How do Psychological Factors affect Household Savings behavior?

TRINH HA THU

s4866096

Radboud University

Abstract

Psychological factors have been emerging as a new source to explain saving behaviors in recent researches. However, their effects are not homogeneous but vary widely across groups. This study aims to analyze and distinguish such groups, in which psychological factors impact on savings differently. Going beyond the traditional OLS regression, this study also employs Finite Mixture Model to identify these latent unobservable classes and how psychological factors affect savings in each class. This approach also allows us to estimate how socio-demographic characteristics of a person can predict which class he/she is more likely to belongs to. Results from Finite Mixture Model on a Dutch representative dataset (n = 923) indicates that psychological factors affect saving behaviors differently between 2 classes: Class 1 – the younger and poorer; and Class 2: the older and well-established. The findings are important because it helps us understand the real drivers of savings among individuals and assist policymakers to customize their actions to improve household savings.

Keywords: Saving behavior; Psychological factors, Latent class, Household finance, Finite mixture model.

Table of contents

How do Psychological Factors affect Household Savings Behavior?

1. Introduction

Household savings is one of the main sectors in national savings, which has been studied extensively over time (Kapounek, Korab, & Deltuvaite, 2016). In general, financial decision-making is affected by financial literacy and the lack of basic financial concepts is likely to lead to the lack of saving planning (Lusardi, 2008). Besides this critical criterion, psychological factors such as self-control (Laibson et al., 1998; Cobb-Clark et al., 2016), optimism (Lim, Hanna, & Montalto, 2011), personality traits (Brown & Taylor, 2014) have been emerging as new sources for explanations because they affect the way people make decisions. Yet, the influence of psychological factors is not homogeneous across income, gender, life-cycle stage; which is also acknowledged in several research (Gerhard, Gladstone, & Hoffmann, 2018). This leads to the following research question:

How can we identify the differences across groups regarding the effect of psychological factors on household savings behaviors?

These differences are usually diagnosed by dividing the samples based on observed variables (e.g. gender, age, income) and comparing the multivariable regression results among those groups. Nevertheless, the relationship between psychological and socio-demographic characteristics is so much more complicated that it can be neglected by such standard technique. The research by Gerhard et al. (2018) is the first one to apply the *finite mixture model* methodology to uncover the role of latent heterogeneity in household savings across different segments. The finite mixture model estimates the proportion of different behavioral types (referred as "classes") in the population, which are distinguished by a certain set of values (Bruhin et al., 2010 cited in Gerhard et al., 2018). By that way, it is possible to evaluate how likely (the probability) a certain socio-demographic variable belongs to a class and gauge the regression coefficients for each class. More specifically, this study identifies two classes, namely “striving” and the “established”, with several distinct socio-economic characteristics on which psychological characteristics influence differently.

Therefore, the objective of this study is to go beyond the traditional variable regression methodology and apply finite mixture model in a different dataset and replicate the work of Gerhard, Gladstone, & Hoffmann (2018). However, unlike their work, I inspect the effect of financial literacy, financial attitude (towards money management), Self-control, Optimism, and Self-Emotion Regulation. It is widely accepted that financial literacy is the key variable to explain household savings behavior (e.g. Lusardi, 2008; Calcagno & Monticone, 2015). In Gerhard et al.'s study (2018), however, only self-assessed questions are used. These questions depend strongly on respondents’ intuition. Besides financial literacy, which is often measured by numerical and knowledgeable questions, I also take into account financial attitude (towards money management) as a part of psychological factors. Moreover, I scrutinize the impact of Self-Emotion Regulation Strategies on household saving, which has never been examined in the past and incorporate a diverse set of socio-demographic variables to assure that the revealed classes are more specific.

This paper makes several contributions to the literature on household finance. First, my study is expected to reveal some major types of Dutch household with certain socio-demographic features, on which the joint effects of psychological factors drive behaviors in different ways. Second, it applies the standard technique OLS regression and the innovative methodological approach (e.g. finite mixture model) at the same time. The results provide supports for the validity of the relationships between socio-economic and psychological factors affirmed by Gerhard et al. (2018) with a different population and new additional factors. Third, my paper overcomes the limitation in measuring financial literacy, which can undermine its actual influence, and uses a diverse set of socio-demographic characteristics background. These insights can help policymakers to improve national saving behaviors since the distinct classification based on socio-demographic characteristics allows them to intervene the target groups and take actions more accurately.

The remainder of this paper is structured as followed. Chapter 2 reviews the prior literature regarding this topic. Chapter 3 introduces the dataset. Chapter 4 describes my methodology about OLS regression as well as finite mixture model and how I can use it to detect the heterogeneity in savings behaviors. Chapter 5 presents my results. Chapter 6 discusses the main findings and their implications, limitations, and future research.

2. Literature Review

2.1. Factors predicting household savings behavior and their interaction

There are several hypotheses regarding the process of household savings behaviors such as life-cycle hypothesis (Shefrin & Thaler, 1988), permanent income hypothesis (Bhalla, 1980). While these hypotheses analyze savings from economic aspects, which concerns about socio-demographic factors such as income and consumption overtimes etc., more and more researches in behavioral economics provide new theories and concepts to predict savings behaviors using insights from psychology discipline. Together with financial literacy (Lusardi, 2008), psychological factors (e.g. self-control, optimism, personality traits…) play a crucial part in financial decision-making process (Laibson et al., 1998; Cobb-Clark et al., 2016; Lim, Hanna, & Montalto, 2011; Brown & Taylor, 2014).

The mentioned factors do not separately and independently influence savings behaviors. The interaction between psychological and socio-demographic characteristics should be taken into account. Saving money is a function of 2 sets of factors: the ability to save and the willingness to save (Gerhard et al., 2018). The ability to save is determined by individuals' socio characteristics such as life-cycle stage, income, household size, occupation (fulltime employees have less time for savings planning), household position (more influential of the spending and saving budget), and is more controlled by circumstances. Whereas, the willingness to save is controlled by psychological characteristics. For example, when it comes to saving decision, people with higher self-control will be more likely to be determined and not to spend money on impulsive purchases, thereby have higher saving rates.

This function suggests that the way psychological factors affect savings outcomes will differ under different conditions. For instance, married people with 2 children living in the urban area will have higher comsumption and living expenses, hence, they possibly have lower ability to save no matter how much they want to save. Previous research has illustrated the differences in saving among groups: the effect of locus of control on wealth accumulation is greater for low-income segments (Cobb-Clark et al., 2016), or men are more likely to save than women (Fisher & Montalto, 2010).

Therefore, it is justified to say that psychological factors have different impact on different socio-demographic groups. Using both OLS linear regression model and finite mixture model approach, we can identify such groups not just based on observable variables such as income, gender, or household head status by observable variables, but also by segmenting the sample according to what best fits the regression model using finite mixture model. Thanks to that, we can understand clearly the heterogeneity of this interaction. The main aim of this study is *to investigate and identify different (latent) classes of households whose savings behaviors are impacted differently by psychological factors.* The fundamental contribution of my study is to categorize households into different groups based on their socio-demographic characteristics and draw inference about the way each group behaves regarding some psychological factors. Therefore, it is necessary to give a brief review of all the factors, why they affect savings behaviors and form an expectation of their impact sign effects in the following sections.

2.2. Financial literacy and Psychological factors

According to Kahneman & Frederick (2007) and Kahneman & Egan, (2011), human make decisions using 2 systems: system 1 – the intuitive system and system 2 – the deliberate system. System 1 is always active and relies on mental operation so it is more likely to lead to fast response but also biases and irrational choices, while System 2 is slower and requires more logical thinking and effort. In a decision such as saving, financial literacy contributes to strengthen system 2, and plays an important role in making a good financial decision (Lusardi, 2008). At the same time, psychological factors (e.g. self-control, optimism, personality traits…) influence system 1 and thereby affect financial decision-making process (Laibson et al., 1998; Lim, Hanna, & Montalto, 2011; Brown & Taylor, 2014; Cobb-Clark et al., 2016).

Individuals are increasingly taking responsibility for their own financial security. Thus, financial literacy determines whether or not a person can make good financial decision (Lusardi, 2008). Usually, financial literacy is measured as a specialized form of knowledge. More specifically, respondents perform a series of numerical tasks and financial computations; or they answer some question regarding certain knowledge of banking rules and financial products. These tests require mathematical solutions so it cannot measure accurately the ability to manage finances in real life situations. Recently, other aspects such as attitudes are also considered and evaluated to present correctly individual financial capability (Atkinson, McKay, Collard, & Kempson, 2007; Overveld et al., 2011). For that reason, in this study, in addition to financial literacy, I also encompass financial attitude towards money management as a psychological factor that can explain household saving behaviors.

