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# Latent-transition approach to evolution of household debt possession patterns in Poland

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**Abstract**

Based on latent transition approach we investigate evolution of debt possession patterns in Poland. We obtain interteporally comparable segments of debt holders and show highly significant role of autoregressive and life-cycle factors in shaping transitions between the segments. With data from three waves (2011 – 2015) and over 36,000 responses from the biennial panel study Polish households – Social Diagnosis - we show that: (1) transition probabilities from any of the indebted states to any other indebted state are higher than transition probabilities to non-active state; (2) households located in a given segment are most likely to remain in the segment, if not for other factors; (3) transitions between segments are shaped by socio-economic covariates - age of household head, income and number of household members; (4) their role differs very considerably between the segments showing that different socio-economic traits shape the evolution of segments; (5) probabilities of mortgage debt, debt for durables or renovation are positively related to income and in line with life cycle predictions, which indicates the role of long term factors in their acquisition; (6) consumption debt is less age related and in some groups also inversely related to income, which shows its short term dependence. The results of the study indicate also that (1) relationship between debt and income depends on relative prevalence of segments on the market and (2) that influence of life-cycle factors can be missing at the aggregate level if mortgage debt does not dominate.

Keywords: household debt, segmentation, latent transition

## 1. Introduction

We could picture a situation, where household financial markets operate without frictions and market imperfections remain absent. In such a case there would be no need to distinguish between different kinds of household assets or liabilities. In extreme, as (Bertola & Hochguertel, 2007) claim "there would not even be a need to distinguish owning from renting, …, savings from borrowing, as each of them could be costlessly and instantly converted from one form to another and from there to consumption." Yet, it is commonly observed that households use credit to finance their purchases but also to bridge temporary drops in income in a very diversified way (Białowolski, 2014). In addition, they rely on a very complex process of acquisition of financial products, which is especially visible in the case of debt (B. Kamleitner & Kirchler, 2007; Bernadette Kamleitner, Hoelzl, & Kirchler, 2012; Kirchler, Hoelzl, & Kamleitner, 2008). In consequence, they end up with differentiated credit instruments addressing their specific needs (Bertola & Hochguertel, 2007).
The scope for consumption motives, which are eventual cause for credit behaviour, was primarily addressed by Keynes (1936). He pointed to Enjoyment, Short sightedness, Generosity, Miscalculation, Ostentation and Extravagance as primary motives for consumption. However, as the life-cycle theory (Friedman, 1957; Modigliani & Brumberg, 1954) became the workhorse of economics, recollection of the behavioural nature of consumption (and credit) proposed by Keynes started to fade. However, the life-cycle theory encountered many problems in explaining household financial behaviour both with respect to saving and debt. Remedies to the household misbehaviour in the basic model comprised various amends and covered among others introduction of liquidity constraints (Hall & Mishkin, 1982; Jappelli & Pagano, 1989), durable goods in utility (Browning, 1989; Mankiw, 1985), uncertainty mostly associated with future income path (Parker & Preston, 2005; Zeldes, 1989) or habit formation (Campbell & Cochrane, 1999; Carroll, Overland, & Weil, 2000). Even though these theory developments seemed to introduce

new and more sophisticated framework to analyse life-cycle behaviour, they still failed to provide sufficient evidence that life-cycle approach is the proper one to analyse household behaviour. Liquidity constraints might be in force but still there might be a group of households simply unwilling to participate in any saving or credit activities, which is corroborated by various survey data (Białowolski & Dudek, 2014). Durable goods play an important role but in the current world the durability of various goods – probably apart from house/apartment – has shortened significantly (Davidson & Bates, 2002) rendering a diminished role for the durables in shaping the life-cycle behaviour with respect to savings and debt. Finally, there is little support for habit formation (Dynan, 2000) or an important role of uncertainty.

Some answers to the puzzling financial market behaviour of households were addressed by introduction of behavioural concepts into the analysis. Developments in the area of self-control pointing to impatience of consumers (Thaler & Shefrin, 1981) led to better understanding of consumer behaviour. Yet, the most recent trend is towards reconciliation of the two approaches, where two types of behaviour (life-cycle and behaviourally driven) meet. One of the approaches was proposed by (Bertaut, Haliassos, & Reiter, 2009), who with the accountant-shopper model try to solve the puzzle of existence of a groups of individuals holding both short-term debt and liquid assets. They suggest that each consumer makes consumption choices in two stages (Bertaut et al., 2009). In the first stage, when she adopts a role of accountant, plans expenditures and makes basic payments. In the second stage, the shopper comes into the stage. He is also rational but less patient. As the accountant is aware of shoppers attitudes, he does not want to leave too much space to the shopper and thus holds positive short-term debt. Based on this approach it is possible to show that households would maintain positive short-term debt even in the light of increasing incomes and financial assets. In the same strain remains the approach of Kahneman (2011) comprising two systems, where duality of human decision making approach is captured with two selves - rational undertaking life-cycle choices and impulsive prone to various behavioural biases.

In this paper we show that neither purely life-cycle nor purely behavioural approach are adequate for an analysis of household financial behaviour

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with respect to debt taking. Our goal is to show that there is a finite number of segments, which define in probabilistic terms household debt behaviour. Till present there has been very little evidence presented that such patterns can be discerned. Works of (Białowolski, 2014; Gunnarsson & Wahlund, 1997; Viaud & Roland-Lévy, 2000) comprise exceptions to this rule. By showing that segments are intertemporally comparable we shape way for analysis of transitions between segments. Distinction of comparable groups allows us to verify, whether postulated by theory relationships like curvilinear shape of debt vs. age (Bernadette Kamleitner et al., 2012; Ngwenya & Paas, 2012; Paas, Bijmolt, & Vermunt, 2007) or lower use of debt among single person households (Chien & Devaney, 2001) are observed universally or present only in certain groups of debt takers. With segmentation approach it is also possible to disentangle confusing relations between income and credit, as households within groups are allowed to behave differently. It is especially important in light of ambiguity in the behaviour of aggregates. Crook (2006) indicates to positive relationship between income and debt, while Gunnarsson & Wahlund (1997) indicate lack of such relationship.

