimate net income from gross income (see Berntsen (1992) for details).<sup>8</sup>

The computed household income in the SOEP <sup>9</sup> is strictly linked to the computed annual household net income. As a consequence of using the an-

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<sup>4</sup>This may be regarded as an argument against a homogeneous welfare level within households. From this reason Guillot/Jeandidier (1992) regard income groups within households.

<sup>5</sup>For employees the questionnaire also asks for their current net income.

<sup>6</sup>One can imagine that a very detailed but precise, formula like question for the average income would not operate successfully in field work.

<sup>7</sup>The taxation was asked for in the next panel wave.

<sup>8</sup>In principle it is possible to use the taxation information from the questionnaire. But this information lacked especially at the beginning of the panel from high item- and unit-nonresponse.

<sup>9</sup>The variable and its components were added to the data base.

nual income all annual gratifications are included. For comparison with the reported income the annual income was divided by 12.<sup>10</sup> Hence, solely by this conceptual difference we will expect that computed income is bigger than reported income.

It has to be mentioned that, in order to compute the household income from its various components, extensive use of data checking - cross-sectional and longitudinal - has been made. Also missing values for components had to be imputed in order to compute total household income. This time-consuming task contrasts with the use of the reported income, where almost no data checking was done for the analysis presented here.

### **3 Comparison of reported and computed income with respect to the level of poverty**

In this section we present a cross-sectional comparison of reported and computed income for the first three waves of the SOEP (1984, 1985, 1986). The means <sup>11</sup> of these household incomes in table 1 differ in all waves by about 650 German Mark. This fairly high difference is reduced to less than half, if we switch from the nominal household income to the equivalence income. The equivalence income accounts for the different household composition and tries to make comparable household incomes with different composition. This is necessary not only for inter- household comparisons but also for intra-household comparisons over time, if the household composition changes over time. The equivalence income is different from a simple per capita income. It also takes into account the needs of the household members <sup>12</sup> as well as the economics of scale.<sup>13</sup>

At least theoretically there are numerous ways to calculate different equivalence scales. As Rohwer (1991) demonstrated, empirical results are quite

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<sup>10</sup>One could, in principle, compute a different version of household income which is conceptually closer to reported income. This version would use reported individual net incomes for employees.

<sup>11</sup>Since we want to display the different income measurements in the sample, no weighting procedure was used to calculate the means, cf. Rendtel (1991, 1992).

<sup>12</sup>The needs of children differ with their age. The scale of needs used in the analysis was in accordance with the German legislation for social aid.

<sup>13</sup>A second adult gets a weight factor 0.8 instead of 1.0.



**Table 1: Comparison of computed and reported household income**

|                         | wave 1<br>(1984)          | wave 2<br>(1985) | wave 3<br>(1986) |
|-------------------------|---------------------------|------------------|------------------|
|                         | computed household income |                  |                  |
| valid cases             | 5313                      | 5081             | 5022             |
| mean                    | 3218.8                    | 3348.9           | 3501.0           |
| mean equivalence income | 1522.9                    | 1585.8           | 1671.0           |
| standard deviation      | 850.0                     | 880.0            | 927.0            |
|                         | reported household income |                  |                  |
| valid cases             | 5579                      | 5010             | 4815             |
| mean                    | 2585.2                    | 2689.2           | 2806.3           |
| mean equivalence income | 1273.9                    | 1307.1           | 1372.6           |
| standard deviation      | 780.0                     | 717.0            | 742.0            |

stable with respect to different scales.

The use of the household composition at the time of the interview may be questionable for the computed income — i.e. the average annual income — if the household composition changed during the year. Since household composition has a great impact on equivalence income, an imprecise account for a changing household composition may introduce a large “measurement” error.<sup>14</sup>

In poverty research two different concepts were used to define the poverty status of a household: one can use a poverty line which is defined by the amount of needs that are considered to be necessary to live at a certain level of welfare. Such a poverty line is based on absolute numbers. Usually such an absolute poverty line is hard to establish. It is much easier to calculate relative poverty lines. The concept of relative poverty states that a household which has less than a given percentage of the average equivalence income at its disposal is considered to be relatively poor. It is still an open question how to choose the percentage of average income that defines the poverty line.

<sup>14</sup>In the SOEP it is possible to reconstruct the household composition for each month in the year. In order to compute the correct equivalence income one would have to know the household income for each month or at least for the periods of different household composition.

