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A study of the perceived material condition in Poland with the use of mixed latent auto-regressive models

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Abstract

Aim: According to OECD, the financial well-being score for Poles is just 9.1 out of a total of 20, whilst the Eurostat reports one of the lowest scores for Polish society. Most of the previous research primarily relied on cross-sectional data. The aim of this study is to provide insights into the income perception of Polish families and its evolution over a 15-year period, using data from a Polish national longitudinal survey.

Methodology: Taking specification of the Social Diagnosis data, the author adopted a mixture of latent autoregressive models. As a result, the study accounted for the unobserved heterogeneity and provided the mean and correlation coefficient for each component of the mixture, as well as described the effect of the observed covariates.

Results: The author identified groups (three mixture components) of families with a similar perception of their financial situation, showing that some families (i.e. one-parent families, multi-families) and those with more children, living in suburbs, and those professionally inactive, are in particular need of greater protection.

Implications and recommendations: There is a limited number of well-rounded financial education programmes that target socio-economic groups other than children and young people in Poland. The author believes that considering subjective information about income evaluation may also help to better recognise the specific financial education needs of people in different stages of life, characterised by various socio-economic features. The main limitation of the study concerns the availability of the most recent data (new waves of the survey are not published any more), therefore future research could assess the material condition of Polish families and compare the results based on other sources of data.

Originality/value: The article present a new approach to the study of the economic perception of Polish families, and deals with the problem of the unobserved heterogeneity. This approach also allows to account for observable (socio-economic) characteristics and survey weights. Moreover, the author compared the results for the presented approach with the other latent variable model techniques.

Keywords: latent variable, random effect, heterogenous data, Social Diagnosis

1. Introduction

In 2021, Poland celebrated 25 years since its accession to the OECD, successfully transitioning over the years from a low to middle-income planned economy to a market-based economy, highly integrating and competing in the global marketplace. Macroeconomic and financial stabilisation, privatisations, changes in business regulations, tax reforms and policies to foster labour market dynamism were key to promote economic growth and convergence to higher-income status (OECD, 2022, p. 16). However, an ageing population, a persistent social and economic development disparity between urban and rural areas and between adults with at least secondary school attainment still present a challenge, whilst the recent massive influx of refugees following Russia's invasion of Ukraine might make matters worse, especially for those with the lowest income position (see OECD, 2022, p. 6).

According to the latest Eurostat data (Eurostat, 2023) and OECD report (2022) the perceived financial satisfaction of Poles is still at a low level. In general, Poles are 'good at making ends meet' and managing their finances, regardless of how limited they are. At the same time, 66.1% of Poles feel that they are just getting by financially, 46.2% think that their finances control their lives, and 36.9% worry about paying for their normal living expenses. These elements have an influence on individuals' financial well-being and in fact Poles' financial well-being score is just 9.1 out of a total of 20, below the OECD-11 average of 9.9 (OECD, 2022, p. 44).

It is interesting to analyse such a low income perception of Polish families, also bearing in mind the evolution of this characteristic over the years. A person's dynamic assessment of his or her own well-being is determined by various personal and contextual factors that are changeable (Brüggen et al., 2017). Life events such as accidents, health and sickness, births and deaths, marriage and divorce, were mentioned as things that can change individual financial lives significantly. Poles mainly express concern about their ability to cope financially with major life events; older consumers are particularly concerned that end-of-life events could force them to drain their savings and become financially dependent upon family members (Consumer Financial Protection Bureau, 2015, p. 42).

This study analysed financial well-being of Poles measured at different points in time based on Polish National longitudinal survey data Social Diagnosis (see Social Diagnosis, 2015 for a description). Most of the recent studies concerning financial-well being presented for other countries are based on cross-sectional data sets. As suggested by many authors longitudinal study allows to show the behaviour changes and better explore relationships between variables (Dittmar et al, 2014; Chzhen, 2016; Mahdzan et al, 2019; Giang & Nguyen 2022; Estela-Delgado et al. 2023; Silva & Dias 2023).

One of the main tasks of social policy is effective assistance to the economically weakest groups of households. Therefore, the key issue is to better describe the economic well-being of households characterised by different socio-economic features and to identify those groups that need this help the most. The author referred to the reference group theory (Townsend, 1979) and considered the socio-economic features of the study, as people tend to compare themselves with others in their reference groups. Many interviewees judged themselves in comparison with others, and often used as a point of reference their family, friends, community, upbringing, their home life, and many aspects of the world they live in as sources of financial knowledge, examples of positive and negative financial behaviours, and much more. Recent research showed that interviewees referenced society broadly as what shapes us through mass culture, social media, and advertising tempting to indulgence to the detriment of one's financial well-being, and in other ways (Consumer Financial Protection Bureau, 2015, pp. 38, 41).