In order to meet the goals, adopted approach should enable to distinguish the number of distinct patterns of behaviour (groups), investigate invariability of these patterns, and intertemporal transitions between them. Additionally, it is essential to provide valid arguments for the source of market evolution and distinguish between household migration between groups associated with inertia and intrinsic modes of credit use, but also investigate a role of household socio-economic characteristics. Hence, we adopt latent transition approach, which enables to capture not only multitude of paths with respect to credit, which can be either life-cycle or behaviourally driven, but also allows to capture intrinsic fuzziness of approach to credit of a given household. With such an approach it is possible to show existence of a mixture of behaviours even at the most basic, household level. To evaluate the credit paths we use data from the largest household panel in Poland – Social Diagnosis Survey and limit our attention to its last three waves 2011, 2013, and 2015.

This paper features at least two innovative points. First, to the best of our knowledge, it is the first approach based on latent transition models, which tries to evaluate stability of changes between patterns of various debt possession, while at the same time investigating plausibility of the assumption of intertemporal pattern comparability. Second, to the best of our knowledge, it is the first attempt to show that households might exhibit both behaviourally and life-cycle driven paths of their credit market behaviour.

To meet these objectives, the paper is organised as follows: in Section 2, we present background for the analysis describing the situation in the area of household debt in Poland – the market subject to subsequent analysis in the paper. A detailed description of methods, including the dataset from the Social Diagnosis Survey, selection of measures and methods used for the analysis follows in Section 3. In Section 4, we describe results obtained with multi-group latent class models and latent transition models. We investigate the determinants of households' participation in the credit market and latent class (segment) membership, while taking into account strength of both transitions and socio-economic variables. Section 5 presents the conclusions of the study.

## 2. Background – data and measures

Household indebtedness in Poland rose quickly from the beginning of 2000 till the onset of the financial crisis (Figure 1). The indebtedness of households went from merely 12% of the Polish GDP in 2003 to 35% in 2015. During the period, the ratio of households' debt to GDP in the EU27 countries averaged at the level of 60% (Pyykkö, 2011) and, from this perspective, the indebtedness of Polish households remained low. Between 2003 and 2009 there was a rapid growth in the penetration rates of credit in all areas – consumer, housing and other. However, just after the outburst of the financial crisis the consumer credit market started to contract in relative terms. Nevertheless, household debt still grew till 2011 due to mortgages. It should be stressed that in the period 2009 – 2011 Polish carry traders were considerably affected by depreciation of the Polish zloty and significant share of indebtedness growth during that period can be attributed to this phenomenon.

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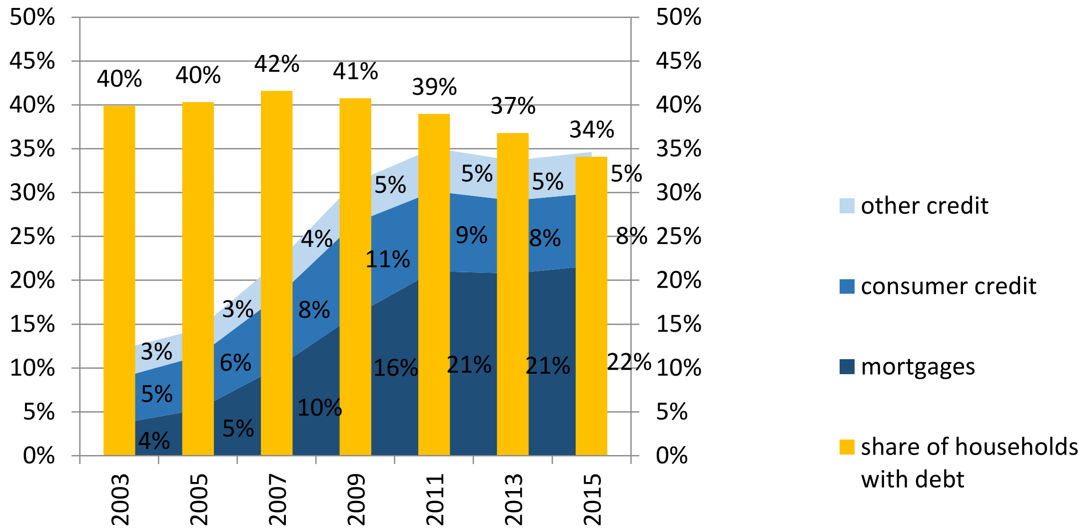
Figure 1 Debt-to-GDP ratio (mortgage, consumer and other debt), share of indebted households in Poland.




Source: National Bank of Poland, Polish Central Statistical Office.

The level of household indebtedness in Poland did not exceed debt levels observed in any of the developed economies. Additionally, the growth trend of debt-to-GDP stopped, which requires further scrutiny and poses additional questions about the reasons for that. However, from the perspective of further analysis the household debt-to-GDP ratio seems to have achieved relative stability during the period 2011 – 2015, which allows to pick that period as reference frame for analysis of debt possession patterns.

