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Is the Subjective Financial Well-being of Polish Households Changing with Time? An Empirical Study Based on Constrained Latent Markov Models

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ABSTRACT

Objective: According to the most recent available Eurostat data from 2018, Poles' satisfaction with their financial situation stood at 6.3 points, which was below the EU average. We focus on how households' behaviours have evolved over the past 15 years and their impact on perceived financial well-being.
Research Design & Methods: To comprehensively assess the financial situation of Polish households, this study leverages the Social Diagnosis panel research, a longitudinal dataset spanning eight waves from 2000 to 2015. We employ latent Markov models with varying numbers of latent structures, incorporating survey weights and different sets of transition matrix constraints to analyse the dynamics of financial behaviours and identify potential shifts over time. We consider a heterogeneous transition matrix (not constrained) where the transitions are allowed to vary freely across time points, and partial-homogeneity, allowing some transition probabilities to vary while others remain stable across time.

Findings: Through these models, we find three latent states of Poles with similar level of income perception and describe the process of changing opinion in the analysed period of time. We demonstrate the self-reported financial satisfaction in each round of the national longitudinal Polish survey with a particular interest in financial behaviours before and after the financial crisis. Our analysis reveals a distinct pattern following the peak of the financial crisis: Individuals exhibited a higher probability of remaining in the unsatisfied group, a lower probability of maintaining full satisfaction, and reduced likelihood of transitioning from dissatisfaction to general satisfaction, particularly during the two waves immediately following the crisis.
Implications/Recommendations: Our findings underscore the critical role of financial well-being in shaping individual behaviour and societal outcomes. These insights can inform policymakers as they allocate public funds, emphasising the need to prioritise policies that support financial stability and resilience. Moreover, the proposed approach could be extended to examine respondent behaviour before and after other significant global events, such as the EU accession (2004), the COVID-19 pandemic, or the Russia-Ukraine war.
Contribution: A key contribution of this approach is our conceptualisation of self-reported income satisfaction as a latent, discrete variable, which we analyse using a particular latent variable modelling techniques. This research addresses a critical gap in understanding the evolving dynamics of households' behaviour and the impact of economic downturns on financial perceptions in developing countries like Poland. Moreover, compared to the most recent studies on financial well-being that also cover other national surveys, we demonstrate changes in attitudes across society by analysing all waves of the national longitudinal survey, accounting for the heterogeneous structure of the data and incorporating survey weights.

Article type: original article.

Keywords: constrained latent Markov model, financial well-being, homogeneity, transition matrix.

JEL Classification: C33, C52, D19, I31.

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1. Introduction

The assessment of the income situation of households, their physical equipment, standard of living and the perceptions of the economic situation of households themselves is an important part of the social survey research. The most frequent subject of research interest is the income differentiation of the population with emphasis on households at the risk of poverty, households with the lowest income, the relation of the income group to the household segmentation in social, age, educational and regional categories (Sirovátka & Mareš, 2009).

To assess the income situation of households, most frequently, objective indicators of wealth (for example, level of income, asset allocation) are considered. This paper examines subjective well-being as a rising indicator of societal advancement, potentially offering a more direct assessment of household prosperity than traditional income metrics (Binder, 2014). First, household income is a difficult or sensitive question for many respondents, and it tends to have a high proportion of missing responses. The use of alternative measures should minimise the effect of unreliable household income data, a significant risk considering well-known difficulties measuring household incomes in many parts of the world (Diego-Rosell, Tortora & Bird, 2018). The second reason is that the subjective material well-being variables are likely to account for most of the variance resulting from direct income effects, as well as indirect effects such as relative income (Clark *et al*., 2005).

Many authors emphasise that non-monetary factors of financial satisfaction can transcend the limitations of income-based measures, enabling researchers to delve into the determinants of material well-being, social welfare, and quality of life (Betti *et al*., 2001; Bialowolski & Weziak-Bialowolska, 2014; Białowolski, 2018). Furthermore, it is widely recognised that perceptions of household income significantly influence subjective well-being. Diego-Rosell, Tortora and Bird (2018) demonstrated that material well-being is a primary driver of subjective well-being across all 153 analysed geopolitical regions.

Poland, a nation situated in Central and Eastern Europe, has recently undergone a period of structural and economic transformation. Despite relatively robust economic growth, income inequality has remained relatively modest compared to neighbouring countries like Ukraine, Lithuania, Latvia, and Russia. Nevertheless, Poles often express dissatisfaction with their financial circumstances.

According to the most recent available Eurostat data from 2018 (Eurostat, 2019), Poles' satisfaction with their financial situation stood at 6.3 points (on a 0–10 scale), which was below the EU average of 6.6 points. These data represent the most recent comprehensive and internationally comparable Eurostat evidence specifically concerning subjective financial well-being across EU countries. Although more recent data on overall life satisfaction are available for 2023, with Poland ranking relatively highly (Eurostat, 2024), similarly detailed cross-country data focusing specifically on satisfaction with one's financial situation have not been included in more recent Eurostat publications.

In this study, we address a critical methodological question: How do relevant constraints imposed on the latent part of the Latent Markov (LM) models improve the measure of fit and facilitate the interpretation of socio-economic issues concerning the self-reported material well-being of Poles observed at different points in time? This research question guides our investigation into the optimal modelling approach for longitudinal data on subjective financial satisfaction. By comparing models with different types of constrains, we aim to demonstrate how appropriate restrictions can enhance both statistical performance and substantive interpretability when analysing temporal patterns in Poles' financial well-being perceptions. This question is particularly relevant given the challenges of analysing subjective economic assessments across different economic cycles and social contexts. The question of the changing households' behaviours and the effects of economic downturn on the perception of the financial position for a developing country like Poland is still understudied. This article fills this gap.

To assess the financial situation of Polish households, our study employs the Social Diagnosis (2015) panel research, encompassing all eight waves conducted between 2000 and 2015. Focusing on individual responses from household heads, we investigate the evolution of subjective financial satisfaction in Poland. Our analysis examines self-reported income positions across survey waves, with particular attention to pre- and post-economic crisis behaviour. To capture the evolving dynamics of Polish households, we employ dynamic discrete latent variable models (Bartolucci, Pandolfi & Pennoni, 2022) that allow for transitions between latent classes (states) over time. We adopt especially LM models (Bartolucci, Farcomeni & Pennoni, 2013), incorporating survey weights often overlooked in previous research. By comparing models with varying numbers of latent structures, constraints, and temporal transitions, we gain insights into the changing financial attitudes of Polish households.

The paper proceeds as follows: In section 2, we review the relevant literature describing the most important studies concerning the subjective assessment of financial situation among the Polish society. Then, we outline the adopted latent variable models, namely LM models with different types of constraints (section 3). The data and main results are presented in section 4, whereas some conclusions are given in section 5.

2. Literature Review

In the following, we describe relevant contributions concerning the perceived income satisfaction of households, in particular in connection with the Polish data and studies based on the other national surveys, so as to clarify which are the novelties of the approach we propose.