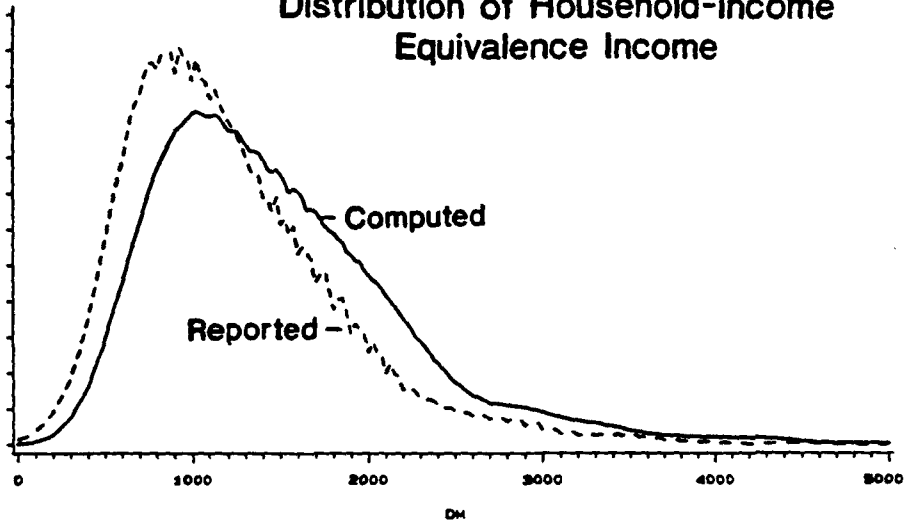
While mostly the 50%-mark is used for the dichotomization of households into poor and non-poor, we additionally used a three state description of poverty, namely less than 40%, between 40% and 60% and above 60% of average equivalence income. Also, in order to study the effect of different categorizations, we used a 4-category scheme which splits the range from 40% to 60% into two separate categories (40% to 50% and 50% to 60%).

If we use the concept of relative poverty line, i.e. different poverty lines for the reported and the computed income were used, table 2 reveals that the resulting poverty rates differ only to a maximum of two percentage points, even if a categorization up to four poverty states is used. The reason for this close coincidence is the very similar shape of the cross-sectional distribution of reported and computed income. Figure 1 displays a kernel estimate <sup>15</sup> of the wave 1 income distributions. One gets the impression that the two densities differ in their lower part only by translation. Note also the unsmooth behaviour of the reported income density which exhibits severe rounding, cf. Rendtel/Schwarze (1991) and Rohwer (1991).

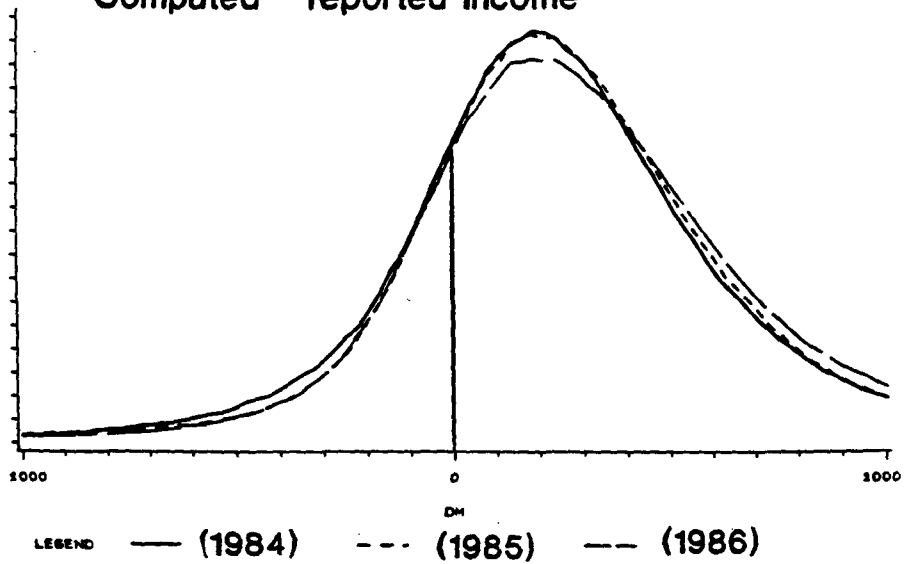
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<sup>15</sup>The kernel function was a normal density with a standard deviation of 100 German Mark. This value corresponds about 0.13 of the standard deviation of the income distribution. The optimal smoothing factor is  $1.06/n^{-1/5} = 0.20$ , if the density to be estimated is normal, cf. Silverman (1986). So there has been a slight undersmoothing in order to preserve a potential multimodality of the income distribution.

# Distribution of Household-Income Equivalence Income



## Distribution of Differences Computed - reported Income



**Table 2: Comparison of percentage of households in different poverty states**

|               | 2 categories |           | 3 categories |       |           | 4 categories |       |       |           |
|---------------|--------------|-----------|--------------|-------|-----------|--------------|-------|-------|-----------|
|               | $\leq 50$    | $\geq 50$ | $\leq 40$    | 40-60 | $\geq 60$ | $\leq 40$    | 40-50 | 50-60 | $\geq 60$ |
| <b>wave 1</b> |              |           |              |       |           |              |       |       |           |
| computed      | 11.8         | 88.2      | 4.9          | 16.1  | 79.0      | 4.9          | 6.9   | 9.2   | 79.0      |
| reported      | 12.9         | 87.1      | 5.9          | 16.9  | 77.2      | 5.9          | 7.0   | 9.9   | 77.2      |
| <b>wave 2</b> |              |           |              |       |           |              |       |       |           |
| computed      | 11.0         | 89.0      | 4.3          | 15.9  | 79.8      | 4.3          | 6.7   | 9.2   | 79.8      |
| reported      | 12.3         | 87.7      | 5.5          | 16.8  | 77.7      | 5.5          | 6.8   | 10.0  | 77.7      |
| <b>wave 3</b> |              |           |              |       |           |              |       |       |           |
| computed      | 10.0         | 90.0      | 4.1          | 14.8  | 81.0      | 4.1          | 5.9   | 8.9   | 81.1      |
| reported      | 11.5         | 88.5      | 4.9          | 15.7  | 79.4      | 4.9          | 6.6   | 9.1   | 79.4      |

Due to the different concepts which exclude annual gratifications for the reported income and include them for the computed income the translation of the respective densities in figure 1 is not surprising. What is more striking is the fact that the order of reported and computed income is reversed in about 1/3 of the cases, i.e. the reported income is higher than the computed income as demonstrated in figure 2. This contradicts the above mentioned hypothesis that — due to omission of single items — the reported household income is always less than the sum of its components. In this case we would have expected that the differences of computed minus reported income are concentrated in the positive range of figure 2.