Results of the largest panel study in Poland – the Social Diagnosis (Czapiński & Panek, 2015) – confirm that since 2009 a constant decrease in the use of credit market is observed among Polish households (Figure 2). Trends indicate that, although there is a constant growth of total value of household debt, the share of participating households is shrinking. It has decreased from 41.6% at its peak in 2007 to 34.1% in 2015. For the purpose of analysis we limit our attention to three waves of the survey. They cover the state of households' credit portfolios for the period from 2011 – 2015 and are gathered in a panel-type study.

During the period of interest the number of households participating in the Social Diagnosis Survey ranged between 11,703 in 2015 and 12,354 in 2013. Ca. 60% of households remained in the panel between consecutive waves.

For the purpose of our study we utilize description of household debt possession patterns in three dimensions: debt source, objectives for taking debt and the value of the debt. The evolution of the share of households with respect to all of the dimensions is presented in Table 1.

Data in Table 1 confirms the decline in the share of debt holders among Polish households between 2011 and 2015. With respect to the debt value, there is a constant trend of increase, which is manifested by growing number of shares of households with debt exceeding their yearly incomes. However, with respect to the source of credit little variability has been noted apart from a considerable increase in the share of households using other financial institutions between 2011 and 2013. As noted by (Bertola & Hochguertel, 2007) household credit portfolios are not very diversified with respect to the product and source, which is confirmed by overwhelming dominance of banks among debt sources. However, household debt behaviour seems to significantly differ with respect to the purposes the debt serves (Białowolski, 2014). With respect to credit target, there is still visible an upward trend in possession of mortgage – indebtedness for house/flat purchase - but also more indebted households tend to finance their holidays. On the other hand consumption related credit starts to decline. It is hard to explain this behaviour solely by the life-cycle patterns as expected high path of income growth strongly favours increase in the share of debt takers and the use of debt for various purposes – also consumption related.

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Table 1 The percentage of households with respect to the value, source and target of a loan/credit (among borrowers) between 2011 and 2015

| | | Wave | | |
|---|---|---|---|---|
| | | 2011 | 2013 | 2015 |
| Share of debt holders | | 39.0% | 36.8% | 34.1% |
| debt value (in the value of monthly income, among debt holders) | < 1 | 22.1% | 19.4% | 16.7% |
| | 1 – 3 | 22.6% | 20.2% | 19.9% |
| | 3 – 6 | 16.7% | 17.0% | 15.7% |
| | 6 – 12 | 14.8% | 13.1% | 11.5% |
| | above 12 | 23.8% | 30.3% | 36.2% |
| credit source (among debt holders) | Banks | 90.6% | 87.8% | 90.6% |
| | other financial institutions | 11.8% | 15.8% | 12.3% |
| | family/friends | 5.1% | 5.4% | 4.4% |
| credit target (among debt holders) | current consumption expenditures (e.g., food, clothing) | 17.5% | 15.5% | 13.5% |
| | fixed charges (e.g., house maintenance) | 8.0% | 8.2% | 6.2% |
| | purchase of durable goods | 36.7% | 34.0% | 32.3% |
| | purchase of a house/flat | 18.0% | 22.8% | 26.1% |
| | renovation of a house/flat | 31.1% | 30.2% | 30.2% |
| | medical treatment | 6.4% | 7.1% | 6.2% |
| | purchase/rent of working equipment | 2.6% | 3.0% | 2.9% |
| | Vacation | 2.6% | 3.0% | 3.8% |
| | repayment of previous debts | 8.0% | 8.2% | 6.7% |
| | development of own business | 5.6% | 4.6% | 5.0% |
| | education/training | 3.3% | 4.3% | 3.8% |
| | other purposes | 10.5% | 11.7% | 12.0% |

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

## 3. Methods

### 3.1. Statistical approach

The segments of households with respect to debt possession patterns are revealed with latent-class modelling, its multi-group extension and latent transition modelling. These techniques allow for accounting for an unobserved heterogeneity in the multidimensional data set. Dimension reduction is primary performed with introduction of a single latent variable describing segments.[1] Multi-group approach (McCutcheon, 2002) is an extension of latent class modelling, which enables additional testing of segment homogeneity and allows for direct comparison of segments between groups. In this paper, different groups correspond to different time points of analysis. Latent transition modelling enables to track changes in segment membership and relate them to socio-economic characteristic.

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:

$$\pi^{A_1 A_2 \ldots A_N X|T}_{m_1 m_2 \ldots m_N kt} = \pi^{X|T}_{kt} \pi^{A_1|XT}_{m_1 kt} \pi^{A_2|XT}_{m_2 kt} \ldots \pi^{A_N|XT}_{m_N kt} \quad (1),$$

[1] More detailed description of the latent class modelling can be found in (Muthén, 2004) or (Białowolski, 2014). Its advantages over other segmentation techniques are well depicted in Vermunt & Magidson (2002). 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).

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where $\pi^{A_1A_2...A_N X|T}_{m_1m_2...m_N kt}$ defines the conditional probability that a respondent with the set of answers ($m_1,m_2,...,m_N$) given in period $t$ belongs to latent class $k$, while $\pi^{X|T}_{kt}$ defines the conditional probability of belonging to class $k$ given period $t$, and $\pi^{A_i|XT}_{m_i kt}$ 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 ($A_1$, $A_2$, ..., $A_N$) are independent of each other, given the latent class $k$.

Multi-group latent class allows to establish comparability of groups between periods and can be described by the following formula:

$$\pi^{A_1A_2...A_N X|T}_{m_1m_2...m_N kt} = \pi^{X|T}_{kt}\pi^{A_1|X}_{m_1 k}\pi^{A_2|X}_{m_2 k}...\pi^{A_N|X}_{m_N k} \qquad (2)$$

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.