Gasiorowska (2015) investigated the influence of money attitudes on the relationship between income and financial satisfaction. The study concerning the Polish households' economic well-being in 2013 was based on the hierarchical regression analysis in the group of 356 Polish internet users. The results showed that the level of households' income was only modestly correlated with subjective economic well-being. However, the author notes that the current income may be an inadequate measure of objective wealth, as it does not necessarily represent all economic resources that contribute to a sense of financial satisfaction.

Zalega (2012) examined the subjective assessment of the material condition and the allocation of monetary resources based on questionnaire interviews with 1,896 households of the 10 biggest Polish cities in the year 2011. In that year, only a few respondents assessed the financial situation of their household as very good (2.9%), while 70% of respondents were dissatisfied with the current disposable income. The author, by means of correlation analysis evaluated the relationship between the self-assessment of financial condition and the other variables, such as age, education, gender and income, in the selected group of households.

Hanusik and Łangowska-Szczęśniak (2013) examined the correlation between Polish households' subjective perceptions of their material circumstances and their income, expenses, and the educational attainment of the household head. The econometric analysis based on probit models showed that there is a strong dependence between self-assessment of the material situation and household income, expenses and a clear differentiation of this assessment depending on the level of education of the head of household. The author presented the results for the cross-sectional data budgets of households carried out by the Statistics Poland (GUS) in 2011.

Wałęga (2015) also analysed subjective material situation of young people's households in Poland based on Statistics Poland household surveys in the years 2000–2012. The results, relying mainly on structure analysis shown that the material situation of young people's households is more favourable than that of other households (with a head of the household older than 35 years). A noticeable general improvement in the subjective assessment of the financial situation was especially observed for young people until 2008. However, in 2012, its deterioration, as a result of the financial crisis, was noted.

Gasińska (2016) discussed the most characteristic subjective opinions and assessments concerning the Poles' income situation. The author emphasised that in recent years there has been a clear improvement in the self-assessment of the material situation of households in Poland. The share of very good grades increased significantly, and at the same time, there was a relatively small decrease in the share of negative grades. In all socio-occupational groups, the number of respondents with low and very low ratings of their situation decreased, and at the same time, though at a different pace, the number of good and very good grades increased. The results are based mainly on Social Diagnosis (2015) data in 2000–2015, however the statistical analysis is limited to the regular summary statistics tables.

Kalinowski and Kozera-Kowalska (2017) analysed the correlation between subjectively perceived income levels and demographic factors such as gender, age, education, household structure, and geographic region among rural residents in Poland. The obtained results based on the 1,067 rural respondents, questioned in 2013, indicated that the factors influencing the positive assessment are education and subjectively assessed household's well-being.

Existing studies based on other national surveys (Verbič & Stanovnik, 2006; Popova & Pishniak, 2017; Brzozowski & Spotton Visano, 2019) are limited by their cross-sectional design, providing an incomplete understanding of subjective financial positions in the analysed societies. Researchers such as Chzhen (2016) and Mahdzan *et al*. (2019) acknowledge the shortcomings of these studies and advocate for the use of national longitudinal surveys to effectively evaluate changes in participant behaviour over time.

Note that the assumption of many of the statistical procedures is the homogeneity of the analysed data. In most of the studies regarding the issue of self-reported income position, it is simply supposed (without prior verification) that the analysed data set is homogeneous and the statistical methods are applied. The problem of heterogeneity of the data is very important, especially when responses are observed on each subject repeatedly over time. Relating to the available studies, one of the important contributions of the provided approach is that we perceive the self-reported income satisfaction as a latent, discrete variable that we analyse by a suitable latent variable model. Compared to the author's previous study (Genge, 2021), we conceive the unobserved heterogeneity dynamically at the same time. The respondents can change the membership of the identified structures (which are referred to as states) over time. A key challenge in this research is model selection, involving the determination of both the number of latent structures (states) and the specific constraints within the LM model. We note that, although the first relevant piece of literature which is specifically devoted to LM models for longitudinal data, is the book by Wiggins (1973), due to technological advancements, these models continue to be developed in modern times (Tullio & Bartolucci, 2022; Brusa, Bartolucci & Pennoni, 2023). The primary advantage of LM models lies in their ability to analyse the evolution of behaviours or phenomena over time. Although prior studies have utilised selected waves and survey weights in their longitudinal analyses (Pennoni & Genge, 2018, 2020), to our knowledge, this is the first study to examine changing households' behaviours using all available waves of a national panel survey while incorporating sample weights. Populations that are oversampled in national data sets have a smaller weight value (Thomas & Heck, 2001). Therefore, incorporating weights into empirical analyses is essential to address the unequal probability of selection, nonresponse, noncoverage, and poststratification. This approach, often referred to as weighting, is a straightforward method for handling disproportionate sampling (Kalton, 1989; Stapleton, 2002).

3. Methodology

3.1. Basic Latent Markov Model

In our investigation, we examine a categorical outcome variable $X^{(t)}$, measured at each time point t, with $t = 1, \dots, T$ ($T = 8$ in our study). The outcome variable $X^{(t)}$ is meant to evaluate the financial well-being of Polish households and includes l_j categories, where l_j represents the number of possible responses for j-th variable, labelled from 0 to $l_j - 1$. We define the vector of outcomes for individual i at time points t as $\boldsymbol{X}\,(X^{(1)}, \dots, X^{(T)})$, which represents repeated observations on the same respondents over time.

It is important to note that we perceive the perception of a household's income as an unobservable, latent characteristic, assessed through questionnaire items. LM models allow us to conceptualise self-reported income position as a time-varying latent variable, denoted as $\boldsymbol{S} = S^{(1)}, \dots, S^{(T)}$, which is considered to be a hidden stochastic process of the first order with u latent states.

A fundamental assumption of the LM model is that the response vectors $X^{(1)}, \dots, X^{(T)}$, are conditionally independent when considering the latent process $\boldsymbol{S}$. Furthermore, the elements $X^{(t)}$ of $\boldsymbol{X}$ are conditionally independent when considering $S^{(t)}$.

The LM model is characterised by various types of parameters that describe:

– the measurement component of the model – the conditional probability distribution of the outcome variable, given the latent states:

$$\phi_{x|s} = p\left(X^{(t)} = x \,\middle|\, S^{(t)} = s\right),\ t = 1, \dots, T,\ s = 1, \dots, u,\ x = 0, \dots, l_{j-1}.$$

– the latent component of the model – the initial π_s and the transition $\pi^{(t)}_{s|\bar{s}}$ probabilities, expressed by the formulas below:

$$\pi_s = p\left(S^{(1)} = s\right),\ s = 1, \dots, u,$$

$$\pi^{(t)}_{s|\bar{s}} = p\left(S^{(t)} = s \,\middle|\, S^{(t-1)} = \bar{s}\right),\ t = 2, \dots, T,\ \bar{s}, s = 1, \dots, u,$$

where s is a realisation of $S^{(t)}$ and $\bar{s}$ is a realisation of $S^{(t-1)}$.