One should add that some people seem to have, and feel they have, a high level of financial well-being, even though they may be far from affluent. On the other hand, some with much higher incomes do not appear to have or feel they have a high level of financial well-being at all (Consumer Financial Protection Bureau, 2015, p. 18). As was suggested, "Rich or poor is a state of mind. People may be financially poor but psychologically rich and vice versa" (Tang et al., 2004, p. 119). Thus one can consider feelings about household income as a latent, invisible feature, only being measured through the questionnaire.

In coping with longitudinal data one needs to consider the unobserved heterogeneity that is not described by observed features (covariates). The measurements given in a few points of time lead to the auto-correlated responses. To explain this form of heterogeneity the random effects (or latent variables) are often proposed at the individual level of the model. Models based on the individual-specific random intercepts with continuous distribution are comprised within the group of random-effects models or generalised linear mixed models (see e.g. Snijders & Bosker, 1999; Skrondal & Rabe-Hesketh, 2004; Hancock & Samuelson, 2008). On the other hand, models with the discrete distribution of the random effects are identified with latent class models (Lazarsfeld, 1950; Bandeen-Roche et al., 1997; Huang & Bandeen-Roche, 2004). A broader approach allows to consider the time varying individual random effects, leading to a latent process for the unobserved heterogeneity. In the case of time varying random effects one can also distinguish between the discrete and continuous case. In the models of the first type (with the time varying and discrete distribution of random intercepts) it is assumed that the individual effects follow a first-order Markov chain which results in latent Markov (LM) models (Wiggins, 1973; Bartolucci et al., 2013). Next, the variability in the response variable is described by the movements of subjects from one class to another in the analysed period of time. Alternatively, the concept based on a continuous-valued latent process implies that the individual effects follow an auto-regressive model of first order (AR(1)), see Chi and Reinsel (1989) and Heiss (2008). Therefore this model is identified as the latent auto-regressive (LAR) model, whilst the latent structure is characterised by only two parameters: the correlation index and the variance of the individual.

The specification of the Social Diagnosis data set, namely the 15 years' duration of the study (eight rounds of the survey, every two years a new round is added) prompted to consider the unobserved factor that may vary during the course of the study and affect the financial satisfaction of Polish families. Therefore, it appeared reasonable to include the time varying random effects in the empirical study of the data at hand. The author focused in particular on longitudinal model based on a mixture of latent AR(1) processes to account for the unobserved heterogeneity occurring for the data measured in different points of time. Each component of the mixture has its own mean and correlation coefficient, but these components have a common variance (see McLachlan & Peel 2000; Bartolucci et al. 2014).

To sum up, the core contribution of this paper consists in a new approach to the study of economic perception of Polish families, dealing with the problem with the unobserved heterogeneity. The latent variable approach allowed to identify homogeneous groups of families with similar feelings concerning their financial position. In addition, this approach took into account the observable (socio-economic) characteristics. The study also compared the results for this approach with LAR or LM models, as well as with time constant latent variable models having discrete distribution (i.e. LC – latent class, LC-IRT latent class combined with IRT theory models).

The organization of this paper is as follows. Section 1 reviews the main trends in the literature concerning financial well-being. Section 2 contains a detailed description of the data set. Section 3 describes the latent variable approach employed in the empirical part of the paper. Section 4 presents the main results of the analysis. Finally, Section 5 outlines the main conclusions.

2. Literature review

Financial well-being is studied as an objective condition when considering material economic resources, and is also a subjective experience when considering and evaluating one's own economic condition (Sorgente & Lanz, 2017; Kaur et al., 2021). Fergusson, Horwood and Beautrais (1981) described economic well-being through the level of financial inputs, such as the level of income, assets and quality of housing. Many other authors consider economic well-being as monetary income, real or full income (see e.g. Sirovátka & Mareš, 2009; Howell et al., 2013; Ahn et al. 2014; Kushlev et al. 2015; Sorgente & Lanz, 2017).

It is widely known that the measurement of income in surveys is often associated with the numerous statistical problems, i.e. income underreporting, item non-response or unit non-response. These problems may seriously affect the estimation of household income, especially at the upper end of income distribution (Clark et al., 2005; Diego-Rosell et al., 2018; Popova & Pishniak, 2017). Many authors suggested using subjective information from survey declarations about happiness or income satisfactions as a solution to evaluate the financial satisfaction (Lewbel & Pendakur, 2008). Alternative (to income-based measures) components of financial satisfaction overcome the limitations of income declarations and enable researchers to analyse the factors that may enhance the evaluation of financial position, social well-being and the quality of life (Białowolski & Węziak-Białowolska, 2014; Białowolski, 2018; Stundziene, 2019). Various studies have shown that objective financial conditions and subjective financial well-being are separate concepts and do not always move in tandem (Giang & Nguyen, 2022).

The most relevant subjective indicators driving financial well-being proposed across the literature measure the individual perceptions and opinions of living conditions, e.g. self-assessed ability to 'make ends meet', satisfaction with one's life, etc. (see Wilhelm & Varcoe, 1991 Clark et al., 2005). Non-monetary approaches also promote the assessments of material conditions based on psychological and behavioural determinants, namely financial behaviour (Kim & Garman, 2003; Sabri et al., 2006), financial literacy and financial knowledge (McNamara, 2007; Lyons, 2008; Netemeyer et al. 2018),) or financial stress (Joo & Grable, 2004; Delafrooz & Paim, 2011).

