Bank i Kredyt 45(2), 2014, 79–104

BANK I KREDYT
BANK & CREDIT

Patterns of debt possession among households in Poland – a multi-group latent class approach

Piotr Białowolski*

Submitted: 28 March 2013. Accepted: 1 October 2013.

Abstract

In this paper, we evaluated patterns of debt possession among households in Poland by applying multi-group latent class models (MGLCM). Households' debt was investigated from the perspective of value, motive and source. MGLCM were used to conduct a segmentation of households with respect to debt possession and to determine the factors that influence segment membership. With data from the Social Diagnosis Survey, we checked whether the number of segments at the five selected measurement occasions (2003, 2005, 2007, 2009 and 2011) was constant, and the segments were of equal meaning. The results advocated for (1) segmentation with 10 distinct groups of households in each of the periods and (2) equal meaning of groups at all measurement occasions. Inclusion of households' socio-economic characteristics improved the overall model fit and enabled decomposition of the total change in the pattern of debt possession between 2003 and 2011. The total effect was decomposed into effects associated with the transition of the Polish credit market and changes in the characteristics of households.

Keywords: households' debt, multi-group latent class models

JEL: C38, O16

* Warsaw School of Economics, Institute of Statistics and Demography; University of Milan, Department of Economics, Management and Quantitative Methods; e-mail: piotr.bialowolski@gmail.com; piotr.bialowolski@sgh.waw.pl.

1. Introduction

The ratio of households' debt to GDP in the EU27 countries averages 60% (Pyykkö 2011). From this perspective, the indebtedness of Polish households, at a level of approximately 35% of GDP, is still low. However, this amount has increased in the medium term. The growth of household indebtedness in Poland has been the subject of several analyses that have focused on household credit aggregates (see Białowolski, Dudek 2007; Rytelewska, Huszczonek 2004). Both of these studies indicate that the credit market for households in Poland was (and remains) considerably underdeveloped, but both studies also indicate that the growth rates of household credit aggregates were much higher than the growth rates of household disposable incomes. These results lead to the conclusion that Polish household indebtedness is still below the long-run equilibrium and that the market is still under transition.

Changes in the amount of debt possession in Polish households can be attributed to two diverse forces. On the one hand, the increased household indebtedness could have been shaped by the transition process related to changes in the attitudes of Polish citizens to acquiring debt. Partial responsibility for this process might be attributed to changes in financial institutions' product offers[1] but also might have been driven to some extent by differences in households' debt strategies.[2] On the other hand, micro-level changes were driven by the evolution of incomes and other socio-economic characteristics of Polish households that were active in the market. This conclusion is in line with arguments provided by Paas, Bijmolt and Vermunt (2007), who indicate that acquisition of financial products is strictly connected to socio-economic characteristics such as age and income level because these factors direct households into different groups of products.

These two forces have direct consequences at the micro level for debt possession patterns. Although there are studies that focus on credit use in Poland using various types of data e.g., Białowolski and Dudek (2007); Białowolski et al. (2011); Wałęga (2010), so far very little attention has been given not only to segmentation of indebted households with respect to their patterns of debt use but also to an analysis of micro-level factors that are responsible for the changes in debt patterns. In the international context, analyses focusing on segmentation of households with respect to debt use are also scarce (Kamleitner, Kirchler 2007). Gunnarsson and Wahlund (1997), using data on both household saving and borrowing, provide segmentation of Swedish households with respect to their financial strategies. They show the existence of different clusters of households that differ in their risk-taking attitudes and behaviour but, due to a lack of information on credit targeting at the household level, they do not provide much detail regarding household borrowing strategies. Another approach is presented by Viaud and Roland-Lévy (2000). Using information from (only) 50 semi-structured interviews that allow in-depth analyses of financial behaviour, they identify different types of households based on their financial strategies. According to the authors' classification, there are only four types of behaviour: "prudent" and "savers", who rarely use credit instruments, and "fragile borrowers" and "prodigal households", who use credit extensively. Thus, this research also has limited applicability to patterns of borrowing.

---

[1] The changes on the supply-side might be even more vital in the case of markets in transition such as Poland, where large groups of households "missed" their life-cycle needs associated with credit products. These households' accessibility to credit products was limited because of the low level of credit market development at certain stages in the members of the households' life cycle.

[2] Arguments for an important role of household-specific characteristics in shaping debt possession can be found in Kirchler, Hoelzl and Kamleitner (2008) and Viaud and Roland-Lévy (2000).

Taking into account all of the arguments stated above, we find that there is a considerable gap in innovative research in the area of debt possession patterns. Studies filling this gap might focus on:

1) segmentation of households with respect to their debt behaviour, which is a prerequisite to establishing debt acquisition patterns;[3]

2) consistency of market segmentation, which is essential for the intertemporal comparison of market segments;

3) distinctions between factors associated with the transition process of the market (including factors connected with supply-side changes during the financial crisis[4]) and the socio-economic determinants of households' demand for debt.

All of these issues are accounted for in this paper with data from the Social Diagnosis Survey, which is conducted in Poland on a biennial basis. The starting point of the analysis is the period-specific segmentation of households with respect to their debt possession patterns. We conduct this analysis with latent class models. Second, we extend the analysis into a multi-group (multi-period) modelling framework, which enables us to check for intertemporal comparability of segments in different periods. Finally, with the multi-group latent class approach, we further develop the analysis by including determinants of debt possession associated with the socio-economic characteristics of households. Combined with information on the evolution of households' socio-economic characteristics during the time period under analysis, we provide a distinction between changes in the market that occurred due to socio-economic changes in Poland from 2003–2011 and changes related to the evolution of attitudes and supply-side factors.

To the best of our knowledge, this study features four innovative points. First, it is the first application of a multi-group latent class approach to establish debt acquisition patterns. Although a similar methodology is used by Bijmolt, Paas, Vermunt (2004) and Paas, Bijmolt, Vermunt (2007), their objective is studying the use of financial products rather than the segmentation of indebted households. Second, this study is the first attempt to describe the debt of Polish households from a multidimensional, survey-based perspective. Third, this is the first study to utilise the measurement invariance feature of multi-group latent class modelling on household debt behaviour. The importance of providing reliable intertemporal comparisons of segmentation results is stressed by Gunnarsson and Wahlund (1997) because only with such results can measures applied by policy makers based on segmentations be considered reliable. Fourth, this paper is the first to use information on segment determinants and the evolution of the socio-economic characteristics of Polish households to decompose changes in household indebtedness.

To meet these objectives, the paper is organised as follows: in Section 2, we present a detailed description of the Social Diagnosis Survey and basic statistics related to debt possession among Polish households with an emphasis on the time evolution. In Section 3, we describe multi-group latent class models with possible applications to the study. Section 4 provides details on the results

[3] Segmentation is important not only to establish patterns of household debt strategies but also may be important for product development and marketing purposes to better communicate product offers to customers (Gunnarsson, Wahlund 1997). Segmentation also provides better, more aggregated knowledge to apply policy measures in the face of major economic events.

[4] The changes observed in the period from 2009–2011, when most of the effects of the financial crisis began to become visible in households, was driven by two factors: (1) changes in households' attitudes with respect to credit products and (2) a substantial change in the policies of banks and financial intermediaries with respect to their core activities. These changes were observed in the increased strictness in providing credit and also by financial regulations introduced by the Polish Financial Supervisory Authority.

of the estimation of multi-group latent class models and evaluates whether the changes in the structure of segments of households on the credit market should be considered significant. The remainder of that section is devoted to a selection of the determinants of households' participation in the credit market and latent class (segment) membership. We investigate whether there is an influence of age of the head of household, household income or household location on latent class membership. Section 5 presents the conclusions of the study.

2. Changes in debt possession in Polish households between 2003 and 2011

The period of analysis covers a time of substantial changes in the Polish credit market for households. There was a rapid growth in the penetration rates of credit in all areas – consumer, housing and other, which was observed during the entire period under analysis (Figure 2).

The most visible increase took place in the market for mortgages, where the penetration rates went up from just 4% in 2003 to 21% in 2011. Consumer credit was also subject to considerable growth between 2003 and 2009, but in the period from 2009–2011, this growth suddenly stopped, and the penetration rate decreased from 11% to 9%. All of these changes are naturally reflected in an assessment of debt provided by households in the Social Diagnosis Survey. Five waves of the survey serve as the source of data for this analysis (Czapiński, Panek 2011). They cover the state of households' credit portfolios for the period from 2003–2011 and are gathered in a panel-type study. The number of households participating in the Social Diagnosis Survey gradually increased during the period of interest. The sample size increased from 3,961 in 2003 to 12,386 in 2011.

