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Developmental patterns of voluntary pensions in CEE countries: Analysis through the Bass Diffusion Model reflecting the observational learning mechanism

Abstract
Global population ageing forces governments to transfer pension risks to individuals and employers by introducing voluntary private components into national pension systems. Diffusion theories in combination with behavioural economics can help to understand the nature of developmental patterns of voluntary pensions. This paper modifies the Bass Diffusion Model by introducing hypotheses regarding the information cascade when joining a voluntary pension schemes, a variance of participants' growth and its moderation effect on the information cascade. We trace the diffusion of voluntary pensions in four CEE countries (Bulgaria, the Czech Republic, Romania, and Ukraine), and show that the modified model delivers better overall performance than previous models both in terms of model fit and understanding this process. In addition, we demonstrate that the modified model allows us to correctly describe the wave-like nature of the evolution of voluntary pension provision caused by pension transformations.
Keywords: voluntary pensions, Bass Diffusion Model, observational learning, information cascade, moderation effect, CEE countries.
JEL classification: C52; G23; P36.

1 Introduction

The global demographic trend–population aging–affects the financial health of national pension systems and increases the burden on national economies. But this is probably the greatest challenge for the aging countries of Central and Eastern Europe (CEE), in which the negative impact of the demographic trend is intensified by the non-completed transformational processes, both in institutional and in mental terms. In the pre-reform period, a generous state pension system operated in the CEE countries, called pay-as-you-go (PAYG), in which the current pension welfare of the elderly is financed by contribution from the current working population. However, in an aging society, PAYG systems become burdensome for the state, while not providing decent pensions to citizens. Therefore, the World Bank has recommended the introduction of multi-pillar pension systems that include voluntary professional and personal funded components. However, the evolution of such systems occurs in different ways.

In this study, using diffusion models, we will explore the evolution of voluntary pension provision in four CEE countries, namely: in Bulgaria, the Czech Republic, Romania, and Ukraine. We chose these countries to ensure, on the one hand, comparability of pension models, and on the other, certain diversity in income, innovative development and demographic aging. The old-age dependency ratio, calculated as the ratio of the number of elderly people (aged 65 and over) to the number of people

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of working age (aged 15–64) according to the World Bank (2019) is the highest in Bulgaria (32.02%) and the Czech Republic (29.00%), followed by Romania (26.69) and Ukraine (24.19%). However, in terms of the sustainability of pension systems, Bulgaria, the Czech Republic and Romania are included in the cluster of lower-spending transition countries; in these countries, life expectancy at retirement is 14–19 years, and pension spending averaging around 35% of GDP per capita (Schwarz and Arias, 2014). At the same time, Ukraine is included in the cluster of high-spending transformation countries (life expectancy at retirement is 14–17 years old, and pension spending is at least 60% of GDP per capita). As for the financial capabilities of the population in terms of private pension savings, according to the World Bank Income Group Classification, selected CEE countries are in different income groups, but the Global Innovation Index does not differ significantly, namely: the Czech Republic (Score is 48.75) is high income economies, Bulgaria (42.65) and Romania (37.59) are upper-middle income economies, and Ukraine (38.52) is lower-middle income economy (Cornell University et al., 2018).

The question arises: do diffusion processes of voluntary pensions in these countries differ? We assume that diffusion theories in combination with behavioral economics help to understand the nature of the specific patterns of development of voluntary pension provision. The purpose of this study is to develop the Bass Diffusion Model (BDM) for voluntary private pension provision that reflects the observational learning mechanism. We assume that potential participants in voluntary pension funds make decisions based on empirical observations of the behavior of previous participants. We introduce three hypotheses: (1) there is an information cascade when joining voluntary pension scheme, (2) the variance of the flow of information on participants' growth is the inverse measure of the perception of pension innovations, and (3) the variance is a moderator of the relationship between the previous participants' growth and imitators' growth. Empirical results show that the Modified Bass Diffusion Model (MBDM) delivers better overall performance than previous models both in terms of model fit and understanding this process. This study contributes both to diffusion theory and to pension research, empirically analyzing the developmental patterns of voluntary private pension provision for the entire period of its existence in four CEE countries using the original and modified Bass Diffusion Models.

The remainder of the paper is structured as follows. Section 2 presents the institutional background of the pension provision in selected countries and a literature review. Section 3 shows the special cases of the BDM for voluntary private pension provision and presents modified hypotheses and a model. Section 4 discusses the results of modeling and hypotheses testing, and then carries out a parametric analysis of diffusion patterns of voluntary pensions in selected CEE countries. Finally, the conclusion and future research perspectives are given in section 5.

2 Institutional background and literature review

2.1 Background for the voluntary private pension systems in selected CEE countries

At present, pension systems in the post-communist countries of CEE are multi-pillar and are based on diversifying the principles of administration and financing of the pensions–publicly and privately managed, redistributive and funded, defined benefit (DB) and defined contribution (DC), personal and occupational with mandatory and voluntary participation. Pillar I in all countries studied (Bulgaria, the Czech Republic, Romania, and Ukraine) is a mandatory public pension insurance system (redistributive DB pension scheme); in fact, it is a slightly reformed PAYG system. Pillar II in Bulgaria and Romania is a privately managed mandatory funded DC pension system based on individual retirement savings accounts. In Ukraine, a similar Pillar II is legally established, but not yet introduced. In the Czech Republic, formally, Pillar II is absent, but there is a third voluntary pillar with