## **4 Comparison of reported and computed income with respect to the dynamics of poverty**

We will now compare the dynamics of poverty in terms of two turnover tables,  $T_{2|1}$  for the turnover of poverty status from wave 1 to wave 2 and  $T_{3|2}$  for the transition from wave 2 to wave 3. Table 3 compares  $T_{2|1}$  and  $T_{3|2}$  for the reported and computed income. The results are displayed for

**Table 3: Comparison of turnover tables between poverty states for computed and reported Income**

|          |           | starting<br>distrib. | transition<br>1 to 2<br>$T_{2 1}$ |      |      | transition<br>2 to 3<br>$T_{3 2}$ |      |      |
|----------|-----------|----------------------|-----------------------------------|------|------|-----------------------------------|------|------|
| computed | $\leq 40$ | 0.05                 | 0.48                              | 0.34 | 0.18 | 0.52                              | 0.32 | 0.16 |
|          | 40-60     | 0.16                 | 0.10                              | 0.59 | 0.31 | 0.08                              | 0.61 | 0.31 |
|          | $\geq 60$ | 0.79                 | 0.01                              | 0.06 | 0.93 | 0.01                              | 0.05 | 0.94 |
| reported | $\leq 40$ | 0.06                 | 0.46                              | 0.35 | 0.20 | 0.41                              | 0.37 | 0.23 |
|          | 40-60     | 0.17                 | 0.10                              | 0.52 | 0.38 | 0.10                              | 0.53 | 0.37 |
|          | $\geq 60$ | 0.77                 | 0.01                              | 0.08 | 0.91 | 0.01                              | 0.06 | 0.92 |

the categorization of income into three states. There is a high agreement of corresponding elements of the turnover-table. Comparing the diagonal elements which measure the stability of the poverty status, the computed income uniformly turns out to be slightly more stable than the reported income.

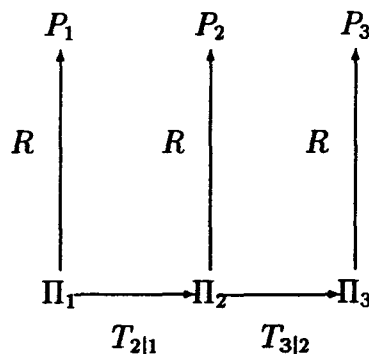
Turnover tables may be used in a mere descriptive manner. In this case no prognosis is made about the entire income profile. If the turnover tables are taken as a model for the entire income profile, this is equivalent to assume that a Markov first-order chain is sufficient to describe the poverty profiles. As a rule Markov first-order chains never fit empirical income data, cf. Shorrocks (1976) and Berntsen/Rendtel (1991) for the SOEP. In our analysis, as well, the comparison of observed and expected frequencies reveals significant discrepancies <sup>16</sup>.

There may be various strategies to improve the Markov chain model. One strategy is to introduce additional covariates to make the risk to stay in poverty more homogeneous within groups with equal covariates, see Kaufmann (1987) for parametric models. But we may also stay within the nonparametric framework of Markov chains. For example we may switch to second order chain models or to a mixture of Markov chains, see Berntsen/Rendtel (1991) for an application of these models to SOEP income data.

<sup>16</sup>For likelihood-ratio test statistics see below.

In this analysis the emphasis is on measurement error. The inclusion of measurement error into the framework of Markov chains dates back to Wiggins (1955, 1973). The problem of estimating such latent Markov models was solved somewhat later, cf. Poulsen(1982), Bye/Schechter (1986) and van de Pol/de Leeuw (1986), see also Langeheine/van de Pol (1990a). The latent Markov model may be represented in a path diagram:

Figure 3: Path Diagram that illustrates a latent Markov Model



The manifest poverty status in each wave is represented by variables  $P_t$  ( $t=1, 2, 3$ ). The latent (or true) poverty position is represented by  $\Pi_t$  ( $t=1, 2, 3$ ). Now transition matrices  $T_{2|1}$  and  $T_{3|2}$  operate on the latent level. The connection to the manifest level is established by a response matrix  $R$ . The elements  $r_{ij}$  of  $R$  are conditional probabilities denoting the probability that a household belongs to category  $j$  on the manifest level given membership in latent poverty position  $i$ . The necessary — in order to identify parameters — but also plausible restriction was made that  $R$  is constant over time.