Some surveys found that the impact of individual factors is essential in self-perception regarding one's own financial position, since it allows control over finances and is able to absorb financial threats, the freedom to make decisions that promote the well-being of the individual (Zhang & Cao, 2010; Ponchio et al., 2019). As a result, financial well-being allows for a state of overall happiness or satisfaction with the financial situations, and covers the greater security with income or savings, thus maintaining material security (Mahdzan et al., 2020). Consequently, appropriate financial behaviour and self-control allow for greater financial well-being (Strömbäck et al., 2017). In line with the results presented above, the study also referred to the grounded in the literature subjective perception of well-being, based on reference group theory (Townsend, 1979). Therefore, the author analysed different socio-economic features (time-constant and time-varying) since self-perception regarding one's own financial position is related to the reference group identified by geographical (neighbourhood) or social criteria (education, class, occupation), or a combination of these (see also Merton & Rossi, 1968; Goedemé & Rottiers, 2011; Bellani, 2013; Popova & Pishniak, 2017).

Some scientists found the importance of the income position assessment measured at different stages of the course of life, since financial situation and income sources frequently change over time (Muennig, 2008; Arber et al., 2014; Brüggen et al., 2017). Thus, contrary to other research based on the cross-sectional national data (e.g. Brzozowski & Visano, 2019; Mahdzan et al., 2019; Popova & Pishniak, 2017; Giang & Nguyen 2022; Estela-Delgado et al. 2023), this study did not focused on the main determinants of one's current financial situation but was especially interested with the changing feelings about household income described by different features measured over time. The author focused on changing income perception based on all waves of the Polish longitudinal survey data, also including time-varying covariates and survey weights, and compared the results achieved for the same Social Diagnosis data applied for the other latent variable model techniques (Genge, 2022; Genge, 2023). The article contrasts the measures of fit and shows the interpretation opportunities of time-varying latent variable models in discrete and continuous case.

3. Data and methodology

3.1. Data

The author analysed data concerning subjective financial well-being of Polish society deriving from the national panel study Social Diagnosis (Social Diagnosis 2015). As presented on the project's website (http://www.diagnoza.com/index-en.html), the aim was to reveal not only the current state of Polish society and the quality of life, but also to follow its changes over recent years, providing an insight into almost the entire process of system transformation since 1989. During each two-year cycle of interviews (with the exception of the first one), with the first sample taken in the year 2000, individual households and their members who represent the nation's diversity of economic and not only economic (e.g. education, problem-solving, lifestyle) aspects of life were surveyed.

The sample design is a nationally representative population aged over 16 years, using two separate questionnaires addressed to the head of the household and its individual members. The perceived financial status is generally measured by the question: "'It is easier to make ends meet?", with response categories defined so that an ordinal variable results, i.e. GD – with great difficulty (0), D – with difficulty (1), CD – with a certain difficulty (2), RE – rather easily (3), E – easily (4). The sample of n = 2768 households was considered, with one respondent per household providing information about the household's financial situation, using survey weights to maintain the representative features of the sample (Ernst, 1989; Verma et al., 2007).

The distribution of the response variable (Table 1) shows that generally more than 75% of the responses were distributed between the categories: with difficulty, with a certain difficulty, and rather easily, being substantially unstable over time. There is a clear decreasing trend in financial perception as difficult, with a corresponding increase in categories of "certain difficulty" and "rather easily". This tendency can be also observed in Figure 1.

Table 1. Weighted distribution of the response variable (%) over the waves of the survey

	Year of survey							
Category	2000	2003	2005	2007	2009	2011	2013	2015
with great difficulty	31.27	26.78	25.20	22.81	16.49	19.15	19.32	12.04
with difficulty	27.19	29.52	22.73	24.77	22.05	12.41	14.07	14.91
with a certain difficulty	28.11	30.52	37.33	26.08	33.21	38.91	44.27	39.01
rather easily	12.64	9.91	12.99	23.55	23.13	25.81	18.54	29.52
easily	0.79	3.26	1.75	2.79	5.12	3.72	3.80	4.52
Total	100%	100%	100%	100%	100%	100%	100%	100%

Source: own calculations in R.