Given the parameters outlined above, the probability mass function of $\boldsymbol{S}$ is defined as follows:

$$p(\boldsymbol{S} = \boldsymbol{s}) = \pi_{s^{(1)}} \prod\nolimits_{t=2}^{T} \pi^{(t)}_{s^{(t)}|s^{(t-1)}},\ s = 1, \dots, u, \tag{1}$$

where $\boldsymbol{s}$ represents a realisation of $\boldsymbol{S}$, including elements $s^{(1)}, \dots, s^{(T)}$. Moreover, the conditional distribution of $\boldsymbol{X}$ given $\boldsymbol{S}$ is computed as:

$$p\left(\boldsymbol{X} = \boldsymbol{x} \,\middle|\, \boldsymbol{S} = \boldsymbol{s}\right) = \prod\nolimits_{t=1}^{T} \phi_{x^{(t)}|s^{(t)}}, \tag{2}$$

for any realisation $\boldsymbol{x}$ of $\boldsymbol{X}$.

The manifest distribution of the response variables in the basic LM model is defined as:

$$p(\boldsymbol{X} = \boldsymbol{x}) = \sum\nolimits_{s} \pi_{s^{(1)}} \pi^{(2)}_{s^{(2)}|s^{(1)}} \dots \pi^{(T)}_{s^{(T)}|s^{(T-1)}} \times \phi^{(1)}_{x^{(1)}|s^{(1)}} \dots \phi^{(T)}_{x^{(T)}|s^{(T)}}. \tag{3}$$

It is important to note that the basic version of the model does not incorporate individual covariates. This framework presumes a uniform latent model for all units and a consistent measurement model across time. Moreover, this version of the model imposes no restrictions on either conditional probabilities or initial and transition probabilities.

To illustrate the progression of the phenomenon of interest, the margnal distribution of each variable $S^{(t)}$ very often are presented in a figure (especially if there are many transition matrices to be analysed). Furthermore, based on the above probabilities the marginal distribution of $X^{(t)}$ may be computed as:

$$p(X^{(t)}=x)=\sum_{s=1}^{u}p(S^{(t)}=s)\phi_{x|s},\ \ x=0,\ldots,l_j-1. \tag{4}$$

3.2. Constrained Latent Markov Model

In the subsequent phase of our analysis, we explore various formulations of the LM model proposed by Bartolucci, Farcomeni and Pennoni (2013) that incorporate constraints related to specific hypotheses of interest. These constraints can pertain to the distribution of the latent process, such as the initial or transition probabilities of the model. Depending on the research objectives, an LM model can also be formulated by imposing constraints on both components.

The following constraint on the initial probabilities may be considered:

$$\pi_s=1/u,\ \ s=1,\ldots,u.$$

This means that, at the beginning of the period of observation, each latent state includes the same proportion of subjects.

Another approach involves imposing constraints on the transition probabilities, which can significantly reduce the model's parameter count. To represent these constraints succinctly, let denote the transition probability matrix with elements $\pi_{s|\bar{s}}^{(t)}$, s = 1, …, u, arranged in a row $(\bar{s})$ by column (s) format.

The most basic constraint on the latent component of the LM model is:

$$\prod^{(t)}=\prod,\ \ t=1,\ldots,T, \tag{5}$$

where $\prod$ is a common transition matrix with elements $\pi_{s|\bar{s}},\bar{s},s=1,\ldots,u$. This aligns with the hypothesis of a time-invariant Markov chain.

A weaker version of the above constraint is:

$$\Pi^{(t)}=\begin{cases}\Pi^{*(1)}, & t=2,\ldots,T^{*}\\ \Pi^{*(2)}, & t=T^{*}+1,\ldots,T,\end{cases} \tag{6}$$

with T^{*} between 2 and $T-1$ and $\Pi^{*(1)}$ and $\Pi^{*(2)}$ being separate transition matrices, with elements $\pi_{s|\bar{s}}^{*(1)}$ and $\pi_{s|\bar{s}}^{*(2)}$, respectively. This aligns with the hypothesis of partial time homogeneity, characterised by two distinct transition matrices: the first applicable until occasion T^{*}, and the second governing transitions subsequent to this occasion (Bartolucci, 2007).

As far as the estimation process is concerned, our study incorporates individual longitudinal sampling weights, denoted as w_i, i = 1, …, n, by maximising a weighted log-likelihood using the Expectation-Maximisation (EM) algorithm (Baum *et al*., 1970; Dempster, Laird & Rubin, 1977). The EM algorithm is applied to estimate the models with latent variables since it is based on the concept of complete data, which is related to the value of every latent variable, further to the response variables (see Bartolucci, Farcomeni & Pennoni, 2013, chapter 3, for more information). Given that the latent configuration is unknown for each respondent, the EM algorithm maximises the observed data log-likelihood by alternating the expectation and maximisation steps until convergence. To prevent convergence to local maxima and comprehensively explore the parameter space, we employ diverse initialisation strategies for the EM algorithm, incorporating both deterministic and random values. To estimate the model, we utilise a specialised function within the LMest package (Bartolucci, Pandolfi & Pennoni, 2017) designed for the software R (The R Core Team, 2025). This function enables the use of multiple initialisations for the EM algorithm.

An essential point in using discrete latent variable whether in basic or advanced forms, is the selection of the number of latent structures (clusters, states, or the number of categories of the discrete latent variable). Following a common rule, initially, we fit the LM model for progressively larger values of u, continuing until we identify the minimum BIC (Schwarz, 1978) and AIC (Akaike, 1973) indices. Subsequently, we attempt to simplify this model by applying various constraints, continuing until further reductions in BIC and AIC are no longer feasible while maintaining the previously determined number of latent states.

To evaluate the quality of the LM model, we also consider the index $\tilde{S}$, a classification quality metric proposed by Bartolucci, Lupparelli and Montanari (2009):

$$\tilde{S} = \frac{\sum_{i=1}^{n} \sum_{t=1}^{T} [\hat{f}^{*(t)}(\boldsymbol{x}) - 1/u]}{(1 - 1/u)nT}, \tag{7}$$

where $\hat{f}^{*(t)}(\boldsymbol{x})$ is the maximum of the posteriori probabilities, with respect to s ($s = 1, \ldots, u$). Note that this measure is based on the entropy index illustrated by Bacci, Pandolfi and Pennoni (2014). The index $\tilde{S}$ ranges from 0 to 1, with a value of 1 indicating perfect classification accuracy and clearly distinguishable latent states. On the other hand, when states are not well separated, most of the probabilities $\hat{f}^{*(t)}(\boldsymbol{x})$ are close to $1/u$ and then $\tilde{S}$ attains value close to its minimum, which is equal to 0.