This model can be applied separately to reported and computed income. However, a simultaneous group analysis (van de Pol/Langeheine (1990)) is more powerful. In this case the groups are defined by reported and computed income. It has to be stressed that one may not overlook that the corresponding estimates are not independent since they stem from the same households. For that reason Chi-square based tests may be misleading. Our emphasis therefore is more on two descriptive measures of fit, namely:

1. BIC (cf. Read/Cressie 1988) is based on information theory:

$$BIC = -2\ln(L) + k\ln(N)$$

where  $L$ =maximum of likelihood function,  $N$ =sample size and  $k$ =number of independent parameters of model. The smaller BIC, the better the fit of the model.

2. Index of dissimilarity  $\Delta$  (cf. Shockey 1988):

$$\Delta = \frac{1}{2N} \sum |f_o - f_e|$$

where  $f_o$  = observed frequency and  $f_e$  = expected frequency and summation is over all cells of the frequency table.  $\Delta$  is normalized between 0 and 1.  $\Delta = 0$  means perfect fit. As in case of BIC there is no precise level that indicates a good fit, "... but a value suggesting fewer than 5% of the cases are misspecified is commonly considered acceptable" (Shockey 1988, p.294).

Latent Markov models offer the possibility to divide the total stability into a part that is correctly represented on the manifest level and a part that is incorrectly represented, cf. Langeheine/van de Pol (1990). The corresponding probabilities are displayed here for the case of three poverty states and three panel waves with obvious generalizations to other cases. The total proportion of stability is characterized by the probability that the latent state remains unchanged over time:

$$\begin{aligned} s_{total} &= \sum_{j=1}^3 P(\Pi_1 = j, \Pi_2 = j, \Pi_3 = j) \\ &= \sum_{j=1}^3 \pi_j T_{2|1}(j, j) T_{3|2}(j, j) \end{aligned} \tag{1}$$

where  $P(\Pi_1 = j) = \pi_j$  ( $j=1,2,3$ ) is the starting distribution of the latent Markov chain and  $T_{2|1}(j, j)$  respectively  $T_{3|2}(j, j)$  are the diagonal elements of the transition matrices  $T_{2|1}$  and  $T_{3|2}$ . The total mobility is the complement of total stability, i.e.  $m_{total} = 1 - s_{total}$ . In case of coincidence of latent and

manifest level we may interpret this as a “true” representation of a poverty profile. Thus we get for the true stability:

$$\begin{aligned}
 s_{true} &= \sum_{j=1}^3 P(P_1 = j, \Pi_1 = j, P_2 = j, \Pi_2 = j, P_3 = j, \Pi_3 = j) \\
 &= \sum_{j=1}^3 \pi_j r_{jj} T_{2|1}(j, j) r_{jj} T_{3|2}(j, j) r_{jj}
 \end{aligned} \tag{2}$$

where  $r_{jj}$  denote the diagonal elements of  $R$ . True mobility is obtained by :

$$\begin{aligned}
 m_{true} &= \sum_{\text{not } k=l=m} P(P_1 = k, \Pi_1 = k, P_2 = l, \Pi_2 = l, P_3 = m, \Pi_3 = m) \\
 &= \sum_{\text{not } k=l=m} \pi_k r_{kk} T_{2|1}(k, l) r_{ll} T_{3|2}(l, m) r_{mm}
 \end{aligned} \tag{3}$$

The simple Markov model and its turnover tables is nested in the class of latent Markov models by restricting the response matrix to the identity matrix. If we let  $R$  free an enormous increase in data fit is achieved.<sup>17</sup> Table 4 displays the estimated <sup>18</sup> parameters of the latent Markov model if three poverty states are used.

If we compare the transition matrices of the reported and the computed income in the latent Markov model there are no major differences with one exception: transitions from the less than 40%-poverty position. Here we find differences of about 7-9 percentage points. But the standard deviation of these parameters, which are not displayed in table 4, are of the same size, so we may conclude that on the latent level both incomes yield quite the same results.<sup>19</sup>

Looking at the response matrices we see that both incomes are quite reliable. Even the middle state (40%-60%) is correctly returned with high

<sup>17</sup>The likelihood-ratio statistic drops from 403.18 (DF=24) to 8.86 (DF=12).

<sup>18</sup>For all computations the program package PANMARK (v.d.Pol et al. (1991)) has been used. The estimates are ML and are obtained by use of the EM-algorithm.

<sup>19</sup>Restricting the latent parameters to be equal between the two incomes, yields a likelihood difference of 7.19 (DF=14). Also the BIC decreases from 34557 to 34439, model 7 vs. model 2 in table 6.