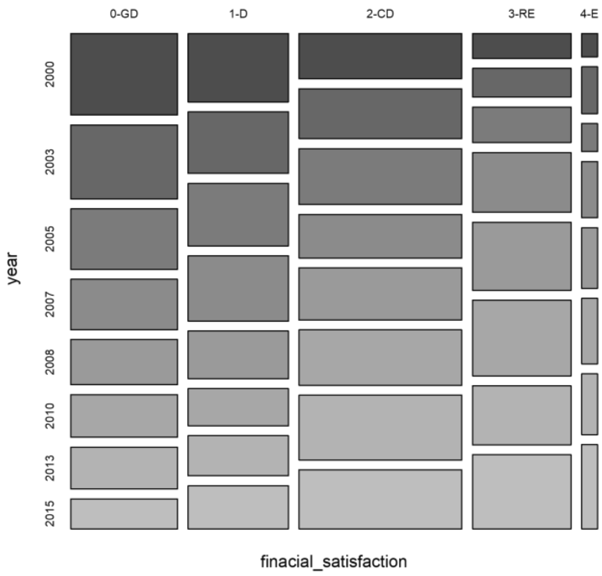

Fig. 1. Mosaic plot for financial satisfaction over the years of the study

Source: own calculations in R.

The author was also interested in the association between self-reported income position and available covariates. Therefore, the following socio-economic features were taken into consideration: **place of living** (1–cities with more than 500,000 inhabitants, 2–cities with 20,000 to 500,00 inhabitants; 3–cities below 20,000 inhabitants and rural areas), **socio-professional status** (1–employees in public sector, 2–farmers, 3–employees in private sector and entrepreneur/self-employed, 4–pensioners, retirees, pupils and students, unemployed, other professionally inactive) and **family type** (1–married without children, 2–married with one child, 3–married with two children, 4–married with three and more children, 5–other family types, i.e. one-parent family, multi-family, non-family-one person, non-family-multi-person).

The majority of the families lived in small towns or in villages, where also the highest and increasing share of child-free and other families could be observed. Considering the socio-occupational position, one could observe the highest (however decreasing) proportion of public sector employees and an increasing percentage of inactive Poles (see also Genge, 2019).

3.2. Methodology

In the longitudinal data analysis the main issue was how to deal with the unobserved heterogeneity that is not reflected by the given covariates (e.g. socio-economic characteristics). When the responses are repeated over time, this may result in the auto-correlated measures. Next, the random effects (or latent variables) were introduced at the individual level of the model. Based on the assumption concerning the latent variable (time-constant or time varying, with a discrete or continuous distribution) different latent variable model formulations were recognised. The choice of the suitable model should rely on the structure of the data at hand and the context of the study. Here the study focused on the approach relying on assumption of time-varying latent variable with continuous distribution, and showing the difference between models with discrete and continuous distributions of the latent trait.

For a sample of *n* households x_{it} denotes the response variable for household *i* at occasion t $(t = 1, \dots, T)$ and $\boldsymbol{z}_{it}$ refers to a column vector of covariates, where $\boldsymbol{x}_i = (x_{i1}, \dots, x_{iT})$ is the vector of response variables, and $\boldsymbol{Z}_i = (\boldsymbol{z}_{i1}, \dots, \boldsymbol{z}_{iT})$ is the matrix of all covariates describing household *i* $(i = 1, \dots, n)$. In the empirical application, the covariate vector includes place of living, socio-professional status, and family type. The ordinal response variable has $J = 5$ categories. Having established the notation and variable definitions, the theoretical model framework was then presented. The statistical methodology employed in this study follows the framework established by Bartolucci et al. (2014), adapted specifically for examining longitudinal patterns in perceived material conditions among the Polish respondents. The following mathematical formulations were based on their latent auto-regressive model structure, with modifications to accommodate the research design and data characteristics.

The first concept was based on continuous latent variables and presumed that every latent process $\alpha_i = (\alpha_{i1}, \dots, \alpha_{iT})$ follows an AR(1) process:

$$\alpha_{i1} = \varepsilon_{i1},$$
$$\alpha_{it} = \alpha_{i,t-1}\rho + \varepsilon_{it}\sqrt{(1-\rho^2)},\ t = 2, \dots, T, \tag{1}$$

where $\varepsilon_{it} \sim N(0, \delta^2),\ t = 1, \dots, T$. Under this parametrization, the innovation entering the recursion is $\varepsilon_{it}\sqrt{(1-\rho^2)}$, so the stationary marginal variance of α_{it} equals δ^2. This presents LAR formulation (see Heiss 2008 for more details).

The second concept was based on discrete latent variables, and presumed that every latent process α_i, follows a first-order homogeneous Markov chain with u states denoted by $\xi_1, \dots, \xi_u$. This chain is described by initial probabilities π_s and transition probabilities $\pi_{s_1 s_2}$

$$\pi_s = p(\alpha_{i1} = \xi_s),\ s = 1, \dots, u,$$
$$\pi_{s_1 s_2} = p(\alpha_{it} = \xi_{s_2} | \alpha_{i,t-1} = \xi_{s_1}), s_1, s_2 = 1, \dots, u, t = 2, \dots, T. \tag{2}$$

Namely, it is assumed that every α_{it} is conditionally independent of $\alpha_{i1}, \ldots, \alpha_{i,t-2}$ given $\alpha_{i,t-1}$, yet besides this assumption, the distribution of $\alpha_{i1}, \ldots, \alpha_{iT}$ is unconstrained.