Finally, the most elaborate form of analysis reported here is latent transition model, where class membership in a given point of time depends on both previously reported class membership and other socio-economic covariates. As it is only the class membership that is subject to autoregressive processes and influenced by socio-economic characteristics, probability of class membership is only subject to influence by those factors:

$$\pi_{kt}^{X|T} = \frac{e^{thresh_{k,t} + \sum_{j=1}^{J} \alpha_{j,k,t-1} \cdot x_{j,t-1} + \sum_{p=1}^{K-1} \beta_{p,k,t-1} \cdot \upsilon_{p,t-1}}}{1 + \sum_{i=1}^{K-1} e^{thresh_{i,t} + \sum_{j=1}^{J} \alpha_{j,k,t-1} \cdot x_{j,t-1} + \sum_{p=1}^{K-1} \beta_{p,i,t-1} \cdot \upsilon_{p,t-1}}} \quad (3),$$

where $\{x_{1,t-1},...,x_{J,t-1}\}$ is a set of explanatory variables in period t-1, while $\alpha_{j,k,t-1}$ represents the estimated parameters, which are set to zero for a selected, reference class. Additionally, $\{\upsilon_{1,t-1},...,\upsilon_{K-1,t-1}\}$ represents a set of binary variables representing class membership in period t-1 with $\beta_{p,k,t-1}$ being parameters associated with transition from class p to k between t-1 and t.

### *3.2. Modelling strategy*

Our approach to analyse debt possession patterns is based on the following assumptions: (1) there is a possibility to detect distinct patterns of credit use and those patterns are comparable intertemporally, (2) distinct patterns are driven, with varying strength, by both autoregressive processes and socio-economic characteristics of households. To verify these assumptions we use the following step-wise approach. At first, we determine the number of classes and subsequently verify the hypothesis of equal intertemporal meaning of latent patterns in the area of household debt possession patterns. Second,[2] we check the influence of segment membership in t-1 on segment membership in t and subsequently search for covariates of latent patterns.

[2] Because the transitions are multiple we modify the approach traditionally used for estimation of the latent transition model. We conduct the analysis stepwise allowing the description of classes to be defined in the first step and not influenced by transition ($\beta_{p,k,t-1}$) and socioeconomic covariates ($\alpha_{j,k}$). In order to maintain the latent character of class membership, we multiply impute the class membership following the latent class membership probabilities obtained in the first step. For this purpose we use set of 10 multiple imputations.

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At each step of the analysis, we adopt the approach based on Bayesian Information Criterion (BIC) (Schwarz, 1978) following the procedure: (1) the optimal number of groups is established in the model with measurement invariance (i.e. satisfying eq. 2) and without measurement invariance (eq. 1); (2) For the final solution, a quality check with the entropy measure is performed;[3] (3) the selected segmentation model is first checked for importance of previous period latent class membership, it is done with the use of information on previous period class membership $\{\upsilon_{1,t-1},...,\upsilon_{K-1,t-1}\}$ and $\beta_{p,k,t-1}$ coefficients are being estimated; (4) the class movement coefficients are checked for equality in the intertemporal setting, i.e. constraint $\forall_{p\in 1,..,K-1;k\in 1,..,K-1}\beta_{p,k,1}=\beta_{p,k,2}$ is imposed on the parameters; (4) socio-economic covariates of class membership are introduced to the model in the stepwise manner starting from age of household head, and following by income, number of household members, education of household head, and place of residence, (5) each covariate is first introduced unconstrained, i.e. diverse impact between periods is possible, then constrained solution in intertemporal setting is checked $\forall_{j\in 1,..,J;k\in 1,..,K}\alpha_{j,k,1}=\alpha_{j,k,2}$, finally insignificant estimates are constrained to zero and those for adjacent categories, if observed to be insignificantly different between each other, are constrained equal.

## 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 2011, 2013 and 2015. During the estimation process, it was established that the best

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

fitting model for 2011 are those with 10 classes, and for 2013 and 2015 the best-fitting model have 9 classes (see Appendix 1).[4] In order to ascertain comparability of latent classes in the intertemporal setting two types of models are estimated - models with unconstrained conditional response probabilities and models with constrained ones. In the latter 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. The values of the BIC for the two specifications of the model are presented in Table 2**.**

Table 2 BIC for latent class models with unconstrained and constrained response probabilities

| BIC | Heterogeneous – latent classes have different meaning | partially homogeneous – latent classes are comparable between periods |
|---|---|---|
| different no. of classes | 278608.3 | --- |
| 11 classes | 279168.5 | 275013.8 |
| 10 classes | 278709.9 | **274969.8** |
| 9 classes | 278957.9 | 275798.3 |

Source: Own calculations in MPlus.

Based on the results, the best fitting model is the 10-class specification with constrained response probabilities, i.e. intertemporally comparable latent classes. The fit of the model also proves to be very good, which is confirmed by the value of the entropy measure (0.976). Item response probabilities, calculated in line with Formula (2) for each latent class in the final model, are presented in Table 3. The final model comprises an implicit description of the latent classes of households in Poland in the credit market. There are ten distinct segments of households active in the credit market (classes 1 – 9) and one segment not active on the market. In order to understand transitions between different segments, we need to provide a more detailed description of those:

[4] Due to very large number of observations it is highly unlikely that the effect observed by Lukočienė, Varriale, & Vermunt (2010) was present. They state that the smaller the sample size, the less likely that one finds the correct number of classes.