**Table 4: Estimates of Latent Markov Model for computed and reported Income**

|           | Latent States        |                      |      |      |                      |      |      | Indicator<br>Response-<br>matrix<br>R |      |      |
|-----------|----------------------|----------------------|------|------|----------------------|------|------|---------------------------------------|------|------|
|           | starting<br>distrib. | transition<br>1 to 2 |      |      | transition<br>2 to 3 |      |      |                                       |      |      |
|           | $\pi$                | $T_{2 1}$            |      |      | $T_{3 2}$            |      |      |                                       |      |      |
| computed  |                      |                      |      |      |                      |      |      |                                       |      |      |
| $\leq 40$ | 0.06                 | 0.69                 | 0.19 | 0.12 | 0.77                 | 0.16 | 0.08 | 0.75                                  | 0.22 | 0.03 |
| 40-60     | 0.16                 | 0.07                 | 0.79 | 0.14 | 0.05                 | 0.81 | 0.14 | 0.02                                  | 0.85 | 0.13 |
| $\geq 60$ | 0.78                 | 0.00                 | 0.03 | 0.97 | 0.00                 | 0.01 | 0.99 | 0.00                                  | 0.02 | 0.98 |
| reported  |                      |                      |      |      |                      |      |      |                                       |      |      |
| $\leq 40$ | 0.05                 | 0.76                 | 0.22 | 0.02 | 0.68                 | 0.28 | 0.04 | 0.78                                  | 0.19 | 0.03 |
| 40-60     | 0.17                 | 0.05                 | 0.81 | 0.15 | 0.05                 | 0.82 | 0.13 | 0.06                                  | 0.76 | 0.18 |
| $\geq 60$ | 0.77                 | 0.00                 | 0.03 | 0.97 | 0.00                 | 0.01 | 0.99 | 0.01                                  | 0.03 | 0.96 |

probabilities. Here the computed income is more reliable than the reported income. As will be shown these differences should not be ignored.

Now we compare total and true stability as well as mobility. In order to make results comparable between reported and computed income latent state parameters have been restricted to be equal for both incomes. As mentioned above this is no serious restriction and consequently in table 5 total stability and mobility are equal for the reported and computed income. For the manifest Markov model total and true values for stability and mobility coincide and here reported income exhibits a higher mobility (0.295) than computed income (0.231). If we switch to the latent Markov model the most striking result is that total mobility has more than halved (0.115). Looking at the percentage of falsely classified income profiles table 5 reveals that the number of wrongly classified stable income profiles is about three times bigger than the respective number of mobile income profiles.

Restricting latent state parameters between the two income measures is not the only way to set equality constraints. One may restrict in different combinations  $R, \pi, T_{i+1|i}$  across incomes and  $T_{i+1|i}$  across time, i.e. stationarity, or  $T_{i+1|i} = I$ , i.e. no mobility. Table 6 displays the corresponding

**Table 5: Comparison of Stability and Mobility of Income Position between manifest and latent Markov models**

|                 | manifest Markov Model |                 | latent Markov Model |                 |
|-----------------|-----------------------|-----------------|---------------------|-----------------|
|                 | computed Income       | reported Income | computed Income     | reported Income |
| total stability | 0.769                 | 0.705           | 0.885               | 0.885           |
| true stability  | 0.769                 | 0.705           | 0.777               | 0.722           |
| error           | -                     | -               | 0.109               | 0.163           |
| total mobility  | 0.231                 | 0.292           | 0.115               | 0.115           |
| true mobility   | 0.231                 | 0.295           | 0.076               | 0.067           |
| error           | -                     | -               | 0.038               | 0.048           |
| total error     | -                     | -               | 0.147               | 0.211           |

**Table 6: Comparison of model fit of different Markov models**

| Type of Markov model   | Model No. | Equality constraints |   |             | Fit measure |        |    |       |          |
|------------------------|-----------|----------------------|---|-------------|-------------|--------|----|-------|----------|
|                        |           | $\pi$                | R | $T_{t+1 t}$ | LR          | P      | DF | BIC   | $\Delta$ |
| manifest               | 1         |                      |   |             | 403.18      | 576.36 | 24 | 34844 | .051     |
| latent, non stationary | 2         |                      |   |             | 8.86        | 8.79   | 12 | 34557 | .004     |
|                        | 3         | x                    |   |             | 9.93        | 9.95   | 14 | 34540 | .007     |
|                        | 4         |                      | x |             | 31.93       | 31.94  | 18 | 34526 | .012     |
|                        | 5         |                      |   | x           | 14.60       | 14.56  | 24 | 34455 | .007     |
|                        | 6         | x                    | x |             | 37.12       | 37.15  | 20 | 34513 | .018     |
|                        | 7         | x                    |   | x           | 16.05       | 16.10  | 26 | 34439 | .010     |
|                        | 8         |                      | x | x           | 62.14       | 61.72  | 30 | 34449 | .025     |
|                        | 9         | x                    | x | x           | 67.58       | 67.01  | 32 | 34436 | .030     |
| latent, stationary     | 10        | x                    |   | x           | 26.13       | 26.02  | 32 | 34395 | .014     |
|                        | 11        | x                    | x | x           | 77.02       | 76.46  | 38 | 34392 | .031     |
|                        | 12        | x                    |   | I           | 130.74      | 129.21 | 38 | 34446 | .029     |
|                        | 13        | x                    | x | I           | 177.01      | 170.10 | 44 | 34438 | .043     |

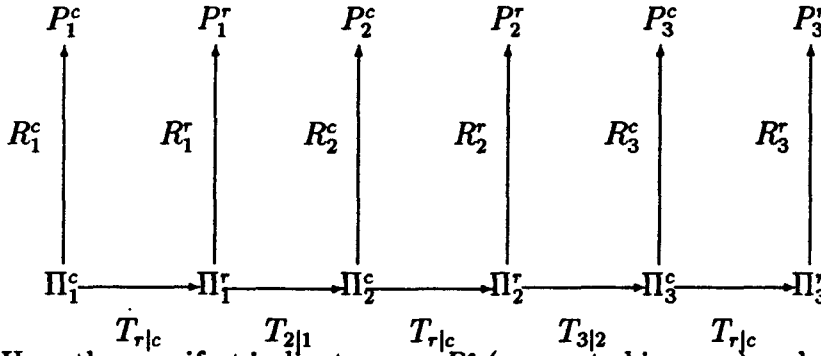
BIC and  $\Delta$  fit measures as well as the likelihood ratio statistic LR and the Pearson statistic P. It reveals that, in addition to the equality of latent parameters between the two incomes,  $T_{t+1|t}$  may be treated as stationary. This corresponds to model no. 10 in table 6. If we additionally restrict R (model no. 11) we get a minor decrease of BIC but LR and P increase remarkably. Thus we may conclude that here are substantial differences in the reliability of the two income measures, while differences on the latent level may be ignored.