However, this greater flexibility refers to a higher number of parameters to estimate (see Bartolucci et al., 2014).

The assumption of local independence for both the continuous and the discrete latent process can be expressed as

$$p(\mathrm{x}_i|\boldsymbol{\alpha_i}, \mathbf{Z_i}) = \Pi_{t=1}^{T} x_{it}\alpha_{it}\mathrm{z}_{it}. \tag{3}$$

Furthermore, under the first concept resulting in LAR model, the manifest distribution of $\boldsymbol{x}_i$ given $\boldsymbol{Z}_i$ has probability mass function

$$p(x_i|\, Z_i) = \int p(x_i|\boldsymbol{Z}_i, \alpha_i\,) f_{LAR}(\alpha_i) d\alpha_i, \tag{4}$$

where $f_{LAR}(\boldsymbol{\alpha}_i)$ denotes the joint marginal density of the T-dimensional latent trajectory under the LAR model. The above expression involves integration over the T-dimensional space $\mathbb{R}^T$, which may be difficult to compute in practice. Therefore, the sequential Gaussian quadrature method was applied (Heiss, 2008).

In the concept based on latent Markov chain, the manifest distribution of x_i given Z_i is described as

$$p(x_i|\boldsymbol{Z}_i) = \sum_{s_1=1}^{u} p(x_{i1}|\xi_{s_1}, z_{i1})\pi_{s_1} \sum_{s_2=1}^{u} p(x_{i2}|\xi_{s_2}, z_{i2})\pi_{s_1 s_2} \ldots \sum_{s_T=1}^{u} p(x_{iT}|\xi_{s_T}, z_{iT})\pi_{s_{T-1} s_T} \tag{5}$$

The sum was efficiently computed by a forward recursion (Baum et al., 1970; Welch, 2003). Then, first the joint distribution of $x_{i1}, \ldots, x_{it}$ and α_{it}, given the covariates, starting from $t = 1$ to $t = T$. In particular, the distribution for $t = 1$ was obtained on the basis of the model parameters, whereas for $t > 1$ it was by employing the results from the previous step of the same recursion. Finally, the distribution of x_i was obtained given the covariates by a suitable marginalisation with respect to α_{iT}.

Based on the concept that the latent process has a distribution given by a mixture of AR(1) processes with common variance for $i = 1, \ldots, n$, the study relies on the standardised AR(1) process given below. Considering that the latent variable $S_i = s$, one assumes that

$$\alpha_{i1}^{*} = \varepsilon_{i1}^{*},$$

$$\alpha_{it}^{*} = \alpha_{i,t-1}^{*}\rho_s + \varepsilon_{it}^{*}\sqrt{(1-\rho_s^2)},\, t = 2, \ldots, T, \tag{6}$$

where $\varepsilon_{it}^{*} \sim N(0,1)$. Likewise, in the standardised formulation, the stationary marginal variance of α_{it}^{*} equals 1. For the ordinal response with J ordered categories, let $\mu_1, \cdots, \mu_{J-1}$ denote the cut points. Conditional on $S_i = s$, we define the corresponding unstandardised latent effect as $\alpha_{it} = \xi_s + \alpha_{it}^{*}\sigma$, where α_{it}^{*} follows the standardised AR(1) process given in (6). In the MLAR model, ξ_s denotes the component-specific location parameter and should not be confused with the support points introduced earlier for the discrete latent-state model. The parameter σ is a scale parameter, and σ^2 is the common variance shared by all mixture components. The cumulative-logit model is then given by:

$$log\left\{\frac{p(x_{it} \geq j|\alpha_{it}^{*}, z_{it})}{p(x_{it} < j|\alpha_{it}^{*}, z_{it})}\right\} = \mu_j + \xi_s + \alpha_{it}^{*}\sigma + z_{it}^{'}\beta, \quad j = 1,2, \ldots, J-1. \tag{7}$$

Note that in the case of MLAR, it was supposed that the population of households was made up of u subpopulations (latent groups), described by parameters specific for those latent subpopulations. However, in the case of LAR model, one could observe the common parameters (for each of those groups), characterising the whole population of households. Then, the probability mass function of the distribution of the vector of responses x_i given all the observable covariates Z_i may be expressed as a mixture of LAR models, and the manifest distribution may be given as

$$p(\mathrm{x}_i|\, \mathrm{Z}_i) = \sum_s \pi_s p_s(\mathrm{x}_i|\, \mathrm{Z}_i), \tag{8}$$

where $p_s(x_i| Z_i)$ is the conditional probability of x_i given Z_i (Bartolucci et al., 2014). Mostly this probability was presented, given that latent effect α^*_{it} follows a standardised AR(1) process:

$$p_s(x_i| Z_i) = \int p(x_{i1}|\alpha^*_{i1}, z_{i1}) f_s(\alpha^*_{i1}) \int p(x_{i2}|\alpha^*_{i2}, z_{i2}) f_s(\alpha^*_{i2}|\alpha^*_{i1}) \dots \tag{9}$$
$$\dots \int p(x_{iT}|\alpha^*_{iT}, z_{iT}) f_s(\alpha^*_{iT}|\alpha^*_{i,T-1}) d\alpha^*_{iT} \dots d\alpha^*_{i2} d\alpha^*_{i1},$$

where $p(x_{it}|\alpha^*_{it}, z_{it})$ is computed on the basis of Equation (7) and

$$f_s(\alpha^*_{i1}) = \phi(\alpha^*_{i1}; 0,1),$$
$$f_s(\alpha^*_{it}|\alpha^*_{i,t-1}) = \phi\left(\alpha^*_{it}; \alpha^*_{i,t-1}\rho_s, 1-\rho_s^2\right). \tag{10}$$