With respect to other psychological factors, there are several studies examining the effects of certain characteristics on saving behaviors, among which the most frequent variables of interest are self-control, optimism, and personality traits. While the impact of optimism and self-control on saving behaviors is quite consistent, personality traits' effects differ in a large variation in these studies (Gerhard et al., 2018). The most common model to measure these traits is Big Five, which includes five factors representing 5 aspects of personality: Extraversion (outgoing), Agreeableness (friendly), Conscientiousness (efficient/organized), Neuroticism (sensitive), Openness (inventive). Although this model has been increasingly applied in saving behavior research (Brown & Taylor, 2014), their findings lack consensus and persistence (Gerhard et al., 2018). Not to mention, the effect of these personality traits can be embedded in other psychological factors. For instance, Ameriks et al. (2004) assert that self-control is linked to "Conscientiousness" while Sharpe, Martin, & Roth (2011) states that optimism has significant positive correlations with "Extraversion and Agreeableness". To avoid the overlap of the effects, I decide to include Self-Control and Optimism (which have sound supporting evidences) as drivers of saving behaviors to retest their impact on saving amount with a different sample and a different methodology while excluding personality traits.

In addition, despite that psychological factors have been frequently touched on, no research studies focus on the effect of emotion on saving behaviors in general and that of Self-Emotion Regulation strategies in particular. Emotion is a powerful predicting driver for such decision making process (Lerner, Li, Valdesolo, & Kassam, 2015). Overveld et al. (2011) propose that the ability to regulate emotion in varied situations might contribute substantially to saving decisions. Hence, I attempt to examine the effect of Self-Emotion Regulation on the total saving amount and how it differs across groups. The next parts will present specifically each psychological drivers and how they influence savings behaviors.

2.3.1. Attitude towards money management

Financial capability includes not only the knowledge but also the attitude towards money. For example, it is not enough if someone is just aware or informed of the necessity of saving plan, they need to consider such long-term plan important (Overveld et al., 2011). Based on five domains of financial capability affirmed by Atkinson et al., (2007), Overveld et al. (2011) use path modeling to analyze the financial attitudes and find out that the most comprehensive financial attitude model has only two dimensions, which they classify as active money management and passive money management. More specifically, active money management refers to a strong attitude in controlling personal finance, for instance, keeping updating finance affair, maintaining budget, regularly checking bank account. Whereas, passive money management indicates a careless attitude about financial matters, for instance, often running out of expenditure, being unaware of current bank account amount, not knowing about the inflation. To measure financial attitudes for this study, I will use this approach to identify these two dimensions: active vs. passive attitude towards money management.

My expectation is that active money management is linked to high saving amounts because people with this trait understand their financial condition, and are more concerned about making ends meet or future finance. On the other hand, passive management is likely associated with low saving amounts because people with this trait have no problem with a “red” account at the end of the months and are likely to let the future reveal itself. In this sense, passive money management is related to Optimism but limits in only financial aspect.

2.3.2. Self-control

Saving is the action of postponing short-term satisfaction for the sake of long-term need. Thus, the ability to delay such gratification involves the exercise of self-control. Self-control refers to the ability to resist temptation and lack of self-control often leads to impulsive spending (Strömbäck et al., 2017). Shefrin & Thaler (1988) indicate that people always have to face conflict between a “planner” (i.e. who thinks about long run) and a "doer" (i.e. who cares about current situations), so self-control stands out in such cases as a key determinant of which action a person will choose. A decision of saving can be considered a similar case. Several studies show that low self-control people often have low wealth accumulation or do not have enough money for retirement (Strömbäck et al., 2017). Therefore, high level of self-control is likely to have positive effect on savings behavior. (Strömbäck et al., 2017). The effect on the youngster is expected smaller than that of the elder because the older and well-establish people usually have less financial limitations and more saving capacity (Katona, 1975).

2.3.3. Optimism

Optimism is usually defined as the positive expectations about future events (Sharpe et al., 2011). Optimistic people mostly have unrealistic positive view about themselves . (Barberis & Thaler, 2003 cited in Virlics, 2013). They tend to overlook the future negative prospects and are less likely to put money aside for such events. On the other hand, optimism can also be related to general happiness. Optimistic people work harder, retire later, have more trust in the institution, and possibly save more. The study by Strömbäck et al., (2017) shows a positive effect of optimism on saving behaviors. There are clearly variations in the effect of optimism in different samples and population.

2.3.4. Self-Emotion Regulation

There is no doubt that emotion can influence our daily decisions, especially when the choice between saving and consuming is a dilemma and involves conflict between short-term and long-term goals. However, Overveld et al. (2011) propose that it is not the emotion per se but the coping style when dealing with emotion (i.e. emotion regulation) which plays an important role regarding financial decisions. It is manifested as the ability to initiate or inhibit emotion when needed. For example, if a person can control his/her immediate emotions effectively, he/she will be less likely to be affected by the biased judgment in System 1.

Whereas, System 2 – using logical thinking – is more likely to be activated and makes a good decision. The strategy each person uses to control emotion is what that matters and separates people apart.

The most common emotion regulation strategies are cognitive reappraisal and expressive suppression, which are regarded to be stable over time (Gross & John, 2003). Cognitive reappraisal means that you reinterpret the meaning of emotion that to change the tendency of an emotional response. By this way, people think of the current problems in a different way and try to solve them. When choosing between saving or not, they interpret saving decision in a positive way and keeps emotional system healthy and functioning (Gross & John, 2003). Hence, the next saving decision will be based on a strong foundation with reasonable thinking. On the contrary, expressive suppression means that you attempt to block ongoing emotion-expressive behavior (Gross & John, 2003). People carrying this strategy is more likely a problem-avoider. Since they constrain real emotions, they can be decisive in saving decision for the first few times, this chain of behaviors may not last long because they feel this action obligatory which would result in a poor record of saving amount in the end. Therefore, I expect that high level of cognitive reappraisal has a positive effect on savings behaviors while high level of expressive suppression is likely to have negative effect.

To sum up, beside the socio-demographic characteristics, I aim to investigate in this study the following factors: financial literacy, financial attitude towards money management, self-control, optimism, self-emotion regulation strategy. Table 1 provides a summary of expect effects of all these factors on saving behaviors.

Table 1: The expected effect of factors on savings behaviors

Factors	**Expected effect**
Financial literacy	Positive
Attitude toward money	

- *Active money management*	Positive
- *Passive money management*	Negative
Self-control	Positive
Optimism	Positive/Negative
Self-Emotion Regulation	
- *Cognitive reappraisal*	Positive
- *Expressive suppression*	Negative

3. Data

3.1. Data Collection and Sample

The data used in this study is the existing data acquired from the LISS panel (Longitudinal Internet Studies for the Social Sciences), administered by CentERdata. The panel is based on a true probability sample of Dutch households drawn from the population register by Statistics Netherlands. It consists of 4500 households, comprising 7000 individuals. This panel data contains questions on not only socio-demographic characteristics such as age, gender, income etc., but also household savings amount and psychological characteristics.

For this study, five datasets are selected. First, to measure household savings behaviors, I use the Wave 3 in 2012 of Panel Economic Situation: Assets. Second, to measure Optimism, I use Wave 5 in 2012 of Panel Personality. Third, to measure self-control, self-emotion regulation and attitude toward money, and financial literacy, I use three different single wave studies datasets. In addition, socio-demographic characteristics of respondents are derived from background data, which are measured monthly using a separate questionnaire. After merging all datasets, there remains 1938 observations. Furthermore, I eliminate all 979 observations in which the respondents answer “Don’t know” or “Prefer not to say” or whose results are missing for the question regarding household saving amount. In addition, I also exclude all 36 answers which respondents indicate a negative number of saving amount. I am thus left with 923 observations for further analysis.

3.2. Dependent variable – Measuring household savings behavior

A self-reported question regarding the total of savings in absolute number is used to measured household savings behaviors. Respondents were asked what the total amount of their saving account or any other kind of savings is, and they can input their exact number. The actual question was: “What was the total balance of your banking account or giro (current accounts), savings accounts, term deposit accounts, savings bonds or savings certificates and bank savings schemes on 31 December 2011?” A new variable is created for the log transformation of the saving values for normalization purpose and will be used for modeling as the dependent variable.

3.3. Explanatory variables

Explanatory variables include firstly financial literacy; secondly socio-demographic characteristics, which plays a key role in predicting different classes or segment probability within the dataset; and lastly psychological factors.

3.3.1. Financial literacy

Financial literacy is measured using the big three questions created by Lusardi (Lusardi & Mitchell, 2011), which assure 4 key principles: Simplicity, Relevance, Brevity, and Capacity to differentiate. These questions capture 3 economic concepts regarding understanding of interest compounding, inflation, and risk diversification (detailed questions can be found in the appendix). There are newly-created variables for each question, which I grant 1 if respondents answer correctly and 0 if respondents do not know or answers incorrectly. Then I sum all the scores of all questions to formulate the final score of each respondent. This result represents the financial literacy.