Table 3 Response probabilities in latent classes (2011 – 2015)

| | Response probabilities | c.1 | c.2 | c.3 | c.4 | c.5 | c.6 | c.7 | c.8 | c.9 | c.10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| credit value (in the value of monthly income) | Zero | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| | < 1 | .026 | .349 | .081 | .063 | .357 | .417 | .222 | .29 | .156 | 0 |
| | 1 – 3 | .035 | .294 | .14 | .118 | .297 | .331 | .244 | .323 | .235 | 0 |
| | 3 – 6 | .053 | .174 | .22 | .185 | .182 | .143 | .205 | .204 | .207 | 0 |
| | 6 – 12 | .084 | .099 | .225 | .193 | .092 | .064 | .161 | .109 | .191 | 0 |
| | above 12 | .801 | .085 | .333 | .441 | .072 | .045 | .169 | .074 | .212 | 0 |
| credit source | Banks | .994 | 1 | .995 | .99 | 0 | .267 | 1 | 1 | 1 | 0 |
| | other financial institutions | .027 | 0 | .017 | .318 | .712 | 1 | .058 | .042 | .041 | 0 |
| | family/friends | .021 | .003 | .016 | .191 | .318 | 0 | .013 | .037 | .013 | 0 |
| credit target | current consumption expenditures (e.g., food, clothing) | .011 | .041 | .011 | .503 | .367 | .052 | .061 | .623 | .038 | 0 |
| | fixed charges (e.g., house maintenance) | .006 | .004 | 0 | .379 | .203 | 0 | .007 | .271 | .004 | 0 |
| | purchase of durable goods | .116 | 1 | .246 | .494 | .115 | 1 | .129 | .033 | .236 | 0 |
| | purchase of a house/flat | 1 | .003 | .052 | .091 | .04 | .004 | 0 | .014 | .014 | 0 |
| | renovation of a house/flat | .111 | 0 | .132 | .468 | .324 | .129 | 0 | .104 | 1 | 0 |
| | medical treatment | .006 | .017 | .024 | .232 | .117 | .03 | .024 | .23 | .034 | 0 |
| | purchase/rent of working equipment | 0 | .002 | .319 | .031 | .009 | .011 | .008 | .005 | .002 | 0 |
| | Vacation | .01 | .012 | .024 | .173 | .041 | .031 | .012 | .038 | .017 | 0 |
| | repayment of previous debts | .009 | .013 | .104 | .524 | .1 | .005 | .026 | .121 | .033 | 0 |
| | development of own business | .008 | .002 | .622 | .051 | .014 | .005 | 0 | .005 | .001 | 0 |
| | education/training | .009 | .015 | .035 | .177 | .043 | .021 | .031 | .083 | .024 | 0 |
| | other purposes | .015 | 0 | .074 | .291 | .155 | .014 | 1 | .019 | .053 | 0 |

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

Class 1 (MORTGAGE DEBTORS) – Households that are extremely highly indebted (80% possess debt exceeding their annual incomes). These households' sources of credit are mostly banks (99.4%) and rarely other institutions. These households comprise the first group of those indebted to finance the purchase of a house or flat (100%). They rarely also use debt to finance the renovation of a house or flat (11.1%) or to purchase durables (11.6%).

Class 2 (BANK FINANCED DURABLE GOODS CONSUMERS) – Households that have a relatively low value of debt (64.3% with debt below their quarterly incomes). These households' acquire their debt from banks (100%) and almost never from elsewhere. The debt is devoted almost solely to purchases of durables (100%).

Class 3 (HOUSEHOLD-BUSINESS DEBTORS) – Households with debts above average that were acquired from a bank (extremely rarely supported by a loan from other source). The debt is designated for development of own business (62.2%), purchase of working equipment (31.9%) and sometimes for the purchase of durables (24.6%).

Class 4 (OVERINDEBTED CONSUMERS) – Households that have high probability of debt in many categories with respect to the purpose and very often with a high value of debt (63.4% with debt exceeding their semi-annual incomes). These households' sources of credit are mainly banks (99%), but they also often search for credit from other financial institutions (31.8%) and from their friends and family (19.1%). In this group, there is a very high probability of credit for current consumption (50.3%) and for repayment of previous debts (52.4%) but also for fixed charges (37.9%), the purchase of durables and renovation of a flat (each of the last two approaching 50%). 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.

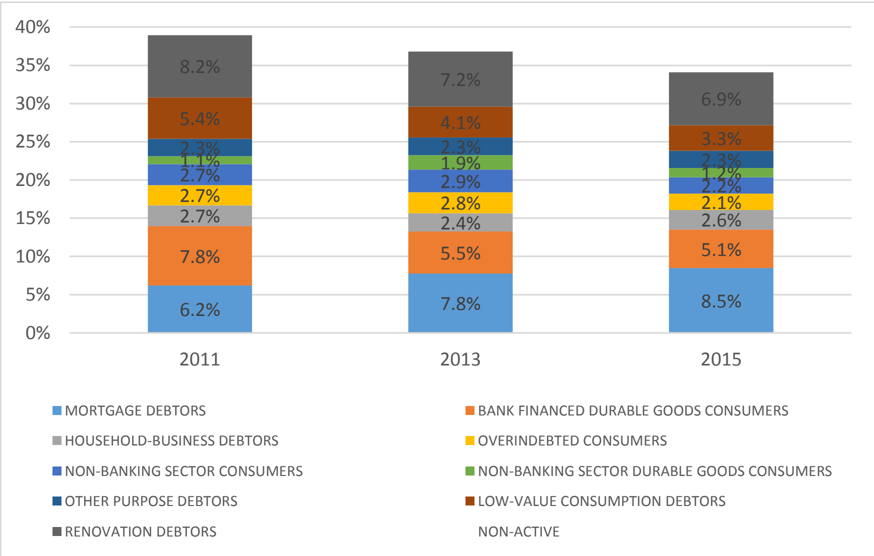
Class 5 (NON-BANKING SECTOR CONSUMERS) – Households that have a low value of debt (65.4% below their quarterly incomes) but who acquire it from outside the banking sector. 71.2% declare loans from other financial institutions and 31.8% from private persons. These households devote their loans mostly to consumption (36.7%) and fixed charges (20.3%) but also to renovation of a flat (32.4%), purchase of durables (11.5%) and medical treatment (11.7%).