Here, $\phi(\cdot; m; v)$ denotes the density of a normal distribution with mean m and variance v.

Similarly to the mixed models, the likelihood function was estimated on the basis on the adapted version of EM algorithm (see Baum et al., 1970; Dempster et al., 1977) combined with a Newton-Raphson (NR) algorithm (see Bartolucci & Farcomeni, 2009; Bartolucci et al., 2014, for more details). The choice of the mixture of the components was based on the Bayesian Information Criterion (BIC; Schwarz, 1978) and Akaike Information Criterion (AIC; Akaike, 1973) considering the parsimony and the goodness-of-fit of the model as well. The study relied on the functions implemented in `LMest` package of R (Bartolucci et al., 2017).

4. Results

This section reports the results obtained by applying the MLAR model compared to the other latent variable approaches assuming time-constant and time varying latent variables having discrete distribution. Table 1 presents the preliminary results for the MLAR model with a different number of mixed components for the data concerning the subjective well-being of Polish families. As regards the latent component selection, the study was based on the AIC and BIC criteria expected to be minimised.

Table 2. Maximum log-likelihood, number of parameters, BIC for the MLAR model, with s=1,…,5

s	LL	*#npar*	BIC	AIC
1	-3074.339	9	6220.438	6166.677
2	-3066.006	12	6201.025	6156.012
3	-3061.732	15	6209.731	6153.463
4	-3065.921	18	6235.364	6167.843
5	-3137.315	21	6395.404	6316.630

Source: own calculations in R.

The values assumed by BIC given in Table 2 led to the choice of two or three mixed components (slightly lower values for two compared to three components). Note that if those criteria indicated a different number of latent components, BIC was mainly preferred (see e.g. Bacci et al., 2014). However, to better compare the MLAR model with the other latent variable models (LC, LC-IRT, LM) presented in the author's previous studies (see Genge 2021, 2023) for the same data (where the lowest BIC value was achieved for *s=3*) and relying also on AIC criterion (the lowest AIC=6153.463 was achieved for *s=3*), the study focused in particular on the model with three components shown below.

The estimates of the parameters of the model selected, i.e. MLAR(3), and of the models with a smaller and higher number of latent components, are presented in Tables 3 and 4. Table 3 reports the estimates for cut points and of regression coefficients, together with the corresponding standard errors for all these models, whereas Table 4 shows the estimates of the parameters representing the latent structure of those models.

Table 3. The estimated parameters, log-likelihood, number of parameters for model MLAR with *s=1,2,3,4*

	MLAR (1)	MLAR (2)	MLAR (3)	MLAR (4)
$\hat{\mu}_1$	4.4910	4.9525	4.9933	5.0490
$\hat{\mu}_2$	2.3780	2.6011	2.6424	2.6478
$\hat{\mu}_3$	-0.9505	-1.0908	-1.0512	-1.1001
$\hat{\mu}_4$	-4.9117	-5.4127	-5.4717	-5.4466
$\hat{\beta}_1$ (*type of family*)	-0.1345 (*0.0593*)	-0.1460 (*0.0680*)	-0.1349 (*0.0682*)	-0.1401 (*0.0602*)
$\hat{\beta}_2$ (*occupat. position*)	-0.3598 (*0.0600*)	-0.4092 (*0.0696*)	-0.4027 (*0.0695*)	-0.4874 (*0.0713*)
$\hat{\beta}_3$ (*place of residence*)	-0.6799 (*0.2006*)	-0.7224 (*0.2247*)	-0.7746 (*0.2288*)	-0.7224 (*0.2404*)
LL	-3074.339	-3066.006	-3061.732	-3065.921
#npar	9	12	15	18
AIC	6166.677	6156.012	**6153.463**	6167.843
BIC	6220.438	6201.025	**6209.731**	6235.364

Source: own calculations in R.

Based on the regression coefficients and their standard errors reported in Table 3, it was concluded that all covariates are significant under every model considered. Concerning the comparison between the MLAR models with different values of *s*, the magnitude of each point estimate generally slightly increased (in absolute value) as *s* went up from 1 to 4, while retaining the same sign. For instance, the effect of occupational position increased from -0.3598 to -0.4874 (with the exception of the 3rd component).