The same analysis that was reported here for the case of three income states may be repeated for two and four income states. In these cases we got similar results: the latent Markov model achieves a good fit of the data, and differences for the latent states may be ignored while differences with respect to R are substantial.

## **5 Estimation of poverty dynamics by simultaneous use of reported and computed income**

Since we have two indicators for the same theoretical construct (the poverty state of the household) and since in a separate analysis both indicators revealed the same dynamics on the latent level, we may try to use both indicators simultaneously as indicators for the poverty state of the household. Latent Markov models with multiple indicators may be reduced to single indicator models with a special structure of transition, see Langeheine/van de Pol (1990b, 1992a, 1992b). The idea is demonstrated by the path diagram:

**Figure 4: Path Diagram that illustrates a 2 Indicator, latent Markov Model**



Here the manifest indicators are  $P_t^c$  (computed income) and  $P_t^r$  (reported income) ( $t = 1, 2, 3$ ). The corresponding latent variables are  $\Pi_t^c$  and  $\Pi_t^r$  ( $t=1, 2, 3$ ). If the transition matrix between  $\Pi_t^c$  and  $\Pi_t^r$  denoted by  $T_{r|c}$  is the identity  $P_t^c$  and  $P_t^r$  measure the same latent construct. A change on the latent level is represented by transition matrices  $T_{2|1}$  (between  $t=1$  and  $t=2$ ) and  $T_{3|2}$  (between  $t=2$  and  $t=3$ ). The connection between latent state and manifest observations is established by response matrices  $R^c$  (between  $\Pi_t^c$  and  $P_t^c$ ) and  $R^r$  (between  $\Pi_t^r$  and  $P_t^r$ ).<sup>20</sup>

However, such a simultaneous analysis of the two manifest income positions is immediately confronted with the problem of sparse contingency tables. With  $T$  panel waves and  $S$  poverty states one gets  $S^{2T}$  possible poverty profiles. In the analysis presented here we have  $N=3944$  households.<sup>21</sup> For  $S = 2, 3, 4$  one gets 64, 729 and 4096 poverty profiles. As a consequence one gets a lot of cells with low expected frequencies. In such cases the chi-square approximation for the goodness-of-fit statistics (likelihood-ratio as well as Pearson) may be misleading. Apparently already for  $S = 3, 4$  the problem arises. Table 7 displays the fit measures of the estimated two-indicator models for  $S = 2, 3$  and 4. Large differences between the likelihood ratio (LR) and the Pearson (P) statistic for  $S = 3, 4$  may be seen as an indication that the chi-square approximation is not valid in these cases, cf. Read/Cressie

<sup>20</sup>If  $T_{r|c}$  is the identity matrix neither  $R^c$  nor  $R^r$  have to be time homogeneous in order to guarantee identification of the model parameters. But it turned out - letting  $R_t^c$  and  $R_t^r$  ( $t=1, 2, 3$ ) free - that BIC became worse and only a minor improvement of  $\Delta$  was achieved.

<sup>21</sup>Households where for all three waves both incomes are available.

Table 7: Model-fit of the 2-Indicator latent Markov model

|              | LR      | P       | DF   | BIC   | $\Delta$ |
|--------------|---------|---------|------|-------|----------|
| 2 categories | 390.37  | 469.48  | 54   | 12142 | 0.063    |
| 3 categories | 1083.34 | 1557.24 | 702  | 21420 | 0.116    |
| 4 categories | 2572.39 | 5109.95 | 4044 | 26103 | 0.174    |

(1988). For  $S = 2$ , where the chi-square approximation holds, a bad fit to the data is indicated. Also  $\Delta$ , the index of dissimilarity, has increased substantially as compared with the separate analysis of the two indicators.<sup>22</sup>

Table 8 displays estimates of the two-indicator model for  $S = 3$  poverty states. A comparison with the corresponding values from table 4 is problematic since the two models are not nested. Similar to LISREL models it holds that the less the indicators are correlated the higher is the estimated measurement error. Therefore we expect a decreased reliability of the indicators for the joint latent income position and resulting from this an increased stability of the joint latent income position. Table 8 shows that the decrease in reliability affects both income measures uniformly, lowering the reliability of the 40% and the 40%-60% state from about 0.75 to approximately 0.60. Note that with respect to the joint latent income position reported and computed income have quite the same response matrix  $R$ . In reverse, stabilities to remain in the corresponding latent states raise from a level of about 0.70 to approximately 0.90. Note, however, that the level of poverty, i.e. the starting distribution  $\pi$ , is in good accordance with table 4. Hence the level of poverty is quite stable under different models of measurement error.