Class 6 (NON-BANKING SECTOR DURABLE GOODS CONSUMERS) – Households with lowest value of debt (74.8% with debt below their quarterly incomes). These households' acquire their debt from other financial institutions (100%) and sometimes from banks (26.7%). The debt is devoted almost solely to purchases of durables (100%), rarely to renovation of flat (12.9%) or current consumption (5.2%).
Class 7 (OTHER PURPOSE DEBTORS) – Households that have slightly 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 (12.9%).
Class 8 (LOW-VALUE CONSUMPTION DEBTORS) – Group of households with below average value of debt (61.3% report debt below their quarterly incomes). These households' sources of credit are almost entirely banks (100%). Although the debt is low, there is a very high probability of debt for current consumption (62.3%) or fixed charges (27.1%). Repayment of previous debts is present in the group of 12.1% members of the segment. Additionally, financing of health care expenditures is present among 22.3% of group members.
Class 9 (RENOVATION DEBTORS) – Households that have a slightly lower than average value of debt. These households' acquire their debt from banks (100%) and rarely from elsewhere. The debt is always devoted to renovation of apartment (100%). Sometimes supported by the purchase of durables (23.6%).
Class 10 (NON-ACTIVE) – Households with no debt.
There is a distinct diversity of credit market participation patterns with very different values of debt, sources and motives for its acquisition. However, each segment is characterised by a distinguishable primary motive for debt possession or clear-cut combination of motives. It is natural that for larger sums, households tend to switch towards the banking sector. It is especially visible in acquisition of debt for housing purposes, which is usually associated with considerable debt values. However, with respect to financing consumption or small durable purchases one can observe competing strategies and banks face competition from the non-financial institutions.

### 4.2. Evolution of segments in time

Comparable pattern of credit market behaviour enables to trace the evolution of the composition of the market between 2011 and 2015. In Figure 2, we present the results of the latent class segmentation providing the composition of the group of active debt holders.

Figure 2 Debt possession patterns among Polish households between 2011 and 2015




During the period of analysis, the share of indebted households was decreasing. However, also the relative role of segments has been changing. MORTGAGE DEBTORS became the dominant group of debt holders, while the BANK FINANCED DURABLE GOODS CONSUMERS have been constantly losing their market share. The groups of households indebted for pure consumption or even over-indebted have been also declining. The declining role of non-banking forms of borrowing is confirmed by the gradual disappearance of the group of households that borrows from the non-banking sector.
In the latent transition approach, the total change in the market structure is attributed to the time evolution of the market and socio-economic characteristics of households that influence participation in the credit market. Following the modelling strategy presented in 3.2 in the model we first

included transitions between latent states. As the model with intertemporally equal transition coefficients proved to be superior in terms of BIC, table 4 depicts odds ratios for transitions between classes in consecutive periods.

Table 4 Odds ratios for transitions between latent classes in consecutive periods

| Class membership in t-1 | Class membership in t: c.1 | c.2 | c.3 | c.4 | c.5 | c.6 | c.7 | c.8 | c.9 | c.10 |
|---|---|---|---|---|---|---|---|---|---|---|
| c.1 | 94.25*** | 5.27*** | 9.47*** | 15.39*** | 2.46* | 3.06** | 7.92*** | 4.02*** | 12.40*** | ref. |
| c.2 | 2.51*** | 9.23*** | 4.98*** | 4.62*** | 4.03*** | 6.23*** | 6.06*** | 4.53*** | 5.73*** | ref. |
| c.3 | 3.43*** | 5.14*** | 52.46*** | 9.54*** | 2.57** | 1.97 | 8.83*** | 6.63*** | 5.02*** | ref. |
| c.4 | 17.89*** | 8.00*** | 13.44*** | 108.09*** | 15.67*** | 8.13*** | 18.71*** | 19.99*** | 15.93*** | ref. |
| c.5 | 1.54 | 3.35*** | 1.07 | 9.68*** | 16.64*** | 6.29*** | 6.39*** | 4.51*** | 5.10*** | ref. |
| c.6 | 4.23*** | 5.77*** | 1.72 | 11.00*** | 7.36*** | 10.39*** | 4.62*** | 3.48*** | 5.47*** | ref. |
| c.7 | 7.40*** | 7.21*** | 7.58*** | 15.86*** | 5.97*** | 2.49* | 23.69*** | 7.32*** | 7.17*** | ref. |
| c.8 | 6.62*** | 5.85*** | 5.16*** | 24.29*** | 7.36*** | 3.99*** | 8.97*** | 21.85*** | 8.70*** | ref. |
| c.9 | 7.27*** | 5.64*** | 5.20*** | 14.94*** | 6.46*** | 5.32*** | 6.94*** | 7.29*** | 21.28*** | ref. |
| c.10 | ref. | ref. | ref. | ref. | ref. | ref. | ref. | ref. | ref. | ref. |

Source: Own calculations in MPlus based on data from The Social Diagnosis.
Note: *** significant at 0.01 level; ** significant at 0.05 level; * significant at 0.1 level.