4. Data and Results

4.1. Data

In the empirical part of the paper, we analyse data concerning self-reported financial status coming from the largest household panel, the Social Diagnosis survey (Social Diagnosis, 2015). Social Diagnosis is a 15-year observational longitudinal study aimed at presenting the well-being, living conditions (financial, societal, cultural) and health issues of the Polish population. To date, data have been collected up until 2015, which is the last issue available. Our analysis centres on the survey question “Is it easy to make ends meet?” which features the following ordered responses: “with great difficulty” (0), “with difficulty” (1), “with some difficulty” (2), “rather easily” (3), “easily” (4). These responses were collected in each wave of the longitudinal survey[1] conducted in 2000, 2003, 2005, 2007, 2009, 2011, 2013, and 2015. The analysed complete data concerns $n = 2{,}768$ (346 complete observations at each point in time).

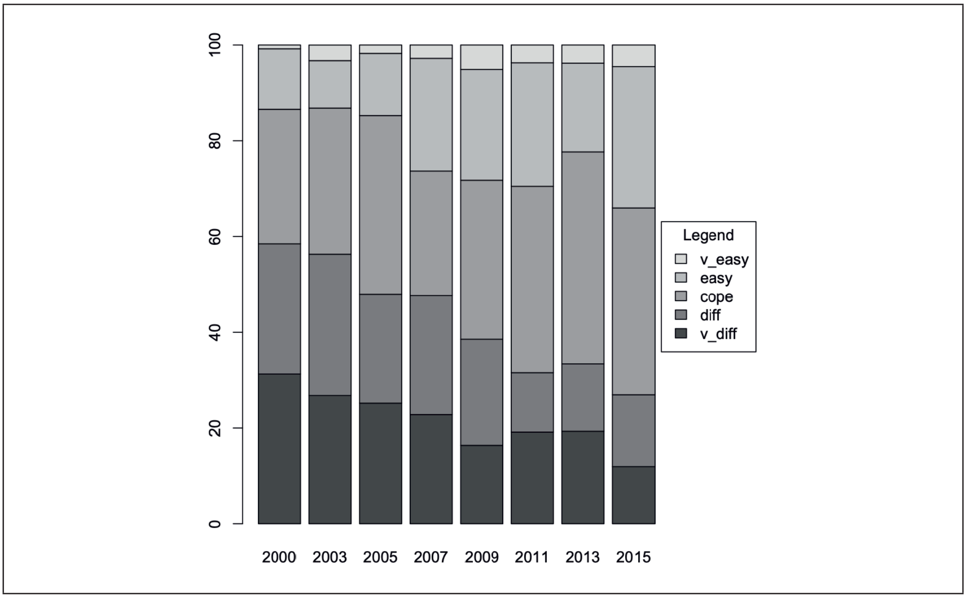

Fig. 1. Distribution of Responses by Year (Including Survey Weights %)
Source: own study.

Figure 1 illustrates the distribution of responses across survey waves, incorporating survey weights to maintain the sample’s representativeness (Ernst, 1989; Verma, Betti & Ghellini, 2007). We note the highest concentration in the middle category (to cope with a certain difficulty). There is a clear difference in the distribution of the responses between the first and the last year of the survey. While the percentage of Poles declaring the worst position is over 30% at the very beginning of the survey and is decreasing with years, for the last category, there is less than 1% in the first round and close to 5% of households reporting the highest financial status in the last round of the survey. We denote the increasing tendency of reporting the

[1] See the data set and its complete documentation in Social Diagnosis (2015) database.

best material position over the years (the increasing share of the highest scored categories), showing the improving financial situation of Polish households in the period of time considered. Our findings align with the research of Panek and Czapiński (2015a, 2015b). However, their study relied solely on summary statistics from the final two survey waves. We also remark that the distribution of the responses has not dramatically changed with the occurrence of the economic crisis. More details and figures representing the analysed data can also be found in the author's previous work (Genge, 2019).

4.2. Empirical Study

In this section, we describe the results obtained from applying latent Markov models to the dataset concerning the material position of Polish households (presented in section 4.1) using the R package LMest (Bartolucci, Pandolfi & Pennoni, 2017). In the initial phase of our analysis, we determined the optimal number of latent states and subsequently explored model simplification through the application of various parameter constraints (see Table 5).

4.2.1. Results for Basic Latent Markov Model

At the first stage, we compared the results for the basic LM models (with heterogeneous transitions) with varying number of latent states. Given that the minimum BIC index value was 6,353.216, a three-state latent structure ($s = 3$) was determined to be the optimal number of latent components. When $s = 3$, we also observed a high classification quality index $\tilde{S} = 0.845$, supporting the presence of well-defined latent structures within the analysed dataset. The estimates of the parameters under the selected LM model with $s = 3$, denoted as *LM-hetero*, are given in Tables 1–3.

The conditional response probabilities under model *LM-hetero* presented in Table 1 enable to characterise Polish households in terms of their perceived financial condition. The first latent state refers to the households with the worst self--reported material well-being, the third state to the households with the highest income perception and the second to those generally satisfied with their material situation. As the number of latent states rises, the likelihood of belonging to the initial category ($x = 0$) diminishes, while the probability of being assigned to the final category ($x = 4$) grows. Respondents assigned to the initial latent state are highly likely to indicate the most challenging financial circumstances $\phi_{x|s} = 0.57$ as opposed to those reporting the same feeling concerning present income belonging to the third state ($\phi_{x|s} = 0.07$). Furthermore, the class-specific scores ϕ_s presented in Table 1 show that the identified latent states are increasing in order. The findings presented here largely align with previous research on LC models (Genge, 2021). However, the latent component of the LM model provides a more nuanced exploration of opinion evolution over time.

Table 1. The Estimates of the Parameters Describing the Measurement Part of the Latent Markov Model with Three States and Heterogeneous Transitions (*LM-hetero*)

$\hat{\phi}_{x\|s}$						
s	$x=0$	$x=1$	$x=2$	$x=3$	$x=4$	$\hat{\phi}_s$
1	0.5666	0.3174	0.1096	0.0045	0.0020	1.5582
2	0.0236	0.2111	0.6338	0.1315	0.0000	2.8732
3	0.0069	0.0129	0.1487	0.6752	0.1563	3.9611

Source: own study.

Table 2 demonstrates that the first latent state was the predominant grouping for the majority of households at the study's outset. Then, Table 3 provides a longitudinal perspective on the phenomenon being studied, focusing on the temporal dynamics of self-reported income classification. We observe that the third latent state is characterised by a strong tendency toward persistence, implying that individuals who report the highest levels of financial satisfaction are unlikely to experience a decline in their perceived financial well-being. Note that, between years 2009 and 2011 ($t = 6$), respondents are much more stable with their negative opinion ($\pi_{11} = 0.90$) and less prone to switch to the generally satisfied group of Poles ($\pi_{12} = 0.10$), compared to the previous transition matrix (characterised by the high probability to switch to the second group). Moreover, the highest chance to switch from the best situated group of Poles to the second, generally satisfied respondents ($\pi_{32} = 0.19$) is observed between the years 2011 and 2013. We might try to explain this behaviour as a slightly worse general economic perception corresponding to the economic crisis.