3.3.2. Socio-demographic characteristics

Data is extracted from Background variable dataset in LISS Panel, which was collected in August 2012 and includes Gender, Age (measured in years and by categories), Gross household Income (log transformed with 37 missing values being replaced by the mean), Level of Education (dummy variable for having a university WO/HBO education), Head of the household (dummy variable if respondent is the head), Number of Children, Number of household member, Occupation (since I suspect that the difference between fulltime and part-time workers can impact the amount of savings, I create a dummy variable if respondent is a fulltime worker), Living with partner, Type of dwelling.

3.3.3. Psychological factors

Several sets of Likert scale questions are used to measure psychological factors. Respondents rate each item on a 5-point scale (for self-control and optimism), on a 6-point scale (for attitude towards money management) or on a 7-point scale (for self-emotion regulation): from Disagree entirely to Agree entirely. A full questionnaire for all variables of interest together with their factor loading, scale and Cronbach's alpha is shown in the appendix (Table 7).

Regarding attitude towards money management, I use the questionnaire first created by British Financial Services Authority, and then developed further by Overveld et al. (2011) to measure the attitude part of financial capability. Active money management attitude is measured by 7 items and passive money management attitude is measured by 4 items in the questionnaire. The Cronbach alphas for both aspects are quite low (0.44 and 0.33 respectively) by traditional standards (alpha should be higher than 0.6).

Self-control is measured by a set of 13-item questionnaire by Tangney et al. (2004), 9 out of those 13 questions need transforming in reversed order. There is one missing value, which is replaced by the mean of the rest. Factor analysis on all constructs is conducted, revealing 6 factors which have eigenvalue above 0 but only one factor has note-worthy item loading. The Cronbach's alpha is 0.78 (higher than 0.6), showing a high internal consistency. The self-control score is created by adding the scores of all statements. High score indicates a high level of self-control and vice versa.

The measurement of Optimism uses Life Orientation Test – Revised (LOT-R) by (F. Scheier, Carver, & W. Bridges, 1995). Respondents are asked to answer a 10-item questionnaire in 5-point scale to identify their optimism versus pessimism. Out of these 10, there are 3 items to measure optimism, 3 items to measure pessimism (will be scored in reversed order), and 4 filler items (will be removed from the analysis). I sum across all items to produce a single score representing for the optimism. Factor analysis is also conducted, showing 1 factors with high eigenvalue (1.8) and noticeable item loading. Cronbach's alpha is 0.72 (higher than 0.6), which provides evidence of internal consistency.

To measure Self-Emotion regulation, respondents are asked to answer 10-items questionnaire designed to determine their tendency to regulate their emotions in two ways: (1) Cognitive Reappraisal and (2) Expressive Suppression (Gross & John, 2003). Each item is set on a 7-point scale, in which 4 items reveal Cognitive Reappraisal tendency and 6 items reveal Expressive Suppression tendency. Factor analysis is carried out separately for two emotion regulation strategies. Both Cognitive Reappraisal and Expression and Suppression show only 1 single factor with notable item loading, and Cronbach's alpha are 0.83 and 0.77 respectively. I then sum up their score of both tendencies separately to formulate the individual scores.

3.4. Summary Statistics

The summary statistics is shown in Table 2. The final sample consists of 56.77% male respondents and 43.23% female respondents. Age ranges from 18 to 90 years old with a mean of 56.01. There are 70.4% of household having no children, while 10.08% households have one child and 12.68% have two children. 2-member households compose nearly half of the sample with 48.32%. In term of education level, since I am interested in if respondent hold a university education, a dummy variable is created to specify this criterion. Based on Statistics Netherlands classification, I consider respondent with Higher Vocational Education (HBO) and University (WO) as university level. Hence, my sample includes 35.54% people who holds a university degree and 64.46% who have lower education. In term of occupation, fulltime workers constitute 45.29% while part-time workers and unemployed people make up to 54.71%. I also create a dummy variable indicating whether or not respondents are fulltime worker. It is impossible to separate part-time workers and the unemployed based on the questionnaire so I combine them together. This group also includes pensioners. Finally, 71.51% of the respondents currently live with partners and 74.65% live in self-owned dwelling or cost-free dwelling.

The total saving amount in bank accounts has a mean of 45028 Euros, which has been normalized by using log function for convenience during model building. Log saving amount ranges from 0 to 16 with a mean of 9.14. In term of psychological factor score, overall scores are showed in Table 2 while detailed statistics for each item within each psychological factor measurement can be found in the appendix.

Table 2: Summary Statistics

	Mean	SD	Min	Max
Dependent Variable				
Total saving amount in Euros	45028.99	280511.53	0	8135049
Log saving amount	9.14	2.21	0	16
Socio-demographic characteristics				
Gender	1.43	0.50	1	2
Head of the household	0.68	0.47	0	1

Age of the household member	56.06	16.71	18	90
Number of household members	2.28	1.17	1	8
Number of living-at-home children	0.54	0.98	0	6
Gross household income in Euros	4075.90	2459.64	0	20712
Type of dwelling (Rental or not)	0.25	0.44	0	1
Living with partner	0.72	0.45	0	1
University	0.36	0.48	0	1
Fulltime worker	0.45	0.5	0	1
Psychological factors				
Optimism	20.86	3.21	8	30
Self-control	45.02	7.42	18	65
Cognitive reappraisal	26.67	5.80	6	42
Expressive suppression	14.61	4.65	4	28
Active money management	28.96	4.71	12	42
Passive money management	10.52	3.10	4	24
Individual Financial Literacy	2.33	0.73	0	3
Observations	**923**			

4. Methodology – Analysis strategy

4.1. OLS Regression

To evaluate the impact of psychological factors on saving behavior and how they differ among observable groups, I conduct a series of OLS regression to have a first look of the data to build up a segmental benchmark based on observable variables. My specification is:

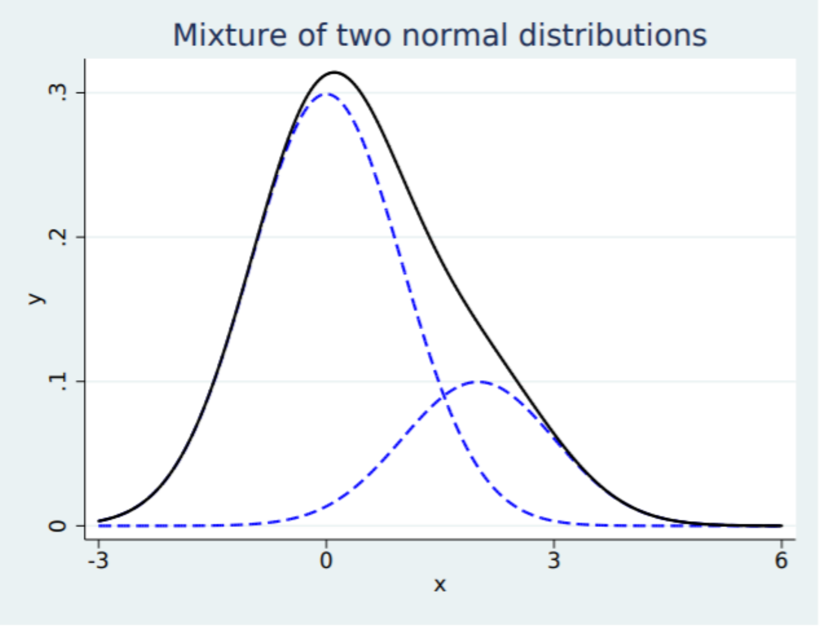
$$Y_i = \beta_0 + \beta_1 Socio_i + \beta_2 Psy_i + \beta_3 Inter + u$$

where Y is the dependent variable – Log of saving amount, i is the index for the individuals of the sample. Vector *Socio* includes all socio-demographic variables, vector *Psy* includes all psychological variables, and vector *Inter* includes all interactions (if any). Correlation between variables is not high enough to cause multicollinearity (see appendix).

4.2. Finite Mixture Model

My hypothesis suggests that within the population there are sub-groups which individuals behave differently but cannot be identified by any observable variables, hence, using Finite Mixture distribution is helpful to classify and model such unobserved heterogeneity (McLachlan & Peel, 2000). As can be seen in the plot, the concept of finite mixture model is that there are some unobserved underlying sub-populations within the whole population.

Figure 1: Mixture of two normal distribution



(Stata Press Publication, 2017)

In my sample, the observed respondents are assumed to come from ***g*** distinct classes $f_1, f_2, \ldots, f_g$ in proportions $\pi_1, \pi_2, \ldots, \pi_g$. The simplest form of g-component mixture is written as below:

$$f(y) = \sum_{i=1}^{g} \pi_i f_i(y|x'\beta_i)$$

where π_i is the probability for the ith class, $0 \leq \pi_i \leq 1$ and $\sum \pi_i = 1$, and $f_i(.)$ is the conditional probability density function for the observed response in the ith class model.