However, the growth of household debt was not linear. The surveys conducted in 2003, 2005 and 2007 covered the period of its rapid increase. The survey conducted in March 2009 evaluated the situation shortly after the onset of the financial crisis. Due to inertia in the patterns of debt possession, the impact of the crisis on households' debt was most likely very limited at the time the data were collected. The supply-side limitations introduced by Polish financial institutions and the Polish Financial Supervisory Authority in reaction to the crisis were either in the preparation stage or were at most present for a very short period of time. The survey performed in 2011 permitted evaluation of the consequences of the financial crisis and of the policy measures undertaken in reaction to it on households' debt.

In the Social Diagnosis Survey, the debt possession of households is described with respect to three dimensions: debt source, objectives for taking debt and the value of the debt. The evolution of the share of households with respect to different loan/credit sources is presented in Table 3.

Table 3 shows that from 2003–2011 there was a rapid increase in the share of households indebted to the banking sector and a significant decrease in the role of other financial institutions and/or private persons. In 2003, most of the indebted households possessed a loan/credit granted by a bank (78.4%), but loans from other financial institutions (mostly financial intermediaries) were also relatively widespread – 29.7% among the indebted households. In the following years, an increase in the role of banks came mainly at the expense of other sources of borrowing. Major changes occurred between 2005 and 2009, when the accessibility of credit from the banking sector increased rapidly, translating into growth from 80.8% to 90.6% in the share of households indebted in banks. There was a considerable parallel reduction in the share of households with loans from other financial institutions. In 2009, the share of such households declined to only 12.4% of all indebted households. The role of private persons was also significantly reduced during that period. In the period with the most rapid growth of the banking sector (2005–2007), the share of households with a loan from private persons slumped from 11.8% to only 5.7%.

An additional consequence of the rapid changes in the credit market for households in Poland was a reduction in the scale of borrowing from diversified sources.[5] In 2003, indebted households obtained their debts from 1.19 sources on average. This average decreased until 2009 and then stabilised in 2011. Currently, the average indebted household holds debt from 1.08 sources, which indicates that households are less inclined to mix loans from the banking sector, financial intermediaries and private persons.

The situation with respect to the objectives of acquiring debt was also the subject of considerable changes during the last decade (Table 4).

Polish households became more goal-oriented in their behaviour on the credit market. In 2003, households with a loan/credit were financing on average 1.84 objectives. In the subsequent surveys, this number declined, finally reaching 1.51 in 2011. This change was most likely a consequence of the increasing affluence of Polish households, which reduced the role of credit as a source of money for current needs. The share of respondents designating the goals of current consumption expenditures and fixed charges decreased very significantly between 2003 and 2011. Increased affluence was also reflected in a decline in the share of households that needed to finance repayments of their previous debts with a new credit/loan. The share of such households decreased the most between 2007 and 2009, which was most likely a consequence of *per capita* income growth. *Per capita* income grew 20% in real terms during the period. The improvement in the financial situation of Polish households was also visible in the lower number of households that applied for credit to finance vacations and/or medical treatment.

The areas in which stabilisation of the share of households was observed include debt for the purchase of durables and debt for financing the renovation of an apartment. These two goals were, however, the most widespread goals among indebted Polish households. Credit only became increasingly popular in the period under analysis for the purpose of house/flat purchases – especially between 2005 and 2009. The share of households financing this expenditure rose from 13.7% in 2003 to 18.0% in 2011.

In addition to changes in the objectives and sources of taking credit, there were very significant changes in the value of debt with respect to average monthly incomes.

An insignificant difference in the structure of the debt to income ratio among households with a credit/loan was observed between 2003 and 2005. In the following years, there was an abrupt increase in the value of debt, which was especially visible in the share of households with debt exceeding their average annual incomes. In 2003, this group accounted for 10.7% of all indebted households, while in 2011 this percentage increased to 23.8%. There was a very little change in the share of households with a value of debt that did not exceed their monthly incomes, which could suggest that low-value loans preserved these households' position in the market. On the other hand, there was a decline in the share of medium-value loans. The share of households indebted at a level ranging between their monthly and their semi-annual incomes declined from 53.0% in 2003 to 39.3% in 2011.

[5] The reduction in the scale of diversified borrowing shows that there was no longer a need to mix loans from banks, financial institutions and other sources in one household. The data do not imply that the total number of loan/credit agreements decreased.

3. The application of MGLCM to the analysis of Polish households' financial behaviour

Latent-class modelling is a technique that allows us to account for unobserved heterogeneity in the sample, which is captured by introducing a latent variable (Muthén 2004). Thus, latent-class modelling can be applied as a segmentation technique, which enables us to not only define the optimal number of homogeneous segments in the market but also to present the distribution of answers to each item (question) based on the latent class. In latent class models, it is assumed that the correlations between indicators (questions) are explained only by the latent class membership. Thus, it is assumed that within the latent class, the answers to different indicators (questions) are independent of one another.[6]

The main advantages of clustering based on latent class models over other clustering methods were summarised by Vermunt and Magidson (2002):

1) latent-class analysis is a modelling-based approach that provides results that can be subject to formal (or semi-formal[7]) testing; it is assumed that data are generated by a mixture of probability distributions;

2) restrictions on parameters can be made and tested to obtain more parsimonious model;

3) no scaling decisions are necessary and the scaling of variables does not affect the result.

A characteristic feature of latent class analysis is that the latent variable is also discrete. Classes are designed to identify groups of individuals who possess a certain pattern of behaviour and to test whether this pattern can be explained by the class membership.

Multi-group latent class modelling is an extension of latent class modelling. It was originally developed for the analysis of latent structures of categorical latent variables across a different number of groups (Kankaraš, Moors, Vermunt 2011). Multi-group latent class modelling serves as a useful tool for segmentation, and it additionally enables testing of the homogeneity of segments' patterns among groups through a series of constraints. In this paper, different groups correspond to different time points of analysis, which allows for testing the equivalence of segments in time. Estimation of the latent class models is performed with a maximum likelihood estimator following the EM algorithm, in which the information on latent class membership is considered missing and thus is derived from the data (Muthén, Shedden, Spisic 1999).[8]

A multi-group latent class model can be defined with N manifest variables $A_1 A_2 .... A_N$ (answers to N questions), each having M_i ($m_1 = 1... M_1$; $m_2 = 1... M_2$; ...; $m_N = 1... M_N$) answer categories, one latent variable X with $k = 1,..., K$ classes and one grouping variable T with $t = 1,..., L$ groups. In this setting, it is possible to define L cross-tables each with N dimensions that represent interrelations between manifest variables in each group (in our case at each time point). Including latent variable X leads to the following form of the model:

$$\pi_{m_1 m_2 ....m_N kt}^{A_1 A_2 ....A_N X\setminus T} = \pi_{kt}^{X\setminus T} \pi_{m_1 kt}^{A_1\setminus XT} \pi_{m_2 kt}^{A_2\setminus XT} \dots \pi_{m_N kt}^{A_N\setminus XT} \tag{1}$$

where $\pi_{m_1 m_2 .... m_N kt}^{A_1 A_2 .... A_N X\setminus T}$ defines the conditional probability that a respondent with the set of answers

---

6 Although detailed information on the distributional assumptions in latent class modelling are beyond the scope of this article, the reader can refer to Walesiak and Gatnar (2009) or Vermunt (2008) for more information.

7 In the group of semi-formal tests, model selection based on the information criteria can be used.

8 A detailed explanation of the estimation procedure with EM algorithm can be found in Vermunt (2008) or Muthén (2004). The discussion of these issues is, however, beyond the scope of the article.

$(m_1, m_2, \ldots, m_N)$ given in period t belongs to latent class k, while $\pi_{kt}^{X\setminus T}$ defines the conditional probability of belonging to class k given period t, and $\pi_{m_i kt}^{A_i\setminus XT}$ defines the probability of providing answer m_i to item A_i given class membership (k) and given the period of analysis (t).

Latent class models in such a specification are based with an assumption of local independence, which implies that the answers to manifest questions $(A_1, A_2, \ldots, A_N)$ are independent of each other, given the latent class k.