Estimates of the odds ratios – mostly significant and all larger than one – indicate that being a debt holder increases transition to the same or other debt holding segment with respect to the NON-ACTIVE segment. It shows a behavioural trait in household behaviour indicating that being a debt holder works in the direction of higher debt holding probability in the following period. It shows that once a household enters in a debt holding pattern, it is more likely to carry on with debt in the following periods. One can also observe very high probabilities of transition to the same debt holding state. Especially high odds ratios are recorded for households remaining in the MORTGAGE DEBTORS, HOUSEHOLD-BUSINESS DEBTORS and OVERINDEBTED CONSUMERS states. In all cases the odds ratios for remaining in the same state vs. transitioning to the NON-ACTIVE state exceed 50.[5] Although in the case of

[5] It should be underlined that the state of overindebtedness does not necessarily have to lead to default on debts. It is more likely income shocks (unemployment) or negative household events (e.g. divorce) that stimulate difficulties with repaying debts (Jentzsch &

MORTGAGE DEBTORS it seems quite natural to remain in a given state as mortgages are products with extremely long maturities, in the case of OVERINDEBTED CONSUMERS very high transition probability indicates strong persistence of debt.

### *4.3. Influence of socio-economic factors on segment evolution*

Additionally to the autoregressive nature of transitions between debt possession states, there is a natural tendency of the state membership to be influenced by the socio-economic variables. Following the procedure depicted in 3.2 we started the evaluation of potential influence of age of the household head, income and number of household members. Among those only the first three were found significant factors influencing the class transition. The odds ratios for transition to a latent in the final model with a set of covariates are presented in Table 5.
In the case of seven out of nine[6] classes the probabilities of transition to a debt holding segment from NON-ACTIVE was at least partially influenced by age. MORTGAGE DEBTORS tend to be extremely strongly influenced by age and it is much more likely to transition to the class for households with head aged 45 or less than for households with older heads. The odds for over 65 year olds are more than six times smaller than for the reference group (25 – 34 years). Very strong life cycle patterns are also observed in the case of HOUSEHOLD-BUSINESS DEBTORS and OVERINDEBTED CONSUMERS. However, in the case of the latter group the odds for being in the class drop significantly only after the age of 55. Moderate life cycle patterns are observed in the groups of BANK FINANCED DURABLE GOODS CONSUMERS and RENOVATION DEBTORS. Both these groups exhibit much lower transition probabilities after the head reaches age of 45 years. There are no groups in which a reversed debt-age pattern would have been obse**rved.**

Riestra, 2006). Consequently, very high transition probabilities pointing to remaining in this state.

[6] The last class serves as reference class.

Table 5 Odds ratios for transitions to a given latent class for socio-economic variables

| | | c.1 | c.2 | c.3 | c.4 | c.5 | c.6 | c.7 | c.8 | c.9 | c.10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| no. of people in household (4 – ref.) | 1 | 0.61*** | 0.62*** | 0.52** | --- | --- | --- | --- | --- | 0.75*** | ref. |
| | 2 | 0.74** | 0.78** | 1.00$^{f}$ | --- | --- | --- | --- | --- | 0.75*** | ref. |
| | 3 | 1.00$^{f}$ | 1.00$^{f}$ | 1.00$^{f}$ | --- | --- | --- | --- | --- | 1.00$^{f}$ | ref. |
| | 5 or more | 1.00$^{f}$ | 1.00$^{f}$ | 1.71*** | --- | --- | --- | --- | --- | 1.00$^{f}$ | ref. |
| real income per equivalent unit in PLN (above 1500 PLN up to 2000 PLN – ref.) | below 500 | 0.40*** | 0.67** | --- | --- | 3.49*** | 1.00$^{f}$ | --- | 1.34** | 0.54*** | ref. |
| | 500 – 999 | 0.59*** | 1.00$^{f}$ | --- | --- | 2.23*** | 1.00$^{f}$ | --- | 1.34** | 1.00$^{f}$ | ref. |
| | 1000 – 1499 | 1.00$^{f}$ | 1.00$^{f}$ | --- | --- | 1.62*** | 1.00$^{f}$ | --- | 1.34** | 1.00$^{f}$ | ref. |
| | 2000 – 2999 | 1.71*** | 1.00$^{f}$ | --- | --- | 1.00$^{f}$ | 0.48*** | --- | 0.64** | 1.00$^{f}$ | ref. |
| | 3000+ | 3.14*** | 1.00$^{f}$ | --- | --- | 1.00$^{f}$ | 0.48*** | --- | 0.64** | 1.00$^{f}$ | ref. |
| age of the head of household in years (35 – 44 years – ref.) | up to 24 | 1.00$^{f}$ | 1.00$^{f}$ | 1.00$^{f}$ | 1.00$^{f}$ | --- | 1.00$^{f}$ | --- | 1.00$^{f}$ | 1.00$^{f}$ | ref. |
| | 25 – 34 | 1.00$^{f}$ | 1.00$^{f}$ | 1.00$^{f}$ | 1.00$^{f}$ | --- | 1.00$^{f}$ | --- | 1.00$^{f}$ | 1.00$^{f}$ | ref. |
| | 45 – 54 | 0.50*** | 0.77** | 1.00f | 1.00f | --- | 1.00f | --- | 1.00f | 0.79** | ref. |
| | 55 – 64 | 0.38*** | 0.75*** | 0.57*** | 0.70** | --- | 1.00f | --- | 1.00f | 0.80** | ref. |
| | 65 and over | 0.15*** | 0.51*** | 0.29*** | 0.42*** | --- | 0.61*** | --- | 0.79** | 0.47*** | ref. |

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

However, in the case of NON-BANKING SECTOR CONSUMERS and OTHER PURPOSE DEBTORS there is no distinct relationship with age. It strongly suggests that behaviour in these groups is not driven by life cycle relationship but rather depends on something else – like behavioural traits of household.