Finite Mixture Model procedure in Stata fits the model using expectation-maximization (EM) algorithm. A prefix “fmm” is added in front of the linear regression command (“fmm: regress”) to fit the models. The output will include two main parts: (1) the results of the class membership and (2) the regression results for each class. Part (1) allows us to understand how socio-demographic variables predict the probability of belonging to certain classes using multinomial logistic regression. Part (2) presents the coefficients of psychological variables in each class. The proportion of each class within the whole population and their predicted mean of total saving amount can be obtained in separate commands, namely “lcprob” and “lcmean” respectively.

5. Results

5.1. How do psychological factors affect saving behaviors? – OLS Linear regression results

First, I model the relationship between psychological factors and saving amount using OLS regression. The socio-demographic and financial literacy variables are included as control variables. Since I use Log transformation of saving amount as dependent variable, one-unit change in the coefficients of the independent variables will results in the percentage change in total household saving amount. Table 3 shows the marginal effect of each psychological variables on Log of saving amount when regressed one by one and as all together. In most regressions, the results are more or less the same, except for some key differences. Unlike my expectation, Self-control has a negative effect of saving amount in both regressions, even though the effect is small (-0.03, p-value < 0.05). In contrast, Optimism does not show statistical significance when regressed alone but has a positive effect on saving amount with larger effect (0.05, p-value < 0.1) when regressed together with other variables. Passive money attitude has a negative effect and the effect size is much higher than Self-control and Optimism (0.07, p-value < 0.05) in both regressions. The rest psychological variables show no statistical significance and the effect size is also small.

Noticeably, financial literacy has positive and significant effect on saving amount in most regressions except the ones including Passive money management. It appears that Passive attitude explains saving amount better than financial literacy. In term of socio-demographic variables, there are significantly positive effects of age (in which "65 years old and older" is clearly differentiated from the rest, p-value < 0.01), income (p-value < 0.01), university level (p-value < 0.1), fulltime worker status (p-value < 0.1), and a significantly negative effect of dwelling status (p-value < 0.01) when it comes to saving behaviors.

Since I expect the effects of psychological factors differ across groups, I include 12 interaction terms corresponding with 4 significant socio-demographic variables and 3 significant psychological variables in the regressions. Especially, for income, I create a dummy for income higher than the median number to separate High Income and Low Income. Even when the interaction terms are regressed one by one or as all together, their effects turn out to be statistically insignificant. Only the interactions between Low/High Income with Passive Money Management Attitude are significant and the effect sign is negative, which indicates that Passive attitude has stronger negative effect on people with higher income (see appendix – Table 9). It is, therefore, difficult to affirm whether there are interactions within these groups divided by socio-demographic characteristics or not.

Table 3: OLS regressions on the association between psychological factors and Log total saving amount (added one by one and all together)

	(1) Optimism	(2) Self-control	(3) Cognitive Reappraisal	(4) Expressive Suppression	(5) Active Attitude	(6) Passive Attitude	**(7) All variables**
Female	0.252	0.280	0.275	0.213	0.248	0.159	0.147
	(0.148)	(0.108)	(0.115)	(0.231)	(0.155)	(0.367)	(0.411)
Head of the household	0.218	0.227	0.221	0.217	0.218	0.184	0.205
	(0.303)	(0.283)	(0.295)	(0.305)	(0.303)	(0.382)	(0.327)
25 - 34 years	-0.731	-0.678	-0.758	-0.752	-0.775	-0.788	-0.677
	(0.074)	(0.098)	(0.064)	(0.066)	(0.058)	(0.053)	(0.097)
35 - 44 years	-0.0687	-0.00518	-0.0771	-0.107	-0.103	-0.118	0.0485
	(0.854)	(0.989)	(0.836)	(0.773)	(0.782)	(0.750)	(0.896)
45 - 54 years	0.302	0.404	0.291	0.257	0.254	0.215	0.432
	(0.405)	(0.273)	(0.422)	(0.478)	(0.483)	(0.552)	(0.239)
55 - 64 years	0.500	0.633	0.503	0.472	0.481	0.444	0.640
	(0.153)	(0.076)	(0.151)	(0.178)	(0.169)	(0.203)	(0.071)
65 years and older	1.233***	1.403***	1.263***	1.248***	1.212***	1.172***	1.434***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
	(0.693)	(0.775)	(0.695)	(0.701)	(0.731)	(0.820)	(0.783)
Number of children living at home	-0.274	-0.229	-0.268	-0.259	-0.243	-0.193	-0.221
	(0.487)	(0.561)	(0.496)	(0.510)	(0.537)	(0.623)	(0.572)
Log Income	0.573***	0.591***	0.592***	0.589***	0.598***	0.594***	0.553***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rental dwelling	-0.730***	-0.735***	-0.744***	-0.751***	-0.741***	-0.704***	-0.653***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Yes, living with partner	0.189	0.288	0.210	0.205	0.239	0.222	0.257
	(0.629)	(0.461)	(0.590)	(0.599)	(0.541)	(0.567)	(0.509)
University (WO/HBO)	0.305	0.368*	0.348*	0.340*	0.352*	0.347*	0.325*
	(0.050)	(0.017)	(0.023)	(0.027)	(0.022)	(0.023)	(0.036)
Fulltime worker	0.396*	0.408*	0.416*	0.402*	0.393*	0.416*	0.434*
	(0.045)	(0.038)	(0.035)	(0.041)	(0.046)	(0.034)	(0.027)

Individual Financial Literacy	0.202*	0.215*	0.221*	0.207*	0.202*	0.188	0.156
	(0.042)	(0.029)	(0.026)	(0.037)	(0.042)	(0.057)	(0.114)
Optimism	0.0348						0.0462*
	(0.112)						(0.040)
Self-control		-0.0192*					-0.0265**
		(0.045)					(0.007)
Cognitive reappraisal			-0.0144				-0.0141
			(0.215)				(0.237)
Expressive suppression				-0.0220			-0.00923
				(0.141)			(0.544)
Active money management					0.0228		0.0175
					(0.110)		(0.235)
Passive money management						-0.0723**	-0.0694**
						(0.001)	(0.003)
Constant	2.328*	3.586**	3.196**	3.257**	2.214	3.859***	4.171**
	(0.036)	(0.001)	(0.004)	(0.003)	(0.051)	(0.000)	(0.001)
Observations	923	923	923	923	923	923	923
Adjusted R^2	0.163	0.164	0.162	0.162	0.163	0.170	0.177

Dependent variable: Log of saving amount
Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

These regression results give us a first look of the data. We can conclude that the amount of savings is different across age, Income and Education level separately; and only Optimism, Self-control, and Passive attitude towards money significantly affects saving amount. Nevertheless, how the effects of psychological factors differ within these groups remains unknown and unproved. Moreover, when these groups overlap, it is impossible to decide whether people with combined traits (e.g. old and High Income, Young and Living in self-owned house) are influenced by psychological factors in saving decisions differently. The data might contain hidden unobserved subpopulations. Therefore, I continue to use Finite mixture model to identify the latent classes within the sample.

5.2. How do psychological factors affect saving behaviors across latent heterogeneity? – Finite Mixture Model Result

The objective of using Finite Mixture model is to know whether this data has one single normal distribution or a mixture of two or more distributions. I believe that there might be at least a group (or class) of low savers and a group of high savers, which psychological factors affect differently. Hence, I use only psychological variables as independent variables to determine the mixtures and Log of saving amount as dependent variable. The probabilities of belonging to a particular class will be predicted by individual socio-demographic characteristics (which I choose only variables that show statistical significance in OLS regression). To run Finite Mixture Model, first of all, the appropriate number of classes should be decided, then the results of finite mixture model will be presented.

5.2.1. Model fit

Model fit refers to the number of latent classes which suits best with the data since the number of subpopulations nested in this sample is still unknown. In order to determine the best model fit for this data, I will perform several model estimations from 1-class option to 3-class option and then compare them based on a set of criteria. I stop at 3-class option to ensure the size of each class large enough for meaningful interpretation (Gerhard et al., 2018).