In this article, the conditional probabilities $\pi_{m_i kt}^{A_i\setminus XT}$ in a latent class model are specified with logistic-type parameterisation. In such a case, the probability of providing a given answer can be defined as follows:

$$\pi_{m_i kt}^{A_i\setminus XT} = \frac{e^{thresh_{m_i,k,t}}}{1+e^{thresh_{m_i,k,t}}} - \frac{e^{thresh_{m_{i-1},k,t}}}{1+e^{thresh_{m_{i-1},k,t}}} \tag{2}$$

where for each question there are $M_{i\text{-}1} \cdot K \cdot L$ estimated thresholds with constraints $\forall k \in K \wedge t \in L \; thresh_{M_0,k,t} = -\infty$ and $\forall k \in K \wedge t \in L \; thresh_{M_i,k,t} = +\infty$.

Latent class membership also depends on the unconditional class membership $\pi_{kt}^{X\setminus T}$ which is estimated with the multinomial logostic regression of the form:

$$\pi_{kt}^{X\setminus T} = \frac{e^{thresh_{k,t}}}{1+\sum_{i=1}^{K-1} e^{thresh_{i,t}}} \tag{3}$$

Measurement invariance, associated with homogeneity of the segmentation pattern between groups, can be defined at two levels. The most basic multi-group latent class model with measurement invariance assumes equality of thresholds for the probabilities of the answers to questions and can be formally stated as: $\forall i \in N; m_i \in M_i;\ k_1, k_2 \in K; t_1, t_2 \in L\, thresh_{m_i,k_1,t_1} = thresh_{m_i,k_2,t_2}$. This level of measurement invariance is sufficient to ensure the structural equivalence of the model (McCutcheon 2002), which takes the form:

$$\pi_{m_1 m_2 \ldots m_N kt}^{A_1 A_2 \ldots A_N X\setminus T} = \pi_{kt}^{X\setminus T} \pi_{m_1 k}^{A_1\setminus X} \pi_{m_2 k}^{A_2\setminus X} \ldots \pi_{m_N k}^{A_N\setminus X} \tag{4}$$

In this specification, the indicator variables – answers to questions – are not directly dependent on the grouping variable (time). The understanding of latent classes (segments), as expressed by its indicators (questions), is invariant of the grouping variable. At this level of measurement invariance, a change in the probability of answering a given question depends only on the latent class membership (not on the time). However, latent class membership probability can change between time points. Such a model can be described as partially homogeneous (Kankaraš, Moors, Vermunt 2011).

A higher level of measurement invariance is obtained in a completely homogenous model, which requires that the probabilities of class membership are constrained to be equal between groups. At this level, the formal definition of measurement invariance also requires that $\forall k \in K; t_1, t_2 \in L \;\; thresh_{k,t_1} = thresh_{k,t_2}$. The model can be formally presented as follows:

$$\pi_{m_1 m_2 \dots m_N kt}^{A_1 A_2 \dots A_N X \backslash T} = \pi_{m_1 m_2 \dots m_N k}^{A_1 A_2 \dots A_N X} = \pi_k^X \pi_{m_1 k}^{A_1 \backslash X} \pi_{m_2 k}^{A_2 \backslash X} \dots \pi_{m_N k}^{A_N \backslash X} \tag{5}$$

which implies that the probability of a given answer set does not depend on the grouping variable (time).

In applied research, this level of measurement invariance is less interesting because, if it is established, it does not allow us to account for differences in group shares between the periods of analysis. However, if this level of measurement invariance is established for some groups only, it might provide interesting insights concerning the characteristics of the groups.

The multi-group latent class analysis can be extended by including descriptive variables that serve as predictors of latent class membership and are included in an equation for:

$$\pi_{kt}^{X \backslash T} = \frac{e^{thresh_{k,t} + \sum_{j=1}^{J} \alpha_{j,k} x_j}}{1 + \sum_{j=1}^{K-1} e^{thresh_{i,t} + \sum_{j=1}^{J} \alpha_{j,k} x_j}} \tag{6}$$

where $\{x_1, \dots, x_J\}$ is a set of explanatory variables, while $\alpha_{j,k}$ represents the estimated parameters, which are set to zero for a selected, reference class.

In the multi-group approach, the comparison between models and the selection of the proper model can be either completely formal, based on the absolute fit defined by tests of likelihood-ratio chi-square (L^2) and Pearson's chi-square (χ^2), or based on the information criteria. With respect to the L^2 and χ^2 tests of absolute model fit, there is a controversy concerning their ability to address sparse tables, which are common in latent class models. These tests reject models too often; the possible flaws might be associated with a lack of the chi-square distribution of the p-value due to the low number of individuals in a given cell of a sparse table (Kankaraš, Moors, Vermunt 2011). Additionally, with a large number of observations, absolute fit tests tend to be too rigorous, and they reject plausible models. A commonly adopted approach is therefore to conduct a model comparison with information criteria, which enables comparisons of different types of models and leads to the selection of the best model.

In this paper, an approach based on the Bayesian information criterion (BIC) is adopted to check for the measurement variance, and the following procedure is applied:

1) the optimal number of groups is established in the model for each period separately;

2) the partially homogeneous model is tested for specification with the same number of latent classes as in the heterogeneous model (period-specific) but also for specifications with an equal number of classes in all periods – ranging from the minimum to the maximum number of latent classes obtained for a single period model;

3) for completely homogeneous specification models, the number of classes ranging from the minimum to the maximum are tested;[9]

4) the preliminary solution is selected based on the information criteria;

[9] In this specification model, a period-specific number of classes cannot be obtained because the latent class probabilities are constrained to be equal.

5) the solution is subject to testing for different constraints associated with the time evolution of latent classes.[10]

With this approach, we check whether heterogeneous, partially homogeneous or completely homogeneous models should be adopted to explain the evolution of the structure of the Polish credit market.

For the analysis of factors influencing the latent class membership, the following procedure is applied: (1) we include all of the possible explanatory variables in the model (age of head of the household, income level, labour market status, number of people in the household and the size of the location of the household); and (2) indicators with the largest p-values are eliminated until only indicators with p-values lower than 0.05 are left.

For the final solution, a quality check with the entropy measure is performed. Each household is classified into its most likely class, and then a table is constructed with rows corresponding to households classified into a given class and column entries give the conditional probabilities of belonging to a given class (Muthén 2004).[11] The entropy measure is defined to vary between zero and one, and entropy values close to one indicate clear classifications based on the model (Muthén 2004).

4. Results

4.1. Number of classes

To detect the number of homogeneous segments at all time points, latent class models are initially estimated separately for 2003, 2005, 2007, 2009 and 2011. During the estimation process, it was established that the best fitting models for 2003 and 2005 are those with 7 classes, for 2007 the best-fitting model has 8 classes and for 2009 and 2011, the best fitting models have 10 classes (see Table 1).[12] Following the procedure for the assessment of measurement invariance presented in Section 3, three types of models are estimated. First, a model with unconstrained class probabilities and unconstrained conditional response probabilities (in a logistic specification – threshold structure) is estimated. In the second step, a model with constrained conditional response probabilities is estimated; however, a possibility of varying class probabilities between time points is left. In this specification, the probabilities of class membership in different groups (time points) can be compared because the meaning of the latent classes is preserved for all of the periods of the analysis. Finally, a model with not only constrained thresholds but also with constrained class probabilities is estimated. In such a specification, it is possible to compare the meaning of the classes and to state that the segmentation of the market does not vary between the time points. However, this specification requires us to set an equal number of latent classes for all of the periods of analysis. The values of BIC for the three specifications of the model are presented in Table 6.

---

[10] The constraints are associated with the pattern of time evolution of the class membership probabilities. We check whether the models with sequential elimination of time-specific parameters are better than the models with an assumed linear trend in the evolution of period-specific parameters.

[11] The detailed formula for the entropy measure can be found in Muthén (2004).

[12] It should be remembered, however, that there are differences in the sample size between the waves of the Social Diagnosis, with a much smaller size sample for 2003 and 2005. As Lukočienė, Varriale and Vermunt (2010) state, the smaller the sample size, the less likely that one finds the correct number of classes.