Regarding model MLAR(3), families with more children as well as the other family types tended to report a worse financial condition than families with no children (the odds ratio was exp(-0.1349) = 0.8738). Similarly, farmers, professionally inactive Poles and those self-employed tended to report a worse income position than the biggest group of regular employees (the odds ratio was exp(-0.4027)=0.6685). Intuitively, the bigger the place of living, the higher the chance of being satisfied with one's income position (exp (-0.7746) = 0.4609 for mid-sized cities and villages compared to big cities). These results are also in line with mosaic plots (see Fig. 2) and the results presented in other (non-longitudinal) studies for other countries, measuring the effect of the similar covariates (Joo & Grable, 2004; Vera-Toscano et al., 2006; Kalra Sahi, 2013; Riitsalu & Murakas, 2019).

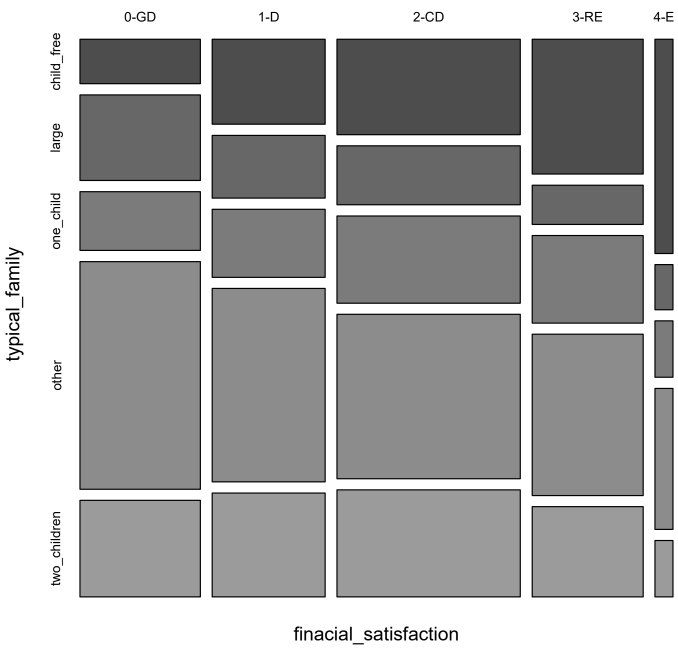

Fig. 2. Mosaic plot for financial satisfaction and type of family covariate

Source: own calculations in R.

Table 4. Estimates of the parameters of the latent process distribution for *MLAR(s)* with different number of classes

	s	$\hat{\xi}_s$	$\hat{\rho}_s$	$\hat{\pi}_s$	$\hat{\sigma}^2$
1	1	0.0000	0.8637	1.0000	8.3065
2	1	-0.3340	0.6661	0.4623	11.1693
	2	0.2871	0.9465	0.5377	
3	1	-0.5340	0.6952	0.4958	10.8557
	2	0.3748	0.9488	0.4868	
	3	4.7291	0.1616	0.0174	

Source: own calculations in R.

The results in Table 4 indicate that that the estimated parameters of the latent structure varied with the number of latent components (MLAR(1), MLAR(2), MLAR(3)).While for the model MLAR(1) all the subjects concentrated in only one class characterised by a very high correlation ($\hat{\rho}_s = 0.86$), the results were more diversified for the other models. With MLAR(2), 54% of the respondents belonged to a class with a high correlation ($\hat{\rho}_2 = 0.95$), whereas for the other respondents (46%) the correlation was much lower ($\hat{\rho}_1 = 0.66$), with a lower mean level for the latent effects ($\hat{\xi}_1 = -0.33$ compared to the second component $\hat{\xi}_2 = 0.29$). Under the third model, MLAR(3), it was observed that two classes had similar sizes, i.e. the subjects were equally distributed between the first two classes. The first class showed the intermediate level of correlation $\hat{\rho}_1 = 0.69$ and the lowest value of support point ($\hat{\xi}_1 = -0.53$), whereas the second class showed the high level of correlation ($\hat{\rho}_2 = 0.95$) and higher (compared to the first component) mean level for the latent effects ($\hat{\xi}_2 = 0.37$). For subjects in the third class comprising 1% of households, the correlation between individual effects in consecutive occasions was rather weak ($\hat{\rho}_3 = 0.16$), hence one may suppose that these respondents with the highest mean level of financial well-being ($\hat{\xi}_3 = 4.73$) were also characterised by sudden changes in unobservable factors affecting their financial perception.

Table 5 compares the goodness-of-fit of the MLAR model with the other latent variable models. While the author's previous research showed the best results for three numbers of latent components both for the latent class and the latent Markov models (based on the discrete distribution of the latent trait), the results in Table 5 are for three numbers of latent groups (states in the case of LM models). In particular, the latent class model with covariates (*LC-cov*) and its constrained version under item response theory parametrisation, i.e. LC-1P-RS-GRM with covariates were considered (the model with constrained difficulty and discrimination item parameters, for more details see Genge 2020, 2021; Genge & Bartolucci 2022).The author also assessed the results for models with time varying latent variable models and discrete distribution (latent Markov models) with covariates having influence on the latent (*LM-cov_latent*) and manifest (*LM-cov_manifest*) parameters of the model (cf. Genge, 2023). Finally, the results for the mixture of LAR models are presented below.