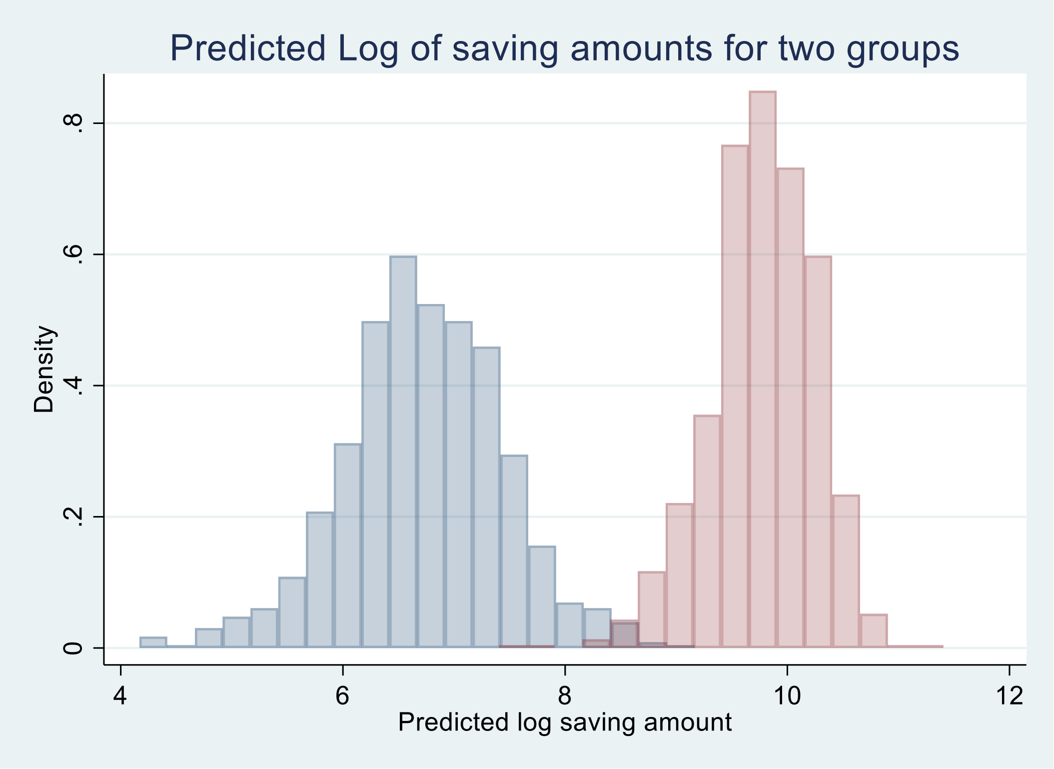
To compare the results obtained from the same estimation approach and choose the best model, Akaike's information criterion (AIC) and Bayesian information criterion (BIC) of (Table 4) are used to evaluate the fitness of each model (Akaike, 1974, Schwarz, 1978). In general, a smaller value in both BIC and AIC indicates a better-fitting model. As can be seen in Table 4, the AIC favors the 3-class model (lowest AIC), whereas the BIC favors the 2-class model (lowest BIC) although the differences across model selection criteria are marginal and not insignificant. Hence, I inspect further the class sizes and the class membership predicted by socio-demographic variables of both model. In 3-class model, one class (out of 3 classes) accounts for only 10% of the whole sample size; this number is quite small and can be problematic when interpreting and generalizing for the whole population. Plus, the class membership predicted by socio-demographic variables is not clearly separated among 3 classes so it is difficult to identify certain groups based on this model. Whereas, the 2-class model has a more balance in class size: one class containing 21.7% respondents and the other containing 78.3% respondents. Moreover, 2 classes are well predicted by socio-demographic variables. I, therefore, proceed with the 2-class model.

Table 4: Model Selection Criteria

	(1) 1-Class	(2) 2-Class	(3) 3-Class
AIC	4041.555	3744.477	3659.697
BIC	4085.004	3879.65	3886.596

Additionally, entropy statistics is calculated to assess how separated the 2 latent classes are from each other. An entropy values greater than 0.80 and approaching 1 indicates a good separation (Ramaswamy et al., 1993). The entropy value of this sample in 2-class model is 0.638, which implies that the two groups are not well-distinguished. However, the model can still be useful since the marginal predicted mean of Log saving amount outcome within each class of this model are clearly different. In detail, one class (Class 1) corresponds with low savers and has the mean of Log saving amount = 6.73 (€837). Whereas, the other (Class 2) corresponds with high savers and has the mean of Log saving amount = 9.77 (€17,500). Figure 2 illustrates the distribution of each class (x-asis: the predicted log of saving amount, y-axis: the density). It can be seen that the Pink distribution represents for the high-saver class whereas the Blue distribution represents for the low-saver class with a wider variation.

Figure 2: Mixture of 2 distributions in 2-class model



5.2.2. How do socio-demographic characteristics predict latent class membership?

Assuming that all individuals share the same probabilities of belonging to a certain class is unrealistic since their particular characteristics can predict which classes they are likely to be related to. Table 5 shows how a certain socio-demographic characteristic can predict the probability of belonging to a certain class. Class 1 is the base outcome. The coefficient in column (1) illustrates how these variables predict the probability of belonging to Class 2 as compared to Class 1. As we can see, being old (65 years and older) (p-value < 0.01), working fulltime (p-value < 0.05), and earning high income (p-value < 0.01) have significantly positive impact on the probability of belonging to class 2. On the other hand, living in self-own/cost-free dwelling has significantly negative impact on the probability of belonging to Class 2 (p-value < 0.01). Given these effects, Class 1 – low savers – refers to "*the youngster, poorer, still striving for living*", whereas Class 2 – high savers – refers to "*the elderly, richer and having well-established financial ability*".

Table 5: The probability of class membership

	(1) Probability of belonging to Class 2 relative to Class 1	p-value
15 - 24 years *(omitted because of collinearity)*	0	(.)
25 - 34 years	-0.553	(0.483)
35 - 44 years	0.355	(0.644)
45 - 54 years	1.024	(0.187)
55 - 64 years	0.860	(0.205)
65 years and older	2.706***	(0.000)
Income higher than median income	1.472***	(0.000)
Rental dwelling	-1.148***	(0.001)
University (WO/HBO)	0.413	(0.264)
Fulltime worker	1.231**	(0.003)

Robust standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

5.2.3. The differences in psychological factors' impact across classes

The differences in psychological factors' impact between two classes are discussed in detail in this section. The proportion of each class is as follows: 21.7% of respondents fall into Class 1 – low savers, and 78.3% of respondents fall into Class 2 – high savers. Table 6 shows the coefficients of psychological factors, how they explain the dependent variables – Log saving amount – in 2 classes, obtained from finite mixture model. As Log transformation of saving amount is the dependent variable, one-unit change in the coefficients of the independent variables will results in the percentage change in total saving amount.

It appears that the sample contains 2 groups with distinct characteristics: one is affected by (some) psychological factors and the other is not affected at all. For Class 1, all of the independent variables do not significantly statistically impact the Log total saving amount, including financial literacy, which is contradict to some previous studies (Atkinson et al., 2007; Lusardi, 2008). However, the sample used by Lusardi (2008), for example, covers only older respondents (with an average age of 65) and examines the effect of financial literacy on retirement planning, while Class 1 is associated with the youngsters and the effect is on saving amount. Hence, these results might not be comparable. Although the youngster, who do not own a solid financial knowledge, can receive greater benefits from one-unit increase in financial literacy, they also suffer the financial constraints that are more likely to drive their behaviors rather than skills or psychological factors. Compared to Class 2, there witnesses a strong effect of financial literacy (p-value < 0.01): one-unit increase in financial literacy results in 40% increase in total saving amount in Class 2. This result is completely in line with the past literature (Atkinson et al., 2007; Lusardi, 2008; Lusardi & Mitchell, 2011; Gerhard et al., 2018). Moreover, recalling the OLS regression results, financial literacy also turns from significant impact to no significant impact on the regressions when Passive money management attitude is added. Therefore, we can say that finite mixture model can separate out the group which is not strongly affected by financial literacy. The chi-square also rejects the null hypothesis that these two coefficients are being equal, thereby proves that financial literacy impact two classes differently.

Optimism has a positive and statistically significantly impact on saving amount in Class 2 (p-value < 0.05), which is similar to the results obtained from OLS regression. One-unit increase in Optimism corresponds to an 5.5% increase in total saving amount. There are many possible explanations for this result since the effect of optimism was not consistent in earlier researches. On one hand, Virlics (2013) suggests that optimism creates a negative impact on intent to save due to the unrealistic future expectation on financial prospect (Barberis & Thaler, 2003 cited in Virlics, 2013), which differs from the result obtained in this study. On the other hand, Strömbäck et al., (2017) propose that optimism can be important to general well-being. Pessimistic people are more likely to suffer pessimistic bias than happy people. Their research also shows a positive effect of optimism on good financial behavior and saving behavior. The results can also be attributed to the stable economy in the Netherlands over time. Thus, Optimism does not play a major role in shaping people saving behaviors. Although optimism have positive impact, the magnitude of impact is not large.