With respect to income, also significant differences between groups are observed. As the debt value is measured relatively to the household income, the larger the influence of income, the more it is expected that exclusion and uncertainty to play a role. Households with relatively low incomes are banned from some types of credit but also experience anxiety related to higher probability of job loss and repayment problems. These two phenomena manifest the most in the group of MORTGAGE DEBTORS. The odds for transitioning to the segment are over three times higher for households with incomes above 3000 PLN than for the reference group (1500-2000 PLN). The group of MORTGAGE DEBTORS is the most affected by the incomes in the direction supported by extensions to the life cycle theory associated with liquidity constraints and uncertainty. In other groups the impact of incomes on participation membership is significantly lower, with examples of some exclusion related to very low incomes in the groups of BANK-FINANCED DURABLE GOODS CONSUMERS and RENOVATION DEBTORS and other examples where the influence of incomes is reversed - NON-BANKING SECTOR CONSUMERS, NON-BANKING SECTOR DURABLE GOODS CONSUMERS and LOW-VALUE CONSUMPTION DEBTORS. In the case of BANK-FINANCED DURABLE GOODS CONSUMERS and RENOVATION DEBTORS there is a notable exclusion of very low income earners, which is consistent with the fact that households from these groups have acquired their debts always from banks, which are very cautious in supplying debt to very low-income households. A different pattern noted from non-banking sector consumers NON-BANKING SECTOR CONSUMERS suggests that these consumers tend to satisfy their consumption needs but fail to obtain financing from banks so they are strongly motivated to search for alternatives – the lower incomes they have the more likely is their transition to the segment. In the group of NON-BANKING SECTOR DURABLE GOODS CONSUMERS the role of low-incomes is not discriminatory but the high incomes tends to limit activity in the sector. Finally, LOW-VALUE CONSUMPTION DEBTORS, who are often indebted in banks, have a limited ability to obtain credit if exhibiting low incomes, so the odds for participation do not increase with decreasing incomes so much as in the NON-BANKING SECTOR CONSUMERS but participation in the group is strongly limited among higher income households.

The last relation that turned out to be significant is related to the number of household members. However, it proved to be significant only for the groups of MORTGAGE DEBTORS, BANK-FINANCED DURABLE GOODS CONSUMERS, HOUSEHOLD-BUSINESS DEBTORS and RENOVATION DEBTORS. Households with more people have to face larger needs – especially related to housing (mortgages and renovation), transportation (cars comprising large durables) or fostering their small business. Thus, their transitions to the groups of debt holders mentioned above are self-sustaining with the assumptions of life-cycle theory. In other groups, the motives for taking debt are less life-cycle related and thus there is no observed relationship between the number of household members and the odds for being in the group.

## 5. Conclusions

In this article, we presented an analysis of households' behaviour with respect to the possession of debt in the longitudinal perspective. We tracked household indebtedness patterns and traced its sources to life-cycle patterns but also to self-persistent behaviour related to transition drivers related to previously exhibited indebtedness pattern. 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 latent transitions 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, which enabled to conduct a valid tracking of time evolution of debt behaviour.

One of the most interesting developments from the study is that there is a very strong persistence in credit behaviour. It is not only related to staying within one group of debt behaviour but also shows that transitions between any group of debt holders is more likely than transitions to the NON-ACTIVE state. Yet, the role of life-cycle factors cannot be ruled out. There is a very strong presence of those factors in the group of MORTGAGE DEBTORS. In this group all factors that proved to be significant (age, income and number of household members) point to a very strong life-cycle behaviour and additionally indicate that extensions of the LCPIH associated with liquidity constraints play a crucial role. It is also visible, but to a lesser extent, in the purchases of durables and renovation expenditures with the use of bank credit. However, groups of households for which the main driver of credit behaviour is consumption are much more inclined to exhibit an inverse probability of debt to income relation, which although to some extent is supported by the findings of the life-cycle theory with respect to the consumption smoothing but also, in the light of very high probabilities of transitioning to the same classes, shows that such behaviour might be intrinsically driven. In some groups transitions cannot be resolved by the life cycle model. It is especially the case of OTHER-PURPOSE DEBTORS but also to some extent manifests itself within the group of OVERINDEBTED CONSUMERS. Their debt behaviour pattern is neither income motivated nor are they liquidity constrained, it does not depend on the number of household members. Transition to this group seems however to be constant during the working life time and only diminish close to retirement age.

However, this paper faces also some limitations. It is still unclear whether the discovered debt behaviour patterns are universal or only observed in Poland, which was subject to analysis. Second, Polish household credit market is still affected by limited availability of credit in the first years of the transition to the market economy. Thus many households did not have a chance to obtain credit during the period, which due to strong persistence of credit might have effects even now.

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Appendix 1. Latent class model BICs for the periods of analysis.

| No. of latent classes | BIC for unrestricted model | | |
|---|---|---|---|
| | 2011 | 2013 | 2015 |
| 2 classes | 76549.666 | 75154.144 | 64020.901 |
| 3 classes | 74588.002 | 72179.615 | 61457.201 |
| 4 classes | 73199.089 | 70580.761 | 60192.197 |
| 5 classes | 72343.302 | 69800.102 | 59746.254 |
| 6 classes | 71686.767 | 69372.04 | 59605.198 |
| 7 classes | 71205.349 | 69206.536 | 59275.087 |
| 8 classes | 70948.634 | 68832.209 | 59052.865 |
| 9 classes | 70692.260 | **68620.199** | **58961.783** |
| 10 classes | **70471.353** | 68746.679 | 58975.377 |
| 11 classes | 70474.126 | --- | --- |

Source: Calculations in Mplus 6.1.