Table 2. Estimates of the Initial Probabilities $\hat{\pi}_s$ for the Three-state, Heterogeneous Latent Markov Model (*LM-hetero*)

s	$\hat{\pi}_s$
1	0.5772
2	0.3406
3	0.1021

Source: own study.

Beginning with the second-to-last wave, namely 2013 (see Table 3 for $t = 8$), an intriguing pattern emerges, i.e., subjects in the first latent state are much less evident compared to other years. Moreover, in this period we can observe the highest transitions from the first to the second ($\pi_{12} = 0.3153$) and from the second to the third latent state ($\pi_{23} = 0.2098$), revealing the tendency to improve in their behaviour in recent years of the study.

Table 3. Calculated Transition Probabilities $\hat{\pi}^{(t)}_{s|\bar{s}}$ for the Three-state Latent Markov Model with Heterogeneous Transitions (*LM-hetero*)

$\hat{\pi}^{(t)}_{s|\bar{s}}$				
t	$\bar{s}$	$s = 1$	$s = 2$	$s = 3$
2	1	0.9018	0.0951	0.0031
	2	0.0199	0.9023	0.0777
	3	0.0000	0.1166	0.8834
3	1	0.8017	0.1798	0.0185
	2	0.0000	0.9880	0.0120
	3	0.0000	0.0000	1.0000
4	1	0.9311	0.0676	0.0013
	2	0.0456	0.7989	0.1556
	3	0.0000	0.0000	1.0000
5	1	0.7285	0.2458	0.0257
	2	0.0000	0.9124	0.0876
	3	0.0000	0.0000	1.0000
6	1	0.8980	0.1020	0.0000
	2	0.0137	0.9450	0.0413
	3	0.0000	0.0026	0.9974
7	1	0.9991	0.0000	0.0009
	2	0.0000	1.0000	0.0000
	3	0.0000	0.1957	0.8043
8	1	0.6847	0.3153	0.0000
	2	0.0000	0.7902	0.2098
	3	0.0000	0.0079	0.9921

Source: own study.

To enhance the clarity of our findings, we present the marginal distribution (4) of the latent states $S^{(t)}$ for each time point t, derived from the initial and transition probabilities outlined in Tables 2 and 3. Specifically, for each survey wave, we calculate the marginal distribution. It is clear from the depicted marginal probabilities (Fig. 2) that the negative opinions are decreasing with years. Actually, a systematic decline in the probability of the first state is observed, accompanied by a corresponding increase in the probability of the third state.

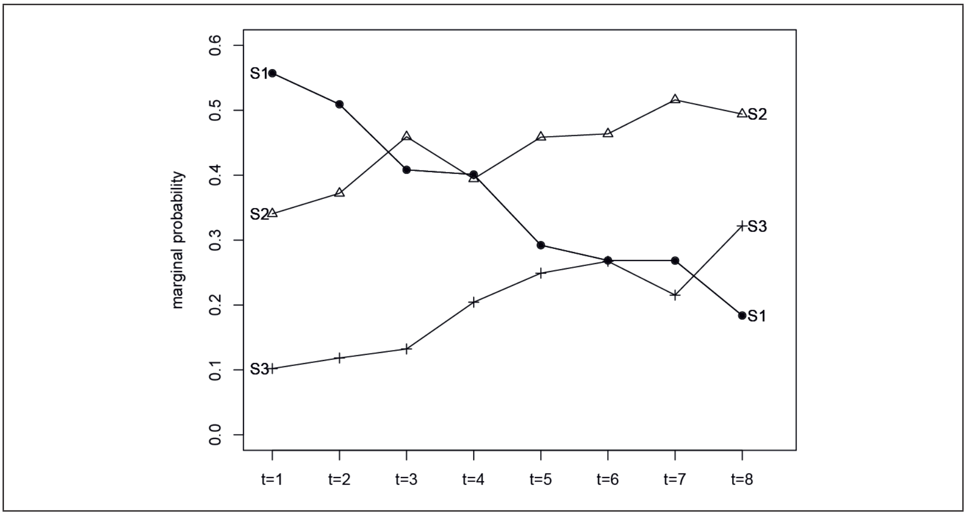

Fig. 2. Calculated Marginal Probabilities $p(X^{(t)} = x)$ for the Three-state Latent Markov Model with Heterogeneous Transitions (*LM-hetero*)

Source: own study.

4.2.2. Results for Constrained Latent Markov Model

The multiplicity of transition matrices (see Table 3) might complicate the straightforward interpretation of their individual elements. Therefore, we subsequently examine a model where transition probabilities exhibit partial time homogeneity, as specified in equation (6), for different values of T^* between $t = 2$ and $t = 8$. This model is identified as *LM-part-hetero*. The outcomes for LM with $s = 3$ and different values of T^* are given in Table 4. For each of these models we present: log-likelihood values ($\hat{l}$), number of parameters (*#par*) *AIC*, *BIC* criteria and $\tilde{S}$ index classification of quality.

Table 4 indicates that the *LM-part-hetero* model with $T^* = 6$ achieves the lowest BIC value (the number in bold). This model posits that individuals transition between latent states differently during the initial five waves compared to subsequent periods.

These results seem to be especially interesting to compare the respondents' behaviour in waves preceding (2000, 2003, 2005, 2007, 2009) and following (2011, 2013, 2015) economic crisis. It is noteworthy that the BIC values for both *LM-hetero* (equal to 6,353.217) and *LM-part-hetero* with $T^* = 6$ (equal to 6,221.312) are superior to the BIC value associated with the traditional LC model (Genge, 2021, p. 13, Table 7).

The conditional probabilities depicted in Figure 3 align closely with the interpretations of latent states as indicators of various Polish financial satisfaction types, as suggested by the estimates in Table 1. In class one, the tallest bars (representing the highest conditional probabilities) were observed for categories 0 and 1, in class two, the final bar was observed for category 2, and in class 3, bar ejections were observed for categories 3 and 4. Consequently, we can retain the previously proposed labels, i.e., S_1 – households with the lowest perceived income, S_2 – households exhibiting general satisfaction, and S_3 – households reporting the highest financial standing.

Table 4. The Selection of Latent Markov Models Ranging from Unconstrained (*hetero*) to Partially Constrained (*part-hetero*) Transition Matrices

s	$\hat{l}$	*#par*	*AIC*	*BIC*	$\tilde{S}$
LM (*hetero*)	–3,015.576	56	6,143.152	6,353.217	0.846
LM (*part-hetero*) $T^* = 2$	–3,038.272	26	6,128.543	6,226.073	0.841
LM (*part-hetero*) $T^* = 3$	–3,037.493	26	6,126.986	6,224.517	0.842
LM (*part-hetero*) $T^* = 4$	–3,037.204	26	6,126.409	6,223.939	0.840
LM (*part-hetero*) $T^* = 5$	–3,035.919	26	6,123.837	6,221.367	0.841
LM (*part-hetero*) $T^* = 6$	–3,035.891	26	6,123.782	**6,221.312**	0.843
LM (*part-hetero*) $T^* = 7$	–3,036.210	26	6,124.419	6,221.949	0.837

Source: own study.