Based on the results, the best fitting model is selected: the 10-class, partially homogeneous specification with varying probabilities of class membership between periods. Further estimations prove that some period-specific parameters in the 10-class, partially homogeneous solution are not significantly different from zero. Moreover, in some cases, a trend in the values of the parameters associated with time can be observed, which implies that there is a similar difference between the estimated thresholds for the consecutive periods in equation (2). Because multi-group latent class models might be tested for the presence of group- (period-) specific effects, two alternative sets of constraints are imposed in the partially homogeneous specification with 10 classes. In the first specification, we check whether the BIC improves for a model with period-specific parameters constrained to zero in the group of parameters with p-values above 0.05. The second specification is based on the parameters obtained in a 10-class, partially homogeneous model, but when a visible trend is observed, the parameters are constrained according to the hypothesised pattern either to follow a linear trend, follow a linear trend with a break in 2009 (associated with the onset of the financial crisis) or be equal for some periods. In the first specification, an improvement in the model's fit is observed (BIC = 344231.707). However, the fit improves even more in the second specification and the BIC amounts to 344147.389. This result advocates for adopting a partially homogeneous model with period-specific thresholds, which however in some classes follow a trend.

4.2. Characteristics of classes in the model with covariates

In the following step, all of the explanatory variables are included to account for class membership. Afterwards, the number of variables is sequentially reduced to eliminate those variables that are insignificantly different from zero. A model with a reduced number of explanatory variables (BIC = 337123.134), where all of the variables are characterised by p-values lower than 0.05, is adopted as the final solution. The fit of the model also proves to be very good, which is confirmed by the value of the entropy measure (0.975). Item response probabilities, calculated in line with formula (2) for each latent class in the final model, are presented in Table 7.

The final model comprises an implicit description of the latent classes of households in Poland in the credit market. There are nine distinct groups of households active in the credit market (classes 1–9) and one group of households not participating in the market. The groups (classes) can be described as follows:

Class 1. Households with a rather low value of debt that is acquired from a bank (rarely supported by a loan from another financial institution). The debt is designated for renovation of a house/flat (100%) and sometimes for the purchase of durables (28.4%).

Class 2. Households that have high probability of debt in many categories with respect to the purpose and very often with a high value of debt (54.7% with debt exceeding their semi-annual incomes). These households' sources of credit are mainly banks (96.8%), but they also often search for credit from other financial institutions (27.1%) and from their friends and family (25.8%). In this group, there is a very high probability of credit for current consumption (57.4%) and for repayment of previous debts (55.8%) and also for fixed charges, the purchase of durables and renovation of a flat (each of the last three exceeding 40%). Due to a very high value of debt and the goals associated with current consumption (or repayment of debts), this group of households can be classified as over-indebted.

Class 3. Households that have an above-average value of debt. This debt is almost always from banks (99.6%) and extremely rarely from elsewhere. These households' objective in taking credit is to develop their business (71.5%) or (a very close counterpart) to purchase working equipment (34.7%). However, these households are only slightly less active than average in acquiring very popular credit products for the purchase of durables (26.3%) and for renovation of a flat (14.5%).

Class 4. Households that have a below-average value of debt. These households' acquire their debt from banks (100%), and they very rarely support the debt with a loan from other sources. They use the debt to finance other purposes (100%) and rarely to purchase durables (14.5%).

Class 5. Households that have a relatively low value of debt (67.3% with debt below their quarterly incomes). Similar to households in latent class 4, these households' acquire their debt from banks (100%) and extremely rarely from elsewhere. The debt is devoted almost solely to purchases of durables (100%).

Class 6. Households that have a low value of debt (69.6% with debt below their quarterly incomes) acquired from the banking sector (100%) and extremely rarely from elsewhere, similar to households from latent classes 4 and 5. These households' debt is devoted to current consumption (61.3%) and fixed charges (30.5%). In this group, there is a significant share of households taking credit for medical treatment (21.7%). They also sometimes take debt to finance the renovation of a flat (14.3%) and for repayment of previous debts (11.6%). Due to the latter feature and because current consumption is the main objective of this group's debt possession, these households can be described as in a pre-over-indebted state.

Class 7. Households that have a low value of debt but who acquire it from other financial institutions (100%) and only rarely from the banking sector (18.0%). These households devote their loans to renovation of a flat (44.1%) and the purchase of durables (38.1%). They also use a credit/ loan to finance other objectives, including current consumption (19.3%), fixed charges (9.1%), medical treatment (8.3%), education and training (8.1%) and vacations (7.9%).

Class 8. Households that are extremely highly indebted (65.5% possess debt exceeding their annual incomes). These households' sources of credit are banks (100%) and rarely from other institutions. These households are indebted to finance the purchase of a house or flat. They rarely also use debt to finance the renovation of a house or flat (12.6%) or to purchase durables (12.0%).

Class 9. Households that acquire loans from friends and family (100%), sometimes supporting these loans with loans from a bank (16.2%) or another institution (10.0%). The value of debt for these households is the lowest among all of the groups (71.9% with debt below their quarterly incomes). Similar to households in class 6, these households use debt to finance their current consumption (57.8%) and/or fixed charges (38.6%). In this group, there is also an above average exposure to credit for medical treatment (17.9%) or for previous debt repayment (17.8%). The most popular credit objectives (renovation of a flat and purchase of durables) occur in this group with a below average frequency (14.5% and 15.5%, respectively). Similar to the households in latent class 6, these households can also be considered pre-over-indebted.

4.3. Evolution of segments in time

The segmentation of the Polish credit market from the perspective of households' behaviour provides insight into the key groups of households present in the market. With latent-class-based segmentation, we can trace the evolution of the composition of the market for the past decade. In Figure 3, we present the results of the MGLCM estimation, providing on the left-hand side the share of households active in acquiring debt and on the right-hand side the composition of the group of active debt holders.

In Poland, the share of indebted households decreased between 2009 and 2011, after the period of stability between 2003 and 2009. However, more fundamental changes are visible with respect to the evolution of the debt-acquiring patterns. In 2003, class 7 was the largest, which indicates that the very important role played by other financial institutions at that time diminished in the following years. The declining role of non-banking forms of borrowing is confirmed by the gradual disappearance of the group of households that borrows from private persons (class 9). At the same time, the more goal-oriented approach to debt possession adopted by Polish households resulted in a decline in the share of households that were prone to externally finance a large number of purposes, as represented by the over-indebted group (class 2).

An inverse situation is observed with respect to class 8, comprising households indebted for the purchase of an apartment/house. The share of these households increased from 6.8% to 16.2% in the period of analysis. A significant upswing is also reported for class 1 (households with credit for renovation of their apartment). In 2011, class 1 accounted for 21.4% of the indebted households, while eight years earlier, class 1 constituted only 13.8%.

In the multi-group latent class approach without covariates, the total change in the market structure is attributed to the time evolution of the market; however, this approach does not allow us to account for the socio-economic factors that influence participation in the credit market. These factors usually include income, information on the life-cycle stage of the household (age of the head of household), location of the household, work status of the head of household, etc. To evaluate the influence of both the transition of the credit market and socio-economic characteristics, the final model with a set of covariates is presented in Table 8.

The results presented in Table 8 serve as the prerequisite for calculating the expected evolution of the share of each credit market segment after accounting for the influence of the socio-economic characteristics of the households (Figure 1). The most visible change was observed with respect to class 7, which consisted of households indebted to other financial institutions. Households with these same socio-economic characteristics tended to move to banks (which are perceived as more transparent and reliable) when the product offer was richer. From the theoretical evolution of class 7 (see Figure 1), it can be observed, however, that over 99% of the change in the share of indebted households in this group was due to the transition process with respect to debt possession, and less than 1% was due to the evolution of the socio-economic characteristics of the households in the Polish economy.

Until 2007, the extremely large momentum in the market for mortgages (see Figure 2) was mostly driven by the transition process of the Polish market associated with greater accessibility to credit for housing purposes. From 2007 onward, although there was a more than twofold increase in the value of mortgages, the market for mortgages was mostly driven by growth in incomes and new waves of young adults (with their families) entering the market. In the case of this group (class 8), the relation between income and class membership was the strongest of all the classes. In terms of the odds for belonging to latent class 8, households with incomes above 3000 PLN were 23 times more likely to belong to that class than those with incomes below 500 PLN. In the case of households indebted to purchase an apartment the influence of age was the strongest in all groups. For the whole period from 2003–2011, approximately 65% of the change in the share of households in class 8 can be explained by the change in the socio-economic characteristics of households, and only 35% of the change resulted from the transition of the credit market in Poland.