Table 6: Regression Results of log total saving amount

	Class 1 Coefficient	Class 2 Coefficient	Chi-square statistics for the equality between coefficients
Individual Financial Literacy	-0.196	0.401***	3.44*
	(0.520)	(0.000)	(0.0635)
Optimism	0.101	0.0538**	0.45*
	(0.137)	(0.007)	(0.0541)
Self-control	-0.0429	0.00848	3.38*
	(0.114)	(0.318)	(0.0661)
Cognitive reappraisal	-0.0360	-0.0197*	0.14
	(0.396)	(0.050)	(0.7063)
Expressive suppression	-0.0694	0.0111	2.11
	(0.194)	(0.370)	(0.1468)
Active money management	0.00710	0.0106	0.00
	(0.885)	(0.397)	(0.9456)
Passive money management	-0.127	-0.0758***	0.41
	(0.103)	(0.000)	(0.5238)
Constant	10.12***	8.187***	
	(0.000)	(0.000)	
Observations	923	923	
Adjusted R^2			

The table presents the coefficients from finite mixture model for each class. The chi-square is obtained from the equality test of 2 class coefficients.
Dependent variable: Log of saving amount
p-value in parentheses (* p < 0.1, ** p < 0.05, *** p < 0.01)

Self-control does not affect significantly in both classes. These results are surprising because not only self-control is long acknowledged to have a positive effect on general good financial behaviors as well as savings behaviors in general (Shefrin & Thaler, 1988; Laibson et al., 1998; Strömbäck et al., 2017; Gerhard et al., 2018), but also it is proved that locus of control has stronger effect on low-income segment than high-income segment (Cobb-Clark et al., 2016). Yet, inspecting further, the result for Class 1 is in line with earlier study by Gerhard et al. (2018), which finds out that self-control only influence people who have the ability to save (richer and well-established), not the ones who experience financial constraints. For class 2, these differences can be explained due to the fact that the measurement of self-control is not similar to another in these cases and their samples target to different groups of population. For example, Strömbäck et al. (2017) choose only part of the scale by Tangney et al. (2004) – as in my study – to measure self-control and combine it with another scale by Antonides et al. (2011). In addition, self-reported data regarding behaviors are easily influenced by subjective opinions, especially when questions are just slightly modified, the answers might not be on a par. Also, there are possibilities that self-control only shows significant impact in certain groups of people and for respondents from this sample, financial literacy and other psychological explain their behaviors better.

With respect to Attitude towards money for Class 2, the impact of Active money management attitude is not statistically significant, while passive money management does have negative effect on total saving amount (p-value < 0.01). One-unit increase in passive money management results in 7.3% decrease in total saving amount. This result indicates that people who are careless about their money (passive attitude) is more likely to have low saving amount. However, even for people who are more alert about their budgets (active attitude), saving money may not be one of their top priorities. This happens only with well-established people, who possess a certain amount of money and assets that requires more effort to manage.

In term of self-emotion regulation strategies, expressive suppressions show no statistical significant impact on Log saving amount in both classes, while cognitive reappraisal has a significantly negative effect on Log total saving amount in Class 2 ($p < 0.1$). Yet, the effect is not strong according to the result. One-unit increase in this score results in 1.8% decrease in total saving amount. This is opposite to the results from the research by Overveld et al. (2011), which brings about the positive correlation between cognitive appraisal and good financial behaviors; and the negative correlation between expressive suppressions and those same behaviors. Nevertheless, considering that the dependent variables in their study and mine are different, the results are not equivalent. Furthermore, saving behavior is a particular behavior while the method to measure self-emotion regulation strategies is designed to fit with emotions from all kinds of situations. This measurement may not be effective to address problem avoiders and problem solvers regarding emotion controlling styles when it comes precisely to saving decisions.

6. Discussion & Conclusion

6.1. Main findings and their implications

The results reveal 2 distinct classes: Class 1 (21.7%) - the younger and poorer; and Class 2 (78.3%) - the older and more well-established. The effects of psychological factors on these 2 classes' saving behaviors are different in several aspects. In general, the older are affected by psychological factors (e.g. Optimism, Cognitive Reappraisal, Passive attitude towards money) while the younger are not. These results are consistent with the theory proposed by Katona (1975) regarding life-cycle. Accordingly, it is expected a larger influence of psychological factors on saving behaviors in Class 2 because they have strong financial abilities, do not suffer financial constraints, and have high ability to save, hence, their saving decisions will rely on psychological constructs. Whereas, in the Class 1, even if these people possess good traits to drive saving behaviors, they do not have enough money for such actions. Our findings demonstrate and emphasize the differences between these 2 groups including: low savers and high saver; and confirm that the ability to save predicts saving behaviors better than the willingness to save for this sample.

Noticeably, there is an imbalance in size between 2 classes (21.7% vs. 78.3%) which can be attributed to the data set’s characteristics: the skewed in ages of the dataset. The LISS panel data is designed to represent for the Dutch general population based on true probability. However, since I am interested in only the absolute savings amount, respondents who do not know or are not willing to share this information are excluded from the LISS data set. This leads to skewed dataset in age, where about 60% of the sample population is from 55 years old and above. Seeing that being “65 years or older” increases the probability of belonging in Class 2, it is possible to say that the results regarding the effect of psychological factors on savings in Class 2 can partly represent the wealthy elderly segment in the Netherlands and how they prepare for retirement.

Considering Class 2, the result is in line with previous research targeting this particular group. First of all, it confirms that financial literacy plays a crucial role to explain saving decisions (the coefficient of the effect is very large – 0.4), as in the work of Lusardi (2008) concerning retirement plan. Second, in term of optimism, my study finds out the positive correlation between optimism and the total saving amount for this class. Older people report higher level of happiness and satisfaction in life than the youngster counterparts (Chowdhury et al., 2014), thereby improving their optimism. In these ages, optimism is usually associated with health and life expectation (the length of life). Hence, it is likely that the more optimism a person is, the more he/she concerns about their future well-being and the more money he/she would put aside to prepare for it. In addition, older adults suffer less negative arousal in case of money loss (Samanez-Larkin et al., 2007 cited in Chowdhury et al., 2014). This characteristic is related to their emotion regulation strategy (maintain positivity and reinterpret situations in a different way). Cognitive appraisal in emotion dealing is expected to have a positive effect on saving amount. This study, however, finds an opposite effect in both classes (but only Class 2 has significant effect). The coefficient effect of Class 2 is found to be a less negative than that of Class 1, which can be explained by higher positivity of the older and well-establish segmentation. In this sense, a good way to boost savings in this group might be to give them a better reason to live and better prospect future scenario.

Passive attitude towards money management is associated with low saving in Class 2 but it shows no significant effect in Class 1. OLS regressions provide evidence that Passive attitude explains total saving amount better than financial literacy because financial literacy's effect turns insignificant whenever Passive Attitude variable is added (chapter 5.1). However, the magnitude of financial literacy found in Class 2 (0.4) is much higher than that of Passive Attitude (-0.1), while they are about the same for Class 1. Finite mixture model helps filter these 2 groups out so we can implement financial literacy education program to suitable targets. Older and well-established people benefit greatly from their knowledge concerning finance and financial management; while attitude can still play a minor role in shaping their saving decisions. Whereas, it is inconclusive to state whether Financial literacy and Passive attitude affect saving amount in Class 1 or not. Yet, for this group, it seems that financial literacy can benefit them as much as a careless attitude towards money management can damage their accounts. Therefore, a duo intervention focusing on both knowledge and attitude can help increase their saving amounts. Besides, as I stated before that Passive attitude towards money and Optimism are partly related, the results prove that Optimism (general Optimism, involved happiness) can lead to good financial behaviors, but Optimism in financial aspect can lead to bad behaviors. Thus, it is important for future studies to separate these 2 when examining the effect of Optimism.

There remains one controversial finding regarding the effect of self-control. This study finds out that self-control either has no effect (finite mixture model) or has negative effect (OLS regression) on saving amount. Most earlier studies show opposite results regardless their varied in methodologies and data samples. Suspecting that the data might be distorted and no longer representative when I have ruled out all respondents who do not know or refuse to provide information about the actual savings, I take a further step to examine the self-control score belonging to the group I have eliminated. Their scores are as equal as that of my actual sample so generalizing this results to the whole population can still be possible. Therefore, the result can be explained due to the specific characteristics of this sample, in which self-control trait does not predict saving behaviors very well. There is also an alternative explanation such that the self-control questionnaire focusing in monetary aspects of human behaviors would be more appropriate than the general one that is employed in this study (see appendix for the questionnaire).

Compared to the results acquired from OLS regressions, the finite mixture model obviously gives us a clearer look on the possible latent groups/segmentations within this sample based on a set of socio-demographic characteristics, and how psychological factors affects saving on each group. This study contributes to the current literature with respect to the heterogeneity of psychological impact on saving behaviors. Several implications can be drawn to assist policymakers in their attempt to improve saving behaviors among households and increase total social savings. First, since we can identify certain groups with similar behaviors, it is easier to customize the program and implement in different groups such as the ones with high ability to save but need to put more effort for saving decisions, or the one with low ability to save. Based on the results, financial literacy education might be only effective for the older and well-establish people to encourage them to prepare for their retirement plan. Financial knowledge education programs are becoming obsolete and no longer bring effective outcomes. Focusing too much on such programs is an easy intervention but it might not be effective for everyone. For the youngster and less wealthy, policies to raise their awareness regarding money management attitudes would be a better choice. In addition, policymaker may consider excluding the segment with high ability to save and possess good financial management traits out of the top priority to save cost and enhance efficiency. Second, the heterogeneity problems in data set do not only existing in household finance but also in several other fields (e.g. marketing, business) that involves human behaviors. Therefore, the new methodology – finite mixture model – can be applied widely to find the latent classes and classify data in these areas as well. My results contribute to prove the robustness of finite mixture model.