However, the estimates of the initial probabilities presented also for each state in Figure 3 are slightly different with respect to those obtained under the LM model with all heterogeneous matrices (see Table 2). Specifically, within the *LM-part--hetero* model, we observe a higher concentration of individuals in the initial (most negative) latent state and a lower prevalence in the final (most positive) latent state at the study's outset.

Examining the estimated transition probabilities in Table 5, we observe distinct patterns between the first five waves and the subsequent waves. Notably, the initial transition matrix (pre-crisis) reveals a significantly higher level of persistence in the third, most positive latent state compared to the second transition matrix. Following the economic crisis, respondents demonstrate a greater tendency to remain within the unsatisfied and moderately satisfied groups (S_1 and S_2) and to transition from the highest satisfaction state to the intermediate satisfaction state (with a probability of $\hat{\pi}^{(t)}_{3|2} = 0.09$). These findings suggest a subtle decline in Polish sentiment, potentially reflecting the broader impact of the economic crisis. This observation aligns with previous research by Helliwell, Huang and Wang (2014) and Chzhen (2016), who identified a decrease in subjective well-being in heavily affected EU countries during the 2008–2011 period (i.e., Greece, Ireland, Italy, Portugal, and Spain). Our results further imply that the crisis may have influenced Polish households in ways beyond mere budgetary constraints.

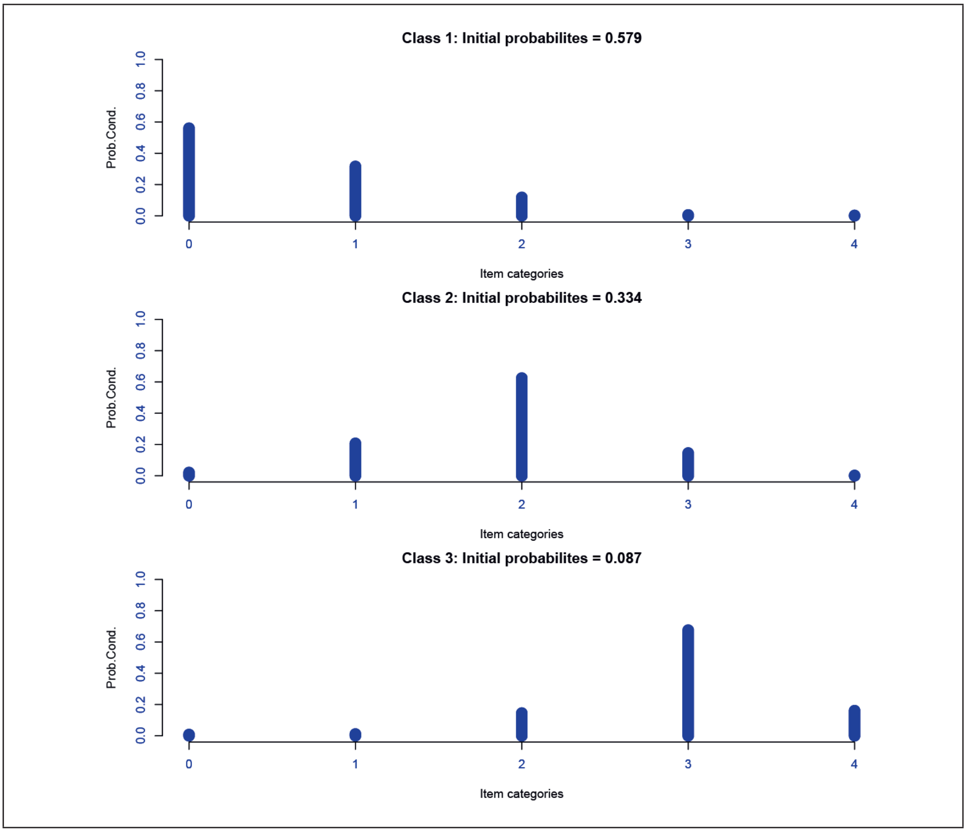

Fig. 3. Conditional Probabilities $\phi_{jx|s}$ for the Latent Markov Model with Three States and Partially Heterogeneouos Transitions (*LM-part-hetero*) and $T^* = 6$

Source: own study, using the R package LMest (Bartolucci, Pandolfi & Pennoni, 2017).

Table 5. Calculated Transition Probabilities $\hat{\pi}^{(t)}_{s|\bar{s}}$ for the Three-state Latent Markov Model with Partial Heterogeneous Transitions (*LM-part-hetero*) for $T^* = 6$

$\hat{\pi}^{(t)}_{s\mid\bar{s}}$				
T^*	s	$s=1$	$s=2$	$s=3$
$\mathrm{I}(t=1,\ldots,5)$	1	0.8503	0.1438	0.0059
	2	0.0124	0.9095	0.0781
	3	0.0000	0.0000	1.0000
$\mathrm{II}(t=6,\ldots,8)$	1	0.8771	0.1229	0.0000
	2	0.0000	0.9456	0.0544
	3	0.0000	0.0923	0.9077

Source: own study.

5. Discussion and Conclusions

This study analyses the evolving patterns of subjective economic well-being among Polish households from 2000 to 2015. Employing LM models with various constraints, we examine the dynamic changes in the financial circumstances of Polish households over this 15-year period, encompassing the global economic crisis. Our study allows us to model the probability of individual household changes over time, identify more adequate structures in the analysed data set than the more popular latent class model (see Genge, 2021). Besides, the LM model with constraints posed on the parameters of the latent process (especially for $T^* = 6$), shows the best measure of fit, sensible pattern behaviour of Polish households, as well as facilitates the interpretation of the analysed data at issue. A notable advantage of our approach is its ability to incorporate survey weights, thereby enabling a more accurate analysis of data from complex social surveys, a practice often overlooked in longitudinal studies.

Even though Poland occupies a lower position in the EU regarding subjective financial well-being based on Eurostat data, we have not witnessed substantial changes in Polish public sentiment following the economic downturn. The analysis of marginal and transition probabilities provided for each point in time shows the increasing tendency of positive self-reporting income position among the Polish households. However, even if Poland is one of the countries that did not suffer a lot in the global economic crisis (Gradzewicz *et al.*, 2014; Helliwell, Huang & Wang, 2014; Chzhen, 2016; Gomułka, 2016), we note slightly higher chance to switch from those declaring the worse financial situation to those mostly satisfied in the years preceding, and especially at the very beginning of the economic crisis, compared to years following this economic event. These results are in agreement with the figures presented in the work of Panek and Czapiński (2013) as well as with the studies of Wałęga (2015) and Zalega (2012). As expected, the deterioration of Polish sentiment is observed with some delay. We notice the higher probability of remaining in the unsatisfied group, lower probability of remaining in the fully satisfied group and lower chance to switch from those unsatisfied to those generally satisfied, especially in the first two waves following the peak of the financial crisis.