In the case of class 5 and class 6, the transition component was not significant and was fixed to zero in the estimation process.[13] In the case of credit for durables, households with low incomes had the most reduced access to the market. It can also be observed that households with a head of household in the age range of 25–44 years turned to this source of credit the most often, while those with heads of households aged over 65 rarely used it. Additionally, households in rural areas and small towns also rarely used such debt, which was most likely a consequence of reduced access to it in those locations. For households acquiring debt mainly for current expenditures (class 6), the level of income acted strongly against the acquisition of such products, while the number of people in a household exceeding 5 was a stimulus for acquiring a loan for current expenditures. As in all of the other classes, class 6 households with the head of household aged 65 or more rarely acquired debt for current consumption. Nevertheless, in the case of credit for durables and credit for current consumption, the influence of age (being 65+) was the lowest among the groups. An interesting observation is that the credit for current consumption was present much less often in rural areas, which was most likely caused by these households' lower accessibility to financial institutions and their higher self-sustainability.

With respect to class 1 and class 4, higher accessibility to a loan/credit for the purposes of durable goods purchases and the financing of other purposes stopped in 2009. After 2009, the conditions for granting credit were significantly strengthened because of both the financial crisis and the Polish Financial Supervisory Committee's regulations. Households began to reduce their demand for house/flat renovations and also attempted to finance other objectives less often. Renovation of a flat/house was the most popular objective for households with middle incomes. Demand for this type of credit was considerably lower for the group of households with average *per capita* income exceeding 3000 PLN. Nevertheless, in both of these groups, the major factor responsible for the overall decrease can be attributed to the transition process of the market (69% and 88%, respectively) and not to the change in the socio-economic characteristics of households.

One of the most specific segments of households in the credit market was the group oriented towards financing their entrepreneurial activities with credit (class 3). The evolution of accessibility to loan/credit in that group was negative. Better accessibility to entrepreneurial financing was observed from 2003–2007, but later it gradually declined. However, changes in the socio-economic characteristics of households counteracted this trend (see Figure 1). Membership in this class was very strongly determined by incomes and (obviously) labour market status. Age of the head of household was an important factor that negatively influenced entrepreneurial credit demand only for households with the head of household over age 64. Contrary to the other classes, only for this group of households was rural location a stimulus for credit demand. The odds of belonging to this group were almost three times higher in rural areas than in major cities.

One of the most interesting groups included households that borrow extensively, finance a number of goals and often do not manage to cope with their obligations – the over-indebted households (class 2). The size of this group has gradually decreased, which was partially a consequence of the transition processes – banks and other financial institutions were less willing to provide credit products

[13] It should be remembered that the transition component is set relative to class 10 (the reference class), which makes the expected share of households in class 5 and class 6 dependent on the relative change in the share of respondents in class 10.

to the over-indebted group (approximately 65% of the change was due to the transition process). On the other hand, gradually increasing income levels, which strongly affected membership in the over-indebted latent classes, stimulated a rapid decrease in the number of such households in Poland. The problem of over-indebtedness was less visible for the group of households with older heads of household and also for households with only one or two members. The problem of over-indebtedness was to a large extent a problem of urban areas. In small towns, the odds of belonging to this group were two times lower than for households in large cities, and for households rural areas, the odds for membership were almost three times lower.

5. Conclusions

In this article, we presented an analysis of households' behaviour with respect to the possession of debt. We tracked household indebtedness patterns with the proposed segmentation technique based on multi-group latent class models. In the scope of the analysis, we identified nine distinct patterns of debt possession in Poland and one group of households without debt. With a multi-group framework, we demonstrated that models in which the rules of segmentation of the market remain constant in all the periods of analysis are superior to the models in which the rules change over time.

One of the most interesting developments from the study is the delineation between the changes observed in the Polish credit market for households that were driven by the transition process of the credit market and those that can be attributed to changes in the socio-economic characteristics of Polish households. We showed that approximately 85% of the changes that occurred in the structure of the debt of Polish households between 2003 and 2011 were due to factors associated with the transition of the Polish market, and only 15% of the changes could be attributed to the evolution of the socio-economic characteristics of households during the period of analysis. Our research showed that households began to use loan/credit products offered on the financial market differently because of changes in not only the product offers but also in their tastes. The most striking example was the market for loans from other financial institutions. A very significant decline in the share of households with such loans could be 99% explained by the transition process of the credit market in Poland. On the other hand, in the group of households taking on mortgages, the transition process was able to explain merely 35% of the huge increase in the size of the group. The transition process of the Polish credit market could also only partially explain the changes in the size of the group of over-indebted households, while for those acquiring debt for the development of their own businesses, the transition of the market acted in the opposite direction (negatively) than households' socio-economic characteristics.

However, this paper is only a starting point in the discussion of debt acquisition patterns among Polish households. Although we presented a clear segmentation of the market and showed its consistency between periods, there is still a room to analyse the transition process in more detail by tracking changes observed over time with regard to the debt acquisition patterns for households included in the Social Diagnosis Survey.

References

Białowolski, P., Czapiński J., Grabowska I., Kotowska I.E., Panek T., Strzelecki P., Węziak--Białowolska D. (2011), Household living conditions Social diagnosis 2011. Objective and subjective quality of life in Poland, *Contemporary Economics* (special issue), 5(3), 50–112.

Białowolski P., Dudek S. (2007), *Growth potential of the Polish household credit market in the light of real convergence of the Polish economy*, Wydawnictwo Uniwersytetu Gdańskiego, Gdańsk.

Bijmolt T.H., Paas L.J., Vermunt J.K. (2004), Country and consumer segmentation: multi-level latent class analysis of financial product ownership, *International Journal of Research in Marketing*, 21(4), 323–340, doi:10.1016/j.ijresmar.2004.06.002.

Czapiński J., Panek T. (2011), *Social diagnosis*, www.diagnoza.com.

Gunnarsson J., Wahlund R. (1997), Household financial strategies in Sweden: an exploratory study, *Journal of Economic Psychology*, 18(2–3), 201–233, doi:10.1016/S0167-4870(97)00005-6.

Kamleitner B., Kirchler E. (2007), Consumer credit use: a process model and literature review, *Revue Européenne de Psychologie Appliquée/European Review of Applied Psychology*, 57(4), 267–283, doi:10.1016/j.erap.2006.09.003.

Kankaraš M., Moors G., Vermunt J.K. (2011), Testing for measurement invariance with latent class analysis, in: E. Davidov, P. Schmidt, J. Billiet (eds.), *Cross-cultural analysis: methods and applications*, Routledge, New York.

Kirchler E., Hoelzl E., Kamleitner B. (2008), Spending and credit use in the private household, *The Journal of Socio-Economics*, 37(2), 519–532, doi:10.1016/j.socec.2006.12.038.

Lukočienė O., Varriale R., Vermunt J.K. (2010), The simultaneous decision(s) about the number of lower- and higher-level classes in multilevel latent class analysis, *Sociological Methodology*, 40(1), 247–283, doi:10.1111/j.1467-9531.2010.01231.x.

McCutcheon A.L. (2002), Basic concepts and procedures in single and multiple-group latent class analysis, in: J.A. Hagenaars, A.L. McCutcheon (eds.), *Applied latent class analysis*, Cambridge University Press, New York.

Muthén B.O. (2004), *Mplus technical appendices*, Muthen&Muthen, Los Angeles.

Muthén B.O., Shedden K., Spisic D. (1999), *General latent variable mixture modelling. Technical report*, unpublished manuscript.

Paas L.J., Bijmolt T.H., Vermunt J.K. (2007), Acquisition patterns of financial products: A longitudinal investigation, *Journal of Economic Psychology*, 28(2), 229–241, doi:10.1016/j.joep.2006.06.006.

Pyykkö E. (2011), Trends in European household credit. Solid or shaky ground for regulatory changes? *ECRI Commentary*, 7, Centre for European Policy Studies, Brussels.

Rytelewska G., Huszczonek E. (2004), *Zmiany w popycie na kredyt gospodarstw domowych*, Materiały i Studia NBP, 172, Narodowy Bank Polski, Warszawa.

Vermunt J.K. (2008), Multilevel latent variable modeling : an application in education testing, *Austrian Journal of Statistics*, 37(3–4), 285–299.

Vermunt J.K., Magidson J. (2002), Latent class cluster analysis, in: J.A. Hagenaars, A.L. McCutcheon (eds.), *Applied latent class analysis*, Cambridge University Press.

Viaud J., Roland-Lévy C. (2000), A positional and representational analysis of consumption. Households when facing debt and credit, *Journal of Economic Psychology*, 21(4), 411–432, doi:10.1016/S0167-4870(00)00011-8.