6.2. Limitation and future research

Some limitations should be noted. First and foremost, this dataset is an existing panel household dataset, hence, some questions were not customized to elaborate my interest. For example, the wording of my dependent variable can be confusing. I am interested in the amount of saving in absolute number that each household currently possesses, but respondents may think of other kinds of accounts or assets. Moreover, since data involving personal information like saving amount is sensitive, there remains much noise in the dataset that truly desires may not be reflected in the answers. In term of psychological characteristics measurement, the survey is also based on self-reported data; it contains subjective questions in order to derive respondents' personality aspects. Confronting to abstract questions (not related to actual behaviors in real life), people can misunderstand the questions or different people understand them in different ways. It, thereby, causes the comparation of these data unreliable. This drawback can be overcome by using customized survey with careful instruction and explanation to guarantee that respondents 'answers are corresponding to their behaviors.

Second, the Cronbach's alpha when assessing active and passive attitude toward money management by the 7-item scale and 4-item scale is quite low. It is suggested that the alpha can underestimate the actual reliability of the scale in some cases (Gerhard et al., 2018) so I accept this result and still include them in my regression. However, there remain probabilities that it can lead to biased results.

Third, my interest is to examine the effect of emotion coping style on saving decisions and saving behaviors. However, saving, especially the accumulated wealth (represented by the total saving amount), depends on a chain of several decisions made in several points of time. Whereas, the questionnaire used in this study does not consider how emotion regulatory strategy changes over time. New method to measure this construct in saving behaviors can be addressed in future researches.

Forth, the sample size for this study is small. Especially when using finite mixture model, it is necessary to have a sample size large enough so that the class size can still be meaningful to interpret. In this case, Class 1 only accounts for 21.7% of the sample (equivalent to about 200 respondents). It is doubtful to claim the results regarding the influence of psychological factors in this class can be generalize and create an inference for similar groups. A larger sample size will benefit for future research using finite mixture model to identify the latent classes.

Fifth, using the absolute amount of saving to evaluate saving behaviors might not be comprehensive enough since there are many other sources of savings which is less liquid such as real estate or insurance. Taking into account these financial instruments along with total saving amount in future research could bring more insights and create complete picture when it comes to saving decisions.

6.3. Conclusion

In conclusion, the hypothesis by Katona (1975) suggests that the ability to save matters more for the young, poor and striving group in explaining their saving behaviors, whilst the willingness to save can be a good predictor for such behaviors in the older, rich, and well-establish group. The results of my study are in line with this hypothesis, where psychological variables show no significant impact on the former group while having significant impact on the latter. Using finite mixture model, I am able to identify these 2 different groups based on socio-demographic characteristics within the dataset and prove that psychological factors affect their saving behaviors varyingly. Additionally, the impact of self-control turns out to be insignificant for both groups whereas financial literacy only influences saving decisions in the older and richer group. This is the first step on the road to understand the latent heterogeneity in psychological factors' effects on saving behaviors.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

Ameriks, J., Caplin, A., Leahy, J., & Tyler, T. (2004). Measuring Self-Control, (February), 21–24. Retrieved from http://www.nber.org/papers/w10514

Atkinson, A., McKay, S., Collard, S., & Kempson, E. (2007). Levels of financial capability in the UK: Results of a baseline survey. *Public Money & Management*, *27*(1), 29–36. https://doi.org/10.1111/j.1467-9302.2007.00552.x

Bhalla, S. S. (1980). The Measurement of Permanent Income and Its Application to Savings Behavior Author (s): Surjit S . Bhalla Source : Journal of Political Economy , Vol . 88 , No . 4 (Aug ., 1980), pp . 722-744 Published by : The University of Chicago Press Stable URL :, *88*(4), 722–744.

Brown, S., & Taylor, K. (2014). Household finances and the “Big Five” personality traits. *Journal of Economic Psychology*, *45*(6191), 197–212. https://doi.org/10.1016/j.joep.2014.10.006

Calcagno, R., & Monticone, C. (2015). Financial literacy and the demand for financial advice. *Journal of Banking and Finance*, *50*, 363–380. https://doi.org/10.1016/j.jbankfin.2014.03.013

Chowdhury, R., Sharot, T., Wolfe, T., Düzel, E., & Dolan, R. J. (2014). Optimistic update bias increases in older age. *Psychological Medicine*, *44*(9), 2003–2012. https://doi.org/10.1017/S0033291713002602

Cobb-Clark, D. A., Kassenboehmer, S. C., & Sinning, M. G. (2016). Locus of control and savings. *Journal of Banking and Finance*, *73*, 113–130. https://doi.org/10.1016/j.jbankfin.2016.06.013

F. Scheier, M., Carver, C., & W. Bridges, M. (1995). *Distinguishing Optimism From*

Neuroticism (and Trait Anxiety, Self-Mastery, and Self-Esteem): A Reevaluation of the Life Orientation Test. *Journal of personality and social psychology* (Vol. 67). https://doi.org/10.1037//0022-3514.67.6.1063

Fisher, P. J., & Montalto, C. P. (2010). Effect of saving motives and horizon on saving behaviors. *Journal of Economic Psychology*, *31*(1), 92–105. https://doi.org/10.1016/j.joep.2009.11.002

Gerhard, P., Gladstone, J. J., & Hoffmann, A. O. I. (2018). Psychological characteristics and household savings behavior: The importance of accounting for latent heterogeneity. *Journal of Economic Behavior and Organization*, *148*, 66–82. https://doi.org/10.1016/j.jebo.2018.02.013

Gross, J. J., & John, O. P. (2003). Individual Differences in Two Emotion Regulation Processes: Implications for Affect, Relationships, and Well-Being. *Journal of Personality and Social Psychology*, *85*(2), 348–362. https://doi.org/10.1037/0022-3514.85.2.348

Kahneman, D., & Egan, P. (2011). *Thinking, fast and slow*. New York: New York: Farrar, Straus and Giroux.

Kahneman, D., & Frederick, S. (2007). Frames and brains: elicitation and control of response tendencies. *Trends in Cognitive Sciences*, *11*(2), 45–46. https://doi.org/10.1016/j.tics.2006.11.007

Kapounek, S., Korab, P., & Deltuvaite, V. (2016). (Ir)rational Households' Saving Behavior? An Empirical Investigation. *Procedia Economics and Finance*, *39*(November 2015), 625–633. https://doi.org/10.1016/S2212-5671(16)30309-4

Katona, G. (1975). *Psychological economics. Psychological economics.* Oxford, England: Elsevier.

Laibson, D. I., Repetto, A., Tobacman, J., Hall, R. E., Gale, W. G., & Akerlof, G. A. (1998).

Self-Control and Saving for Retirement. *Brookings Papers on Economic Activity*, *1998*(1), 91. https://doi.org/10.2307/2534671

Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and Decision Making. *Annual Review of Psychology, 66*(1), 799–823. https://doi.org/10.1146/annurev-psych-010213-115043

Lim, H., Hanna, S. D., & Montalto, C. P. (2011). Consumer Optimism and Saving Behavior. *Proceedings of the Academy of Financial Services.*, (October), 1–22.

Lusardi, A. (2008). Financial Literacy: An Essential Tool For Informed Consumer Choice? *Journal of Chemical Information and Modeling*, 29. https://doi.org/10.1017/CBO9781107415324.004

Lusardi, A., & Mitchell, O. S. (2011). Financial literacy around the world: An overview. *Journal of Pension Economics and Finance*, *10*(4), 497–508. https://doi.org/10.1017/S1474747211000448

McLachlan, G., & Peel, D. (2000). Finite Mixture Models. *John Wiley & Sons.*

Ramaswamy, V., Desarbo, W. S., Reibstein, D. J., & Robinson, W. T. (1993). An Empirical Pooling Approach for Estimating Marketing Mix Elasticities with PIMS Data. *Marketing Science*, *12*(1), 103. https://doi.org/10.1287/mksc.12.1.103

Risk and Rationality: Uncovering Heterogeneity in Probability Distortion. (2010). *Econometrica*, *78*(4), 1375–1412. https://doi.org/10.3982/ECTA7139

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

Sharpe, J. P., Martin, N. R., & Roth, K. A. (2011). Optimism and the Big Five factors of personality: Beyond Neuroticism and Extraversion. *Personality and Individual Differences*, *51*(8), 946–951. https://doi.org/10.1016/j.paid.2011.07.033

Shefrin, H. M., & Thaler, R. H. (1988). The Behavioral Life Cycle Hypothesis. *Economic*

Inquiry, *26*(4), 609–643. https://doi.org/10.1111/j.1465-7295.1988.tb01520.x

Stata Press Publication. (2017). *Stata finite mixture models reference manual*. Retrieved from http://www.stata.com/manuals/fmm.pdf

Strömbäck, C., Lind, T., Skagerlund, K., Västfjäll, D., & Tinghög, G. (2017). Does self-control predict financial behavior and financial well-being? *Journal of Behavioral and Experimental Finance*, *14*, 30–38. https://doi.org/10.1016/j.jbef.2017.04.002

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *J Pers*, *72*(2), 271–324. https://doi.org/http://dx.doi.org/10.1111/j.0022-3506.2004.00263.x.

van Overveld, M., Smidts, A., Peffer, G., & Atkinson, A. (2011). How financially capable are the Dutch? A first exploration on financial capability and the role of emotion regulation in a representative sample of Dutch households.