As a result of decreased reliability of measurements one gets a further drop in total mobility - from 0.115 in table 5 to 0.061 - and a higher total stability - from 0.885 in table 5 to 0.939.

<sup>22</sup>In order to justify  $T_{r|c} = I$ , we estimated also a model without this restriction. It turned out that this restriction was not significant.

Table 8: Estimates of the 2-Indicator latent Markov model

| Indicators R      |                   |           |                 |                   |           |      |
|-------------------|-------------------|-----------|-----------------|-------------------|-----------|------|
| computed Income   |                   |           | reported Income |                   |           |      |
| $\leq 40$         | 40-60             | $\geq 60$ | $\leq 40$       | 40-60             | $\geq 60$ |      |
| 0.62              | 0.37              | 0.02      | 0.61            | 0.35              | 0.05      |      |
| 0.05              | 0.62              | 0.33      | 0.09            | 0.59              | 0.32      |      |
| 0.00              | 0.02              | 0.98      | 0.01            | 0.04              | 0.95      |      |
| Latent States     |                   |           |                 |                   |           |      |
| starting distrib. | transition 1 to 2 |           |                 | transition 2 to 3 |           |      |
| $\pi$             | $T_{2 1}$         |           |                 | $T_{3 2}$         |           |      |
| 0.06              | 0.95              | 0.05      | 0.00            | 0.85              | 0.12      | 0.03 |
| 0.20              | 0.00              | 0.93      | 0.07            | 0.00              | 0.89      | 0.11 |
| 0.74              | 0.00              | 0.02      | 0.98            | 0.00              | 0.00      | 1.00 |

Table 9: Comparison of model fit between latent Markov model (LM) and partially latent Mover-stayer model (PLMS)

| Number of Categorizations | model | LR      | P       | DF   | BIC   | $\Delta$ |
|---------------------------|-------|---------|---------|------|-------|----------|
| $S = 2$                   | LM    | 390.37  | 469.48  | 54   | 12142 | 0.063    |
|                           | PLMS  | 175.11  | 192.18  | 52   | 11943 | 0.039    |
| $S = 3$                   | LM    | 1083.34 | 1667.24 | 702  | 21420 | 0.116    |
|                           | PLMS  | 849.93  | 1269.93 | 699  | 21212 | 0.094    |
| $S = 4$                   | LM    | 2572.39 | 5109.95 | 4044 | 26103 | 0.174    |
|                           | PLMS  | 2422.61 | 4716.89 | 4040 | 25987 | 0.165    |

## 6 Estimation of poverty dynamics by a partially latent Mover-Stayer model

The model fit of the two-indicator model as shown in table 7 is unsatisfactory. A potential drawback of this model is, that the reliability of measurements depends solely on the present latent position. But there may be income profiles that are far away from the poverty line during all three periods of interest. Even if the amount of income is due to some measurement error their relation with respect to the poverty line is correctly measured resulting in a manifest stable poverty profile. Therefore it seems reasonable to assume that there is a difference in reliability between poverty profiles that indicate "never poor" and poverty profiles that indicate "sometimes poor".

The following partially latent Mover-Stayer (PLMS) model incorporates such different reliabilities. In such a model the reliability of an income measurement depends not only on the actual latent income but also on the entire income profile. The PLMS model assumes that a part of the population consists of stayers with constant poverty status and no measurement error. The PLMS model introduces  $S$  new parameters: the proportion  $\delta^S$  of stayers in the sample and the distribution of the initial poverty states  $\pi_i^S$ , ( $i=1, \dots, S-1$ ) in the stayer sample. Response and transition matrices are restricted for the stayers to the identity matrix.

As table 9 reveals these parameters are significant for all categorizations of income and lead to a substantial improvement in model fit. For  $S = 3$  the estimated PLMS model is displayed in table 10. More than half of the poverty profiles belong to the stayer group ( $\delta^S = 0.543$ ) which turned out to be a mere above-poverty group ( $\pi_3^S = 0.97$ ). The movers still exhibit a high stability on the latent level, which is of about the same size as in simple two-indicator models. Thus exclusion of stayers from the mover group did not introduce a higher mobility. In fact reliabilities of the manifest income positions dropped again, especially reliabilities for the above-poverty state. A comparison of  $R^c$  and  $R^r$  reveals that computed income is to some extent more reliable for the joint income position than reported income.