We remark that most of the studies concerning subjective assessment of the financial situation in Poland are carried out on the specified subsamples of Poles (for example, young people's households, biggest Polish cities), showing the results for questionnaire response variables in one or few years of the survey, based on summary statistics tables or different regression techniques, assuming the homogeneity of the analysed data. Moreover, compared to the most recent works illustrated also for the other national surveys (see i.e., Chzhen, 2016; Popova & Pishniak, 2017; Brzozowski & Spotton Visano, 2019; Mahdzan *et al.*, 2019), we show the changes of attitudes among the society, presented for all waves of the national longitudinal survey, accounting for heterogenous structure of the data, and including survey weights. We confirmed also that constraints imposed on the transition matrix of the LM model gives better measure of fit and facilitate the interpretation of the socio-economic issue regarding self-reported material well-being of Poles analysed at different points in time. Consequently, our findings can inform policymakers as they allocate public funds, emphasising the importance of considering financial well-being. In a subsequent study (Genge, 2023), we compare our results with a homogeneous LM model that incorporates time-varying covariates, enabling a more nuanced understanding of evolving households' behaviours. This approach aids in identifying specific types of households (characterised by varying socio-economic factors) that may require enhanced social protection.

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Conflict of Interest

The author declares no conflict of interest.

References

Akaike, H. (1973). Information Theory as an Extension of the Maximum Likelihood Principle. In: B. N. Petrov, F. Csaki (Eds), *Proceedings of the 2nd International Symposium on Information Theory* (pp. 267–281). Akademiai Kiado.

Bacci, S., Pandolfi, S., & Pennoni, F. (2014). A Comparison of Some Criteria for States Selection in the Latent Markov Model for Longitudinal Data. *Advances in Data Analysis and Classification*, *8*, 125–145. https://doi.org/10.1007/s11634-013-0154-2

Bartolucci, F. (2007). A Class of Multidimensional IRT Models for Testing Unidimensionality and Clustering Items. *Psychometrika*, *72*, 141–157. https://doi.org/10.1007/s11336-005-1376-9

Bartolucci, F., Farcomeni, A., & Pennoni, F. (2013). *Latent Markov Models for Longitudinal Data*. Chapman and Hall/CRC.

Bartolucci, F., Lupparelli, M., & Montanari, G. E. (2009). Latent Markov Model for Longitudinal Binary Data: An Application to the Performance Evaluation of Nursing Homes. *Annals of Applied Statistics*, *3*(2), 611–636. https://doi.org/10.1214/08-AOAS230

Bartolucci, F., Pandolfi, S., & Pennoni, F. (2017). LMest: An R Package for Latent Markov Models for Longitudinal Categorical Data. *Journal of Statistical Software*, *81*(4), 971–985. https://doi.org/10.18637/jss.v081.i04

Bartolucci, F., Pandolfi, S., & Pennoni, F. (2022). Discrete Latent Variable Models. *Annual Review of Statistics*, *9*, 425–452. https://doi.org/10.1146/annurev-statistics-040220-091910

Baum, L. E., Petrie, T., Soules, G., & Weiss, N. (1970). A Maximization Technique Occurring in the Statistical Analysis of Probabilistic Functions of Markov Chains. *Annals of Mathematical Statistics*, *41*(1), 164–171. https://doi.org/10.1214/aoms/1177697196

Betti, G., Dourmashkin, N., Rossi, M., Verma, V., & Yin, Y. P. (2001). *Study of the Problem of Consumer Indebtedness: Statistical Aspects Final Report*. Report to the Commission of the European Communities. Directorate-General for Health and Consumer Protection, Commission of the European Communities. ORC Macro.

Bialowolski, P., & Weziak-Bialowolska, D. (2014). The Index of Household Financial Condition, Combining Subjective and Objective Indicators: An Appraisal of Italian Households. *Social Indicators Research*, *118*(1), 365–385. https://doi.org/10.1007/s11205-013-0401-0

Białowolski, P. (2018). Hard Times! How Do Households Cope with Financial Difficulties? Evidence from the Swiss Household Panel. *Social Indicators Research*, *139*(1), 147–161. https://doi.org/10.1007/s11205-017-1711-4

Binder, M. (2014). Subjective Well-being Capabilities: Bridging the Gap Between the Capability Approach and Subjective Well-being Research. *Journal of Happiness*, *15*, 1197–1217. https://doi.org/10.1007/s10902-013-9471-6

Brusa, L., Bartolucci, F., & Pennoni, F. (2023). Tempered Expectation-maximization Algorithm for the Estimation of Discrete Latent Variable Models. *Computational Statistics*, *38*, 1391–1424. https://doi.org/10.1007/s00180-022-01276-7

Brzozowski, M., & Spotton Visano, B. (2019). "Havin' Money's Not Everything, Not Havin' It Is": The Importance of Financial Satisfaction for Life Satisfaction in Financially Stressed Households. *Journal of Happiness Studies*, *21*, 573–591. https://doi.org/10.1007/s10902-019-00091-0

Chzhen, Y. (2016). Perceptions of the Economic Crisis in Europe: Do Adults in Households with Children Feel a Greater Impact? *Social Indicators Research*, *127*, 341–360. https://doi.org/10.1007/s11205-015-0956-z

Clark, A., Etilé, F., Postel-Vinay, F., Senik., C., & Van der Straeten, K. (2005). Heterogeneity in Reported Well-being: Evidence from Twelve European Countries. *The Economic Journal*, *115*(502), 118–132. https://doi.org/10.1111/j.0013-0133.2005.00983.x

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum Likelihood from Incomplete Data via the EM Algorithm (with Discussion). *Journal of the Royal Statistical Society: Series B* (*Methodological*), *39*(1), 1–38. https://doi.org/10.1111/j.2517-6161.1977.tb01600.x

Diego-Rosell, P., Tortora, R., & Bird, J. (2018). International Determinants of Subjective Well-being: Living in a Subjectively Material World. *Journal of Happiness*, *19*, 123–143. https://doi.org/10.1007/s10902-016-9812-3

Ernst, L. (1989). Weighting Issues for Longitudinal Household and Family Estimates. In: D. Kasprzyk, G. Duncan, G. Kalton, M. P. Singh (Eds), *Panel Surveys* (pp. 139–159). Wiley.

Eurostat. (2019). *Subjective Well-being – Statistics*. Retrieved from: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Subjective_well-being_-_statistics (accessed: 1.08.2025).

Eurostat. (2024). *Quality of Life Indicators – Overall Experience of Life*. Retrieved from: https://ec.europa.eu/eurostat/statistics-explained/index.php/Quality_of_life_indicators_-_overall_experience_of_life (accessed: 1.08.2025).

Gasińska, M. (2016). Dochody gospodarstw domowych w Polsce – wybrane obiektywne i subiektywne ujęcia i dane. *Zeszyty Naukowe Uczelni Vistula*, *50*(5), 100–142.