Table 5. Maximum log-likelihood, number of parameters, BIC and AIC values for different latent variable models

model	$\hat{l}$	*#npar*	BIC	AIC
LC-cov	-2995.033	104	6588.187	6198.067
LC-1P-RS-GRM-cov	-3089.913	21	6300.599	6221.825
LM-cov_latent	-2980.327	44	6213.705	6048.654
LM-cov_manifest	-3067.197	15	6220.661	6164.394
MLAR	-3061.732	15	6209.731	6153.463

Source: own calculations in R.

Regarding the goodness-of-fit measured by maximum log-likelihood, BIC and AIC criterion it was observed that both the LM model and the MLAR gave much better results compared to latent class models (the traditional and its constrained IRT version, i.e. the LC and LC-IRT model). Note that MLAR achieved a slightly higher level of the goodness-of-fit than the LM model, however they all show highly comparable results. The debate on which model is more appropriate, and between the continuous and the discrete latent process formulation, is open. Even if one can observe a slightly better parsimony of the MLAR model, it should be remembered that the interpretation potentials of LM (following the first order Markov chain), especially those including covariates having influence on the latent part of the model. Finally, the detailed analysis of the transition matrices (of LM) affected by socio-economic characteristics of the population varying with time allowed to better identify households especially prone to switching to a group with the worst self-reported financial position.

5. Discussion and conclusions

This article provides the empirically study of the evolution of financial perception of the Polish families, based on Polish National longitudinal survey data, Social Diagnosis. The author adopted the extended version of the LAR model relying on a mixture of AR(1) processes characterised by the average values and correlation coefficients (separate for each component of the mixture) and common variance to evaluate the financial well-being of Polish households measured at multiple time occasions. Compared to other works concerning the perception of satisfaction with one's material situation, which mainly relied on the selected years of the study (Wałęga, 2015; Kalinowski & Kozera-Kowalska, 2017; Chatterjee et al., 2019; Mahdzan et al., 2019; Silva & Dias, 2023), this study accounted for the heterogenous structure of the longitudinal data also using survey weights. The article shows that other types of families (e.g. one-parent families, multi-families) and those with more children, living in suburbs, being professionally inactive, were in special need of greater protection. Those results are in line with the author's previous research [Genge 2019, 2021, 2023] as well as with other (non-longitudinal) studies concerning subjective financial well-being for different socio-economic features in other countries [see e.g. Brzozowski & Visano, 2019; Israel & Spannagel, 2019; Riitsalu & Murakas, 2019]. The author analysed three mixtures of components corresponding to different latent AR(1) processes. Each of these components had its own specific correlation parameter. In this way, the study could take into account the latent trend and sudden changes which may occur in the data measured over the years. Both LM and MLAR indicated the highest goodness-of-fit compared to other latent variable models applied in this study. Even if the MLAR model presented a slightly higher BIC value (than the LM model) within the data at hand, the paper reflected the wide interpretation of prosperity for the time-varying latent variable models with discrete distribution. Similarly to the author's previous work, groups of families with similar perception of financial situation were identified. However, it should be emphasised that LM models are able to better describe families with stable opinions or prone to switch to a worse position over time. Thus it was also shown that families with more children were in a better position than those living within other family types as they slightly improve their assessment over the years (Genge, 2023).

Although one could observe a rather positive trend with income satisfaction over the years (slightly improved self-assessment of material condition), there remained a considerable room for improvement and a need to support the groups of Poles that exhibit low levels of financial wellbeing. Poland is still not only one of the EU countries with the lowest level of subjective material well-being, and the Eurobarometer data from July 2023 also showed that Poland ranks 6th from bottom (on the European scale) in terms of the level of financial knowledge of society. In 2024, economic education in Poland demonstrated that variable such as financial well-being made it possible to develop financial education programmes that have an impact on families with the lowest level of income. Better management of financial affairs could help to control, improve financial skills and decisions, and achieve financial and personal well-being.

Currently in Poland there is a limited number of well-grounded financial education programmes that target socio-economic groups other than children and young people (OECD, 2022, p. 127). The author believes that considering subjective information about income evaluation may also help to better recognise the specific financial education needs of people in different stages of life. Typically, these are households with three or more children, living in rural areas, including the unemployed or people out of the labour market, or those living off pension or disability benefits. They are also more often excluded from the formal financial sector, have lower savings (or no savings at all) and higher rates of indebtedness. Those specific groups exposed to poverty not only need greater social protection but may also require targeted financial education interventions. In fact, behavioural factors such as spending restraint, active savings, and no borrowing for daily expenses, allow for greater financial well-being (cf. Carton et al., 2022).

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