Table 10: Estimates of the PLMS model

| "Mover"-Group          |                               |                                   |       |           |                                   |       |           |
|------------------------|-------------------------------|-----------------------------------|-------|-----------|-----------------------------------|-------|-----------|
| proportion<br>$\delta$ | starting<br>distrib.<br>$\pi$ | transition<br>1 to 2<br>$T_{2 1}$ |       |           | transition<br>2 to 3<br>$T_{3 2}$ |       |           |
| 0.457                  | 0.13                          | $\leq 40$                         | 40-60 | $\geq 60$ | $\leq 40$                         | 40-60 | $\geq 60$ |
|                        | 0.28                          | 0.94                              | 0.02  | 0.04      | 0.83                              | 0.10  | 0.07      |
|                        | 0.59                          | 0.00                              | 0.86  | 0.14      | 0.01                              | 0.85  | 0.14      |
|                        |                               | 0.00                              | 0.06  | 0.94      | 0.00                              | 0.00  | 1.00      |
| Indicators             |                               |                                   |       |           |                                   |       |           |
|                        |                               | computed Income<br>$R^c$          |       |           | reported Income<br>$R^r$          |       |           |
|                        |                               | 0.51                              | 0.45  | 0.04      | 0.50                              | 0.44  | 0.06      |
|                        |                               | 0.05                              | 0.77  | 0.18      | 0.10                              | 0.59  | 0.31      |
|                        |                               | 0.01                              | 0.10  | 0.89      | 0.03                              | 0.21  | 0.76      |
| "Stayer"-Group         |                               |                                   |       |           |                                   |       |           |
| proportion<br>$\delta$ | starting<br>distrib.<br>$\pi$ | transition<br>1 to 2<br>$T_{2 1}$ |       |           | transition<br>2 to 3<br>$T_{3 2}$ |       |           |
| 0.543                  | 0.01                          | 1.0                               | 0.0   | 0.0       | 1.0                               | 0.0   | 0.0       |
|                        | 0.02                          | 0.0                               | 1.0   | 0.0       | 0.0                               | 1.0   | 0.0       |
|                        | 0.97                          | 0.0                               | 0.0   | 1.0       | 0.0                               | 0.0   | 1.0       |
| Indicators             |                               |                                   |       |           |                                   |       |           |
|                        |                               | computed Income<br>$R^c$          |       |           | reported Income<br>$R^r$          |       |           |
|                        |                               | 1.0                               | 0.0   | 0.0       | 1.0                               | 0.0   | 0.0       |
|                        |                               | 0.0                               | 1.0   | 0.0       | 0.0                               | 1.0   | 0.0       |
|                        |                               | 0.0                               | 0.0   | 1.0       | 0.0                               | 0.0   | 1.0       |



## 7 Conclusions

Our starting point was the question whether different measurements of the household net income lead to different estimates of poverty level and poverty dynamics.

A thorough inspection of self-assessed income and income computed from the components revealed that differences in these two measurements are not only due to the fact that respondents tend to forget single components. More important seem also vague aspects which relate to time, like **regular income** and **average earning** in the questionnaire. While net income refers to an annual income equivalence income, which is the starting point for poverty determination, is strongly affected by household composition which may vary over time. Although there are reasons for a systematic bias in the SOEP — computed income includes annual gratification while reported income excludes these payments — the relation of computed and reported income is reversed in a large proportion of households, i.e. computed income is lower than reported income.

With respect to the concept of relative poverty both measurements yield very similar estimates of poverty level as well as turnover between poverty states. As far as only these characteristics are of interest this might advocate for the use of reported income which is much simpler available. In case one wishes to analyze the impact of welfare transfers on poverty dynamics one would have to switch to computed income which delivers as a by-product of the summation of components also the single components.

Although the two incomes yield similar estimates, there are serious doubts about the reliability of these estimates since the assumption of correct measurement of the income states has become questionable. If one switches to latent Markov chain models, which are direct generalizations of separate bivariate turnover tables, the estimated poverty levels remain quite the same but the estimated poverty transitions exhibit a virulent sensitivity with respect to measurement error. There is a direct trade-off between the reliability of the measurement and the probability to stay in the same poverty state. In this context analysis of level is apparently more stable than analysis of change, cf. Bound et al. (1990).

The latent Markov models we used are flexible in that they are non-linear and non-parametric, and fit well with the question of interest, namely mobility of household income in the vicinity of the poverty line, disregarding

income mobility above the low income-range. In this special context this is a clear advantage over LISREL models.

This model class also avoids to assume independence of errors from true states, as many standard models of measurement error do, see for example Fuller (1987) and Schneeweiß/Mittag (1986). As Bound et al. (1990) show, this assumption is unrealistic for individual incomes and may exaggerate the effect of measurement error. But in the latent markov model each state is allowed to have its own error distribution and the estimates clearly indicate that this error distribution depends on the poverty states.

Bound et al. (1990) also observed that errors on incomes are correlated over time and that this may reduce the effect of measurement error for change analysis. One has to admit that such a possibility is ignored by the latent Markov models. It is not obvious how correlated errors can be build into the framework of latent Markov chains. In a way the PLMS model is a step into that direction, since it allows for a part of the sample — the stayers — perfectly correlated errors : If a household belongs to that group all measurement errors are equal and zero. Yet this introduction of “ correlated errors ” did not increase the mobility between poverty states for the mover group.

We conclude that — although both incomes (reported and computed) yield quite similar high manifest transition rates between poverty states — these results are to some extent misleading suggesting that there is a high exchange between poverty and non-poverty population. This interpretation overlooks the possibility that a household which dropped out of poverty in one year may drop back into poverty in the next year <sup>23</sup>. The use of two poverty measurements makes it possible to discriminate between such unstable poverty profiles and an imprecise measurement of the poverty level. We found good reasons to believe, that a great deal of mobility between poverty states is due to measurement error.

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<sup>23</sup>Recurrent poverty during their first 16 years is by far the most frequent poverty pattern for children in the PSID, cf. Ashworth et al. (1992)

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