Gasiorowska, A. (2015). The Impact of Money Attitudes on the Relationship between Income and Financial Satisfaction. *Polish Psychological Bulletin*, *46*(2), 197–208. https://doi.org/10.1515/ppb-2015-0026

Genge, E. (2019). Graphical Tools of Discrete Longitudinal Data Presentation in R. *Econometrics. Advances in Applied Data Analysis*, *23*(3), 26–39. https://doi.org/10.15611/eada.2019.3.03

Genge, E. (2021). LC and LC-IRT Models in the Identification of Polish Households with Similar Perception of Financial Position. *Sustainability*, *13*(8), 4130. https://doi.org/10.3390/su13084130

Genge, E. (2023). An Evaluation of Self-reported Material Well-being Using Latent Markov Models with Covariates. *Longitudinal and Life Course Studies*, *14*(4), 514–541. https://doi.org/10.1332/175795921X16719290621875

Gomułka, S. (2016). Poland's Economic and Social Transformation 1989–2014 and Contemporary Challenges. *Central Bank Review*, *16*(1), 19–23. https://doi.org/10.1016/j.cbrev.2016.03.005

Gradzewicz, M., Growiec, J., Kolasa, M., Postek, Ł., & Strzelecki, P. (2014). *Poland's Exceptional Performance during the World Economic Crisis: New Growth Accounting Evidence* (NBP Working Paper No. 186). Narodowy Bank Polski.

Hanusik, K., & Łangowska-Szczęśniak, U. (2013). Uwarunkowania samooceny sytuacji materialnej gospodarstw domowych w Polsce w 2011 r. *Konsumpcja i Rozwój*, *1*(4), 83–98.

Helliwell, J. F., Huang, H., & Wang, S. (2014). Social Capital and Well-being in Times of Crisis. *Journal of Happiness Studies*, *15*, 145–162. https://doi.org/10.1007/s10902-013-9441-z

Kalinowski, S., & Kozera-Kowalska, M. (2017). Samoocena sytuacji dochodowej ludności wiejskiej o niepewnych dochodach. *Handel Wewnętrzny*, *4*(369), 110–121.

Kalton, G. (1989). Modeling Considerations: Discussion from a Survey Sampling Perspective. In: D. Kasprzyk, G. Duncan, G. Kalton, M. P. Singh (Eds), *Panel Surveys* (pp. 575–585). Wiley.

Mahdzan, N. S., Zainudin, R., Sukor, M. E. A., Zanir, F., & Ahmad, W. M. W. (2019). Determinants of Subjective Financial Well-being Across Three Different Household Income Groups in Malaysia. *Social Indicators Research*, *146*, 699–726. https://doi.org/10.1007/s11205-019-02138-4

Panek, T., & Czapiński, J. (2013). Warunki życia gospodarstw domowych. Dochody i sposób gospodarowania dochodami. Diagnoza Społeczna 2013. Warunki i jakość życia Polaków – Raport (Special issue). *Contemporary Economics*, *7*, 40–53. https://doi.org/10.5709/ce.1897-9254.97

Panek, T., & Czapiński, J. (2015a). Household Living Conditions. Income and Income Management. In: J. Czapiński, T. Panek (Eds), *Social Diagnosis 2015. The Objective and Subjective Quality of Life in Poland* (pp. 34–47). The Councing for Social Monitoring.

Panek, T., & Czapiński, J. (2015b). Warunki życia gospodarstw domowych. Dochody i sposób gospodarowania dochodami. In: J. Czapiński, T. Panek (Eds), *Diagnoza społeczna 2015. Warunki i jakość życia Polaków* (pp. 36–50). Rada Monitoringu Społecznego.

Pennoni, F., & Genge, E. (2018). *Predicting Trends of Institutional Confidence through a Hidden Markov Model with Survey Weights and Missing Responses*. ERCIM WG on Computational and Methodological Statistics 11th International Conference of the ERCIM WG on Computational and Methodological Statistics, 12th International Conference on Computational and Financial Econometrics, University of Pisa, 14–16 December.

Pennoni, F., & Genge, E. (2020). Analysing the Course of Public Trust via hidden Markov Models: A Focus on the Polish Society. *Statistical Methods and Applications*, *29*, 399–425. https://doi.org/10.1007/s10260-019-00483-9

Popova, D., & Pishniak, A. (2017). Measuring Individual Material Well-being Using Multidimensional Indices: An Application Using the Gender and Generation Survey for Russia. *Social Indicators Research*, *130*, 883–910. https://doi.org/10.1007/s11205-016-1231-7

The R Core Team. (2025). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing.

Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistic*, *6*(2), 461–464. https://doi.org/10.1214/aos/1176344136

Sirovátka, T., & Mareš, P. (2009). Poverty, Deprivation and Social Exclusion: The Unemployed and the Working Poor. In: M. C. Fournier, C. S. Mercier (Eds), *Economics of Employment and Unemployment* (pp. 1–32). Nova Science Publishers.

Social Diagnosis. (2015). *Objective and Subjective Quality of Live in Poland*. J. Czapinski, T. Panek (Eds). Council for Social Monitoring. http://www.diagnoza.com/index-en.html (accessed: 15.10.2016).

Stapleton, L. M. (2002). The Incorporation of Sample Weights into Multilevel Structural Equation Models. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(4), 475–502. https://doi.org/10.1207/S15328007SEM0904_2

Thomas, S. L., & Heck, R. H. (2001). Analysis of Large-scale Secondary Data in Higher Education Research: Potential Perils Associated with Complex Sampling Designs. *Research in Higher Education*, *42*, 517–540. https://doi.org/10.1023/A:1011098109834

Tullio, F., & Bartolucci, F. (2022). Causal Inference for Time-varying Treatments in Latent Markov Models: An Application to the Effects of Remittances on Poverty Dynamics. *Annals of Applied Statistics*, *16*(3), 1962–1985. https://doi.org/10.1214/21-AOAS1578

Wałęga, A. (2015). Sytuacja materialna a konsumpcja gospodarstw domowych ludzi młodych w Polsce. *Konsumpcja i Rozwój*, *2*(11), 61–73.

Wiggins, L. M. (1973), *Panel Analysis: Latent Probability Models for Attitude and Behavior Processes*. Elsevier.

Verbič, M., & Stanovnik, T. (2006). Analysis of Subjective Economic Well-being in Slovenia. *Eastern European Economics*, *44*(2), 60–70.

Verma, V., Betti, G., & Ghellini, G. (2007) Cross-sectional and Longitudinal Weighting in a Rotational Household Panel: Applications to EU-SILC. *Statistics in Transition*, *8*(1), 5–50.

Zalega, T. (2012). Diagnoza sytuacji materialnej polskich gospodarstw domowych w okresie kryzysu finansowo-ekonomicznego. *Management and Business Administration. Central Europe*, *20*(5), 50–82. https://www.doi.org/10.7206/mba.ce.2084-3356.29