Walesiak M., Gatnar E., eds. (2009), *Statystyczna a naliza d anych z w ykorzystaniem p rogramu R* , Wydawnictwo Naukowe PWN, Warszawa.
Wałęga G. (2010), Determinanty zadłużenia gospodarstw domowych w Polsce w świetle wybranych teorii konsumpcji, in: Z. Dach (ed.), *Otoczenie ek onomiczne a z achowania p odmiotów r ynkowych*, Polskie Towarzystwo Ekonomiczne, Kraków.

Acknowledgements

This work was a part of the project realized during author's stay at the University of Milan as a Visiting Researcher. Financial support was provided by the Collegium of Economic Analyses at Warsaw School of Economics.

Appendix

Table 1

Latent class model BICs for the periods of analysis

No. of latent classes	**BIC for unrestricted model**				
	2003	**2005**	**2007**	**2009**	**2011**
2 classes	29349.776	28316.920	39128.532	81579.451	76549.666
3 classes	28760.524	27563.485	38152.615	79706.263	74588.002
4 classes	28191.615	27122.462	37599.420	78290.421	73199.089
5 classes	28120.525	27021.176	37111.750	77354.982	72343.302
6 classes	28109.434	26926.512	37010.231	76785.171	71686.767
7 classes	28107.718	26918.971	36938.402	76263.461	71205.349
8 classes	28132.096	26939.353	36855.417	75914.120	70948.634
9 classes	–	–	36872.248	75557.279	70692.260
10 classes	–	–	–	75331.111	70471.353
11 classes	–	–	–	75366.834	70474.126

Source: calculations in Mplus based on data from the Social Diagnosis.

Table 2

Latent classes – item answer probabilities for a model without covariates

		Results in probability scale									
		class 1	class 2	class 3	class 4	class 5	class 6	class 7	class 8	class 9	class 10
Credit value (in the value of monthly income)	credit ownership	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000
	zero	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000
	< 1	0.198	0.059	0.101	0.240	0.376	0.342	0.309	0.050	0.428	0.000
	1–3	0.266	0.183	0.184	0.290	0.294	0.359	0.364	0.069	0.308	0.000
	3–6	0.230	0.237	0.225	0.202	0.162	0.166	0.191	0.087	0.142	0.000
	6–12	0.174	0.242	0.253	0.143	0.101	0.080	0.077	0.147	0.070	0.000
	above 12	0.132	0.279	0.237	0.125	0.068	0.053	0.059	0.647	0.052	0.000
Credit source	banks	1.000	0.970	0.996	1.000	1.000	1.000	0.146	1.000	0.076	0.000
	other financial institutions	0.056	0.265	0.025	0.042	0.018	0.010	1.000	0.042	0.102	0.000
	family/friends	0.015	0.257	0.043	0.012	0.006	0.019	0.015	0.023	1.000	0.000
Credit target	current consumption expenditures (e.g., food, clothing)	0.056	0.572	0.016	0.041	0.046	0.625	0.193	0.019	0.555	0.000
	fixed charges (e.g., house maintenance)	0.008	0.477	0.009	0.012	0.008	0.306	0.092	0.007	0.370	0.000
	purchase of durable goods	0.283	0.431	0.248	0.146	1.000	0.039	0.374	0.116	0.151	0.000
	purchase of a house/flat	0.016	0.088	0.049	0.003	0.007	0.012	0.093	1.000	0.049	0.000
	renovation of a house/flat	1.000	0.458	0.141	0.000	0.000	0.107	0.438	0.131	0.140	0.000
	medical treatment	0.043	0.351	0.014	0.031	0.022	0.207	0.082	0.004	0.169	0.000
	purchase/rent of working equipment	0.004	0.047	0.329	0.004	0.006	0.007	0.005	0.002	0.003	0.000
	vacation	0.022	0.103	0.012	0.007	0.016	0.026	0.078	0.010	0.006	0.000
	repayment of previous debts	0.036	0.540	0.050	0.032	0.015	0.119	0.061	0.010	0.158	0.000
	development of own business	0.000	0.070	0.772	0.002	0.000	0.003	0.013	0.009	0.019	0.000
	education/ training	0.026	0.228	0.033	0.027	0.012	0.108	0.080	0.010	0.029	0.000
	other purposes	0.061	0.260	0.062	1.000	0.000	0.035	0.137	0.022	0.098	0.000

Source: calculations in Mplus based on data from the Social Diagnosis.

Table 3

The percentage of households with respect to the source of a loan/credit (among borrowers) for 2003–2011

Source of a loan/credit	2003	2005	2007	2009	2011	P-value for the difference 2011–2003
Banks	78,4	80,8*	87,9***	90,6***	90,9	0.000
Other financial institutions	29,7	23,9***	18,1***	12,4***	11,9	0.000
Family/friends	10,8	11,8	5,7***	4,3***	5,1*	0.000
Average total no. of sources	1,19	1,16	1,12	1,07	1,08	

Note: difference with respect to the previous survey: *** significant at 0.01 level; ** significant at 0.05 level; * significant at 0.1 level.

Source: calculations based on the Social Diagnosis Survey.

Table 4

The percentage of households with respect to the objectives of taking a loan/credit (among borrowers) for 2003–2011

Objectives of a loan/credit	2003	2005	2007	2009	2011	P-value for the difference 2011–2003
Purchase of durable goods	38.6	39.9	37.0*	38.5	37.0	0.255
Renovation of a house/flat	33.9	33.2	36.0*	34.9	31.2***	0.051
Purchase of a house/flat	13.7	11.1**	14.6***	16.6**	18.0*	0.000
Current consumption expenditures (e.g., food, clothing)	22.7	23.1	17.5***	17.7	17.5	0.000
Other purposes	14.0	13.9	12.0*	12.9	10.5***	0.000
Fixed charges (e.g., house maintenance)	15.3	14.4	12.1**	8.7***	8.0	0.000
Repayment of previous debts	10.2	10.7	11.5	7.5***	7.9	0.005
Medical treatment	10.8	10.9	9.7	8.4*	6.4***	0.000
Development of own business	8.3	7.0	6.5	6.0	5.6	0.000
Education/training	8.8	9.6	6.5***	4.7***	3.4***	0.000
Purchase/rent of working equipment	3.3	3.1	3.3	3.4	2.5***	0.095
Vacation	4.2	3.2	3.2	3.2	2.5**	0.000
Purchase of stock	0.4	0.0**	0.3**	0.2	0.1	0.049
Average total no. of objectives	1.84	1.80	1.70	1.63	1.51	

Notes: difference with respect to the previous survey: *** significant at 0.01 level; ** significant at 0.05 level; * significant at 0.1 level.

Source: calculations based on the Social Diagnosis Survey.

Table 5

The percentage of households with respect to the value of a loan/credit (among borrowers) for 2003–2011

Value of a loan/credit (relative to household's monthly income)	2003	2005	2007	2009	2011
Up to monthly income	23.6	24.4	23.8	24.3	22.1
Above monthly income – up to quarterly income	32.6	31.1	28.7	24.0	22.6
Above quarterly income – up to semi-annual income	20.4	18.7	19.4	18.4	16.7
Above semi-annual income – up to annual income	12.7	14.1	12.5	14.3	14.8
Above annual income	10.7	11.7	15.7	18.9	23.8
P-value of the chi-square test for differences in consecutive waves	–	0.482	0.009	0.000	0.000

Notes: difference with respect to the previous survey: *** significant at 0.01 level; ** significant at 0.05 level; * significant at 0.1 level.

Source: calculations based on the Social Diagnosis Survey.

Table 6

BIC for heterogeneous, partially homogeneous and completely homogeneous models

BIC	Heterogeneous	Partially homogeneous	Completely homogeneous
Different no. of classes	352815.833	346527.263	–
10 classes	–	344405.594	344592.348
9 classes	–	345485.717	345719.600
8 classes	–	346610.769	346885.934
7 classes	–	348659.039	349862.964

Source: calculations in MPlus.