Virlics, A. (2013). Emotions in Economic Decision Making: A Multidisciplinary Approach. *Procedia - Social and Behavioral Sciences*, *92*(Lumen), 1011–1015. https://doi.org/10.1016/j.sbspro.2013.08.792

Appendix

Financial Literacy Questionnaire

Question 1: Suppose you have 100 euros on a savings account and the interest is 2% per year. How much do you think you will have on the savings account after five years, assuming that you leave all your money on this savings account: more than 102 euros, exactly 102 euros, less than 102 euros?

1. more than 102 euros
2. exactly 102 euros
3. less than 102 euros
4. I don't know
5. I would rather not say

Question 2: Suppose that the interest on your savings account is 1% per year and that inflation amounts to 2% per year. After 1 year, would you be able to buy more, exactly the same, or less than you could today with the money on that account?

1. more than today
2. exactly the same as today
3. less than today
4. I don't know
5. I would rather not say

Question 3: A share in a company usually offers a more certain return than an investment fund that only invests in shares.

1. true
2. not true
3. I don't know
4. I would rather not say

Table 7: Psychological variables and their item loadings

	Item	**Mean**	**SD**	**Item Loading**	**Alpha**
Attitude t/w money	*(Scale 1 – 6)*				
Active					0.44
	I perceive it as a personal success if I manage to obtain the best deal	4.18	1.33	0.34	
	I like to keep myself up-to-date on the economy in the Netherlands	3.99	1.35	0.30	
	I like to keep myself up-to-date on the economy in the Netherlands	5.13	0.97	0.40	
	It is important for me to know exactly how much money I have in my purse or wallet each day	3.21	1.57	0.48	
	It is wise to discuss your choice for financial products (e.g. a mortgage, loan, savings account) with family, friends and acquaintances	3.39	1.64	0.05	
	If I need to take out a loan to cover ongoing expenses, then I have failed	4.26	1.69	0.20	
	I find it important to take regular stock of the amount of money in my bank account	4.8	1.19	0.57	
Passive					0.33
	I do not believe that ordinary people need to know anything about the level of inflation in the Netherlands	2.30	1.23	0.32	
	It doesn't matter to be in the red at the end of the month	2.01	1.32	0.26	
	Shopping around for the cheapest item only saves you very small amounts	3.22	1.42	0.25	
	The future will take care of itself	2.98	1.41	0.38	
Self-control	*(Scale 1 – 5)*				0.78
	I am good at resisting temptation	3.55	1.01	0.44	
	I refuse things that are bad for me	2.99	1.17	0.31	
	People would say that I have iron self-discipline	2.75	1.10	0.27	
	I am able to work effectively toward long-term goals	3.30	1.03	0.13	
	I have a hard time breaking bad habits (reversed)	3.12	1.15	0.53	

	I am lazy (reversed)	4.06	1.04	0.54	
	I say inappropriate things (reversed)	4.17	0.96	0.46	
	I do certain things that are bad for me, if they are fun (reversed)	3.20	1.13	0.62	
	I wish I had more self-discipline (reversed)	3.34	1.19	0.63	
	Pleasure and fun sometimes keep me from getting work done (reversed)	3.52	1.13	0.52	
	I have trouble concentrating (reversed)	3.64	1.1	0.43	
	Sometimes I can't stop myself from doing something, even if I know it is wrong (reversed)	3.47	1.08	0.67	
	I often act without thinking through all the alternatives (reversed)	3.91	0.94	0.51	
Optimism	(Scale 1 – 5)				0.72
	In uncertain times, I usually expect the best	3.31	0.79	0.35	
	I'm always optimistic about my future	3.56	0.79	0.50	
	Overall, I expect more good things to happen to me than bad	3.66	0.74	0.59	
	If something can go wrong for me, it will (reversed)	3.41	0.87	0.52	
	I hardly ever expect things to go my way (reversed)	3.41	0.88	0.59	
	I rarely count on good things happening to me (reversed)	3.52	0.88	0.69	
Self-emotion regulation	*(Scale 1 – 7)*				
Cognitive Reappraisal					0.83
	When I want to feel more positive emotions (such as happiness or pleasure), then I change whatever I am thinking about at that moment	4.47	1.35	0.67	
	When I want to experience less negative emotions, I change whatever I am thinking about at that moment	4.43	1.38	0.68	
	When I am in a stressful situation, I make myself think about the situation in a way that helps me stay calm	4.9	1.32	0.38	
	When I want to feel more positive emotions, then I change the way I am thinking about the situation at that moment	4.33	1.29	0.78	

	I control my emotions by changing the way I think about the situation in which I find myself	4.33	1.30	0.70	
	When I want to feel less negative emotions, then I change the way I am thinking about the situation at that moment	4.32	1.31	0.75	
Expressive Suppression					0.77
	I keep my emotions to myself	4.12	1.59	0.65	
	When I experience positive emotions, I make sure not to express them	2.91	1.48	0.56	
	I control my emotions by not expressing them	3.65	1.50	0.76	
	When I experience negative emotions, I make sure not to express them	3.93	1.49	0.64	

Results from STATA

Table 8: Correlation between independent variables

	Financial literacy	Optimism	Self-control	Cognitive reappraisal	Expressive suppression	Active attitude	Passive attitude
Financial Literacy	1						
Optimism	0.176***	1					
Self-control	0.00452	0.162***	1				
Cognitive reappraisal	0.0251	0.136***	0.0782*	1			
Expressive suppression	-0.0290	-0.133***	0.00878	0.139***	1		
Active attitude	0.0782*	0.0211	0.109***	0.125***	-0.0314	1	
Passive attitude	-0.0717*	-0.0209	-0.147***	0.0541	0.140***	-0.258***	1

Table 9: OLS regressions including interactions between psychological variables and socio-demographic variables

	(1) log saving amount	
Female	0.189	(0.299)
Head of the household	0.162	(0.454)
25 - 34 years	-0.587	(0.861)
35 - 44 years	0.629	(0.824)
45 - 54 years	1.665	(0.554)
55 - 64 years	1.996	(0.442)
65 years and older	2.535	(0.313)
Number of household members	0.127	(0.744)
Number of living-at-home children	-0.233	(0.559)
Log brutto income	0.467**	(0.002)
Rental dwelling	-1.706	(0.253)
Yes, living with partner	0.226	(0.568)
University (WO/HBO)	-0.189	(0.894)
Fulltime worker	0.412*	(0.037)
Individual Financial Literacy	0.199*	(0.048)
Optimism	0.0794	(0.312)
Self-control	-0.0449	(0.203)
Cognitive reappraisal	-0.0173	(0.156)
Expressive suppression	-0.00361	(0.815)
Active money management	0.0170	(0.255)
Passive money management	-0.0238	(0.807)
25 - 34 years # Optimism	0.0564	(0.579)
35 - 44 years # Optimism	-0.115	(0.247)
45 - 54 years # Optimism	-0.0670	(0.484)
55 - 64 years # Optimism	0.0155	(0.862)
65 years and older # Optimism	-0.0566	(0.520)
25 - 34 years # Self-control	-0.00260	(0.959)
35 - 44 years # Self-control	0.0287	(0.523)
45 - 54 years # Self-control	0.0130	(0.770)
55 - 64 years # Self-control	-0.0235	(0.561)
65 years and older # Self-control	-0.000716	(0.985)
25 - 34 years # Passive attitude	-0.0851	(0.502)
35 - 44 years # Passive attitude	0.0681	(0.565)
45 - 54 years # Passive attitude	-0.0201	(0.860)
55 - 64 years # Passive attitude	-0.0394	(0.713)
65 years and older # Passive attitude	0.0249	(0.810)
High income # Optimism	0.0185	(0.638)
High income # Self-control	0.0285	(0.102)
High income # Passive attitude	**-0.140****	**(0.001)**
Rental dwelling # Optimism	-0.00908	(0.856)
Rental dwelling # Self-control	0.0272	(0.205)
Rental dwelling # Passive attitude	0.00424	(0.932)
University # Optimism	-0.0339	(0.501)
University # Self-control	0.00516	(0.808)

University # Passive attitude	0.0950	(0.056)
Constant	4.129	(0.120)
Observations	923	
Adjusted R^2	0.182	

Dependent variable: Log of saving amount
p-value in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.0