Table 7

Response probabilities in latent classes

		Results in probability scale									
		class 1	**class 2**	**class 3**	**class 4**	**class 5**	**class 6**	**class 7**	**class 8**	**class 9**	**class 10**
	credit ownership	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000
Credit value (in the value of monthly income)	zero	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000
	< 1	0.199	0.055	0.099	0.240	0.379	0.337	0.304	0.048	0.397	0.000
	1–3	0.263	0.168	0.191	0.290	0.294	0.359	0.362	0.064	0.322	0.000
	3–6	0.229	0.230	0.232	0.201	0.160	0.166	0.196	0.087	0.155	0.000
	6–12	0.175	0.244	0.252	0.143	0.099	0.086	0.079	0.146	0.077	0.000
	above 12	0.134	0.303	0.226	0.126	0.067	0.053	0.059	0.655	0.049	0.000
Credit source	banks	1.000	0.968	0.996	1.000	1.000	1.000	0.180	1.000	0.162	0.000
	other financial institutions	0.049	0.271	0.023	0.038	0.015	0.006	1.000	0.040	0.100	0.000
	family/friends	0.015	0.257	0.040	0.011	0.005	0.010	0.015	0.023	1.000	0.000
Credit target	current consumption expenditures (e.g., food, clothing)	0.048	0.574	0.021	0.029	0.042	0.613	0.193	0.017	0.578	0.000
	fixed charges (e.g., house maintenance)	0.006	0.478	0.008	0.009	0.005	0.305	0.091	0.004	0.386	0.000
	purchase of durable goods	0.284	0.431	0.263	0.145	1.000	0.063	0.381	0.120	0.155	0.000
	purchase of a house/flat	0.020	0.087	0.043	0.004	0.005	0.021	0.096	1.000	0.045	0.000
	renovation of a house/flat	1.000	0.454	0.145	0.000	0.000	0.143	0.441	0.126	0.145	0.000
	medical treatment	0.040	0.341	0.014	0.029	0.021	0.217	0.083	0.002	0.179	0.000
	purchase/rent of working equipment	0.000	0.048	0.347	0.002	0.001	0.002	0.005	0.002	0.003	0.000
	vacation	0.022	0.103	0.011	0.009	0.016	0.026	0.079	0.011	0.006	0.000
	repayment of previous debts	0.036	0.558	0.054	0.032	0.015	0.116	0.059	0.010	0.178	0.000
	development of own business	0.003	0.075	0.715	0.000	0.000	0.003	0.013	0.012	0.017	0.000
	education/ training	0.026	0.239	0.042	0.027	0.012	0.095	0.081	0.010	0.034	0.000
	other purposes	0.060	0.259	0.068	1.000	0.000	0.052	0.139	0.023	0.099	0.000

Source: calculations in MPlus based on data from the Social Diagnosis.

Table 8

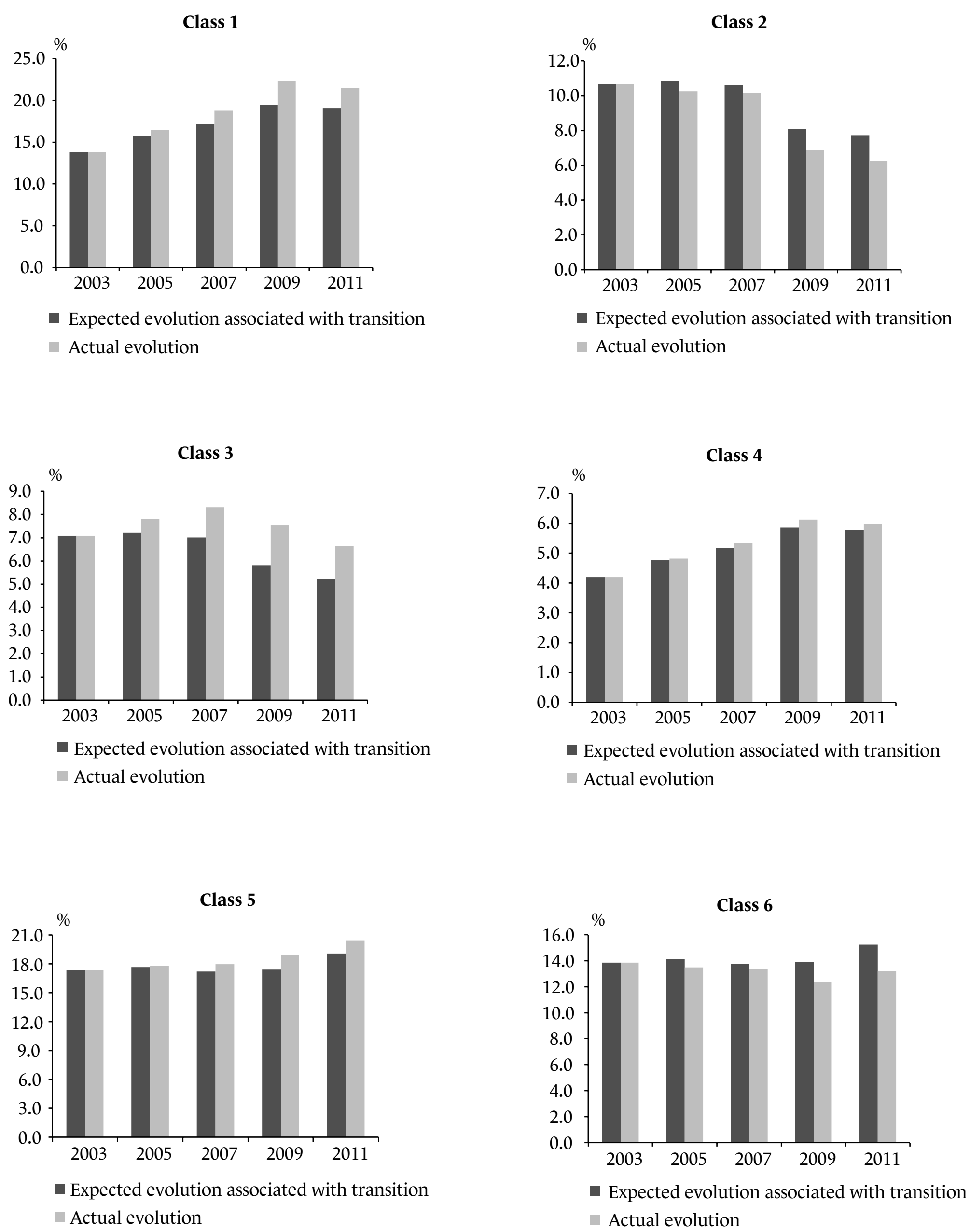
Parameter estimates for latent class model with covariates

		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
Time evolution	2003	-0.242	0.438	0.414	-0.223	0.000[f]	0.000[f]	1.221	-0.303	0.512	ref.
	2005	-0.121	0.438	0.414	-0.112	0.000[f]	0.000[f]	0.916	-0.303	0.897	ref.
	2007	0.000[f]	0.438	0.414	0.000[f]	0.000[f]	0.000[f]	0.611	0.000[f]	0.000[f]	ref.
	2009	0.121	0.146	0.207	0.112	0.000[f]	0.000[f]	0.305	0.000[f]	0.000[f]	ref.
	2011	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
No. of people in household	1	-0.900	-1.321	-1.507	-0.405	-0.902	0.000[f]	-0.425	-1.095	0.000[f]	ref.
	2	-0.368	-0.363	-0.564	0.000[f]	-0.396	0.000[f]	-0.227	-0.530	0.000[f]	ref.
	3	0.000[f]	0.000[f]	-0.310	0.000[f]	-0.227	0.000[f]	0.000[f]	0.000[f]	0.000[f]	ref.
	4	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	5 or more	0.198	0.000[f]	0.499	0.000[f]	0.000[f]	0.338	0.000[f]	0.000[f]	0.000[f]	ref.
Real income per equivalent unit	up to 500 PLN	-1.130	0.564	-0.463	0.000[f]	-0.760	0.277	-0.201	-1.410	2.119	ref.
	above 500 PLN up to 1000 PLN	-0.221	0.447	-0.262	0.000[f]	-0.184	0.277	-0.201	-0.535	0.891	ref.
	above 1000 PLN up to 1500 PLN	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	above 1500 PLN up to 2000 PLN	0.000[f]	-0.450	0.000[f]	0.000[f]	0.000[f]	-0.402	0.000[f]	0.385	0.000[f]	ref.
	above 2000 PLN up to 3000 PLN	0.000[f]	-0.559	0.401	0.000[f]	0.000[f]	-0.725	-0.201	0.937	0.000[f]	ref.
	above 3000 PLN	-0.374	-0.626	0.849	0.000[f]	0.000[f]	-1.103	-0.876	1.727	0.000[f]	ref.
Labour market status	employed	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	unemployed	-0.502	0.000[f]	-1.746	-0.873	0.000[f]	0.000[f]	-0.966	-1.085	0.000[f]	ref.
	not active	0.000[f]	0.000[f]	-1.929	0.000[f]	0.000[f]	0.000[f]	-0.812	-0.353	0.000[f]	ref.

Age of the head of household	up to 24 years	0.000[f]	0.000[f]	0.000[f]	-1.614	0.000[f]	0.000[f]	-1.081	0.000[f]	1.129	ref.
	25–34 years	0.255	0.000[f]	0.000[f]	0.000[f]	0.355	0.000[f]	-0.396	1.593	0.376	ref.
	35–44 years	0.309	0.000[f]	0.000[f]	0.000[f]	0.310	0.000[f]	0.000[f]	1.321	0.000[f]	ref.
	45–54 years	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	55–64 years	0.000[f]	-0.297	0.000[f]	0.000[f]	0.000[f]	0.000[f]	-0.333	0.000[f]	-0.376	ref.
	65 years and over	-0.666	-1.527	-0.618	-0.788	-0.484	-0.526	-0.770	-0.932	-1.129	ref.
Place	cities with 100,000 inhabitants or more	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	cities with 20,000–100,000 inhabitants	0.000[f]	-0.441	0.000[f]	0.000[f]	0.000[f]	0.000[f]	0.000[f]	0.000[f]	0.000[f]	ref.
	towns up to 20,000 inhabitants	0.208	-0.787	0.524	0.000[f]	-0.151	0.000[f]	-0.200	-0.497	0.000[f]	ref.
	rural areas	0.231	-0.984	1.069	0.000[f]	-0.268	-0.615	-0.499	-0.709	-0.426	ref.

Source: calculations in Mplus based on data from the Social Diagnosis; f = fixed parameters.

Figure 1
Decomposition of changes associated with the transition of the Polish credit market for households



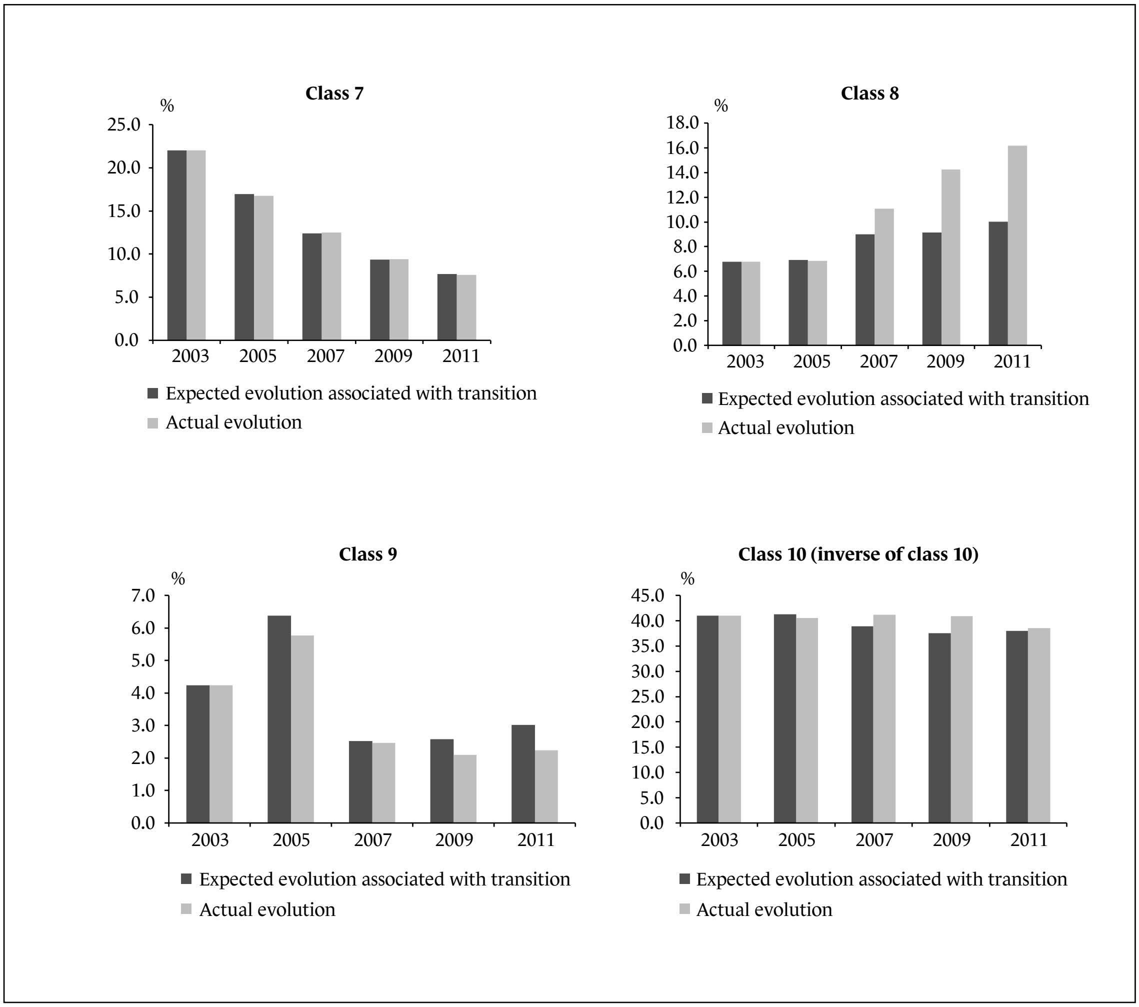
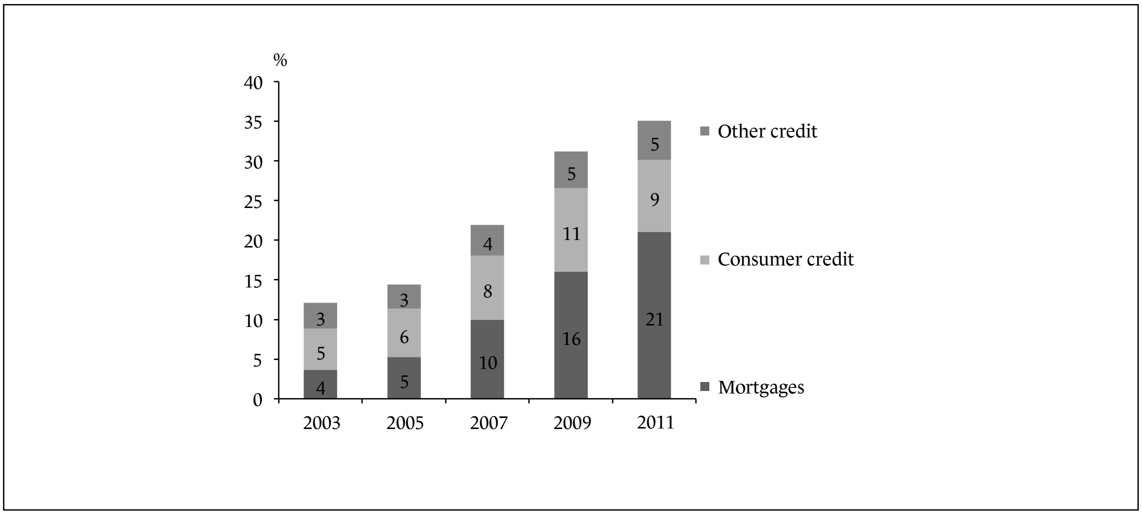

Class 7
%
25.0
20.0
15.0
10.0
5.0
0.0
2003 2005 2007 2009 2011
Expected evolution associated with transition
Actual evolution
Class 8
%
18.0
16.0
14.0
12.0
10.0
8.0
6.0
4.0
2.0
0.0
2003 2005 2007 2009 2011
Expected evolution associated with transition
Actual evolution
Class 9
%
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
2003 2005 2007 2009 2011
Expected evolution associated with transition
Actual evolution
Class 10 (inverse of class 10)
%
45.0
40.0
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
2003 2005 2007 2009 2011
Expected evolution associated with transition
Actual evolution

Figure 2
Relationship to GDP of housing, consumer and other credit for households in Poland



Source: Narodowy Bank Polski, Polish Central Statistical Office, Pyykko (2011).

Figure 3
Households' activity in the credit market in Poland between 2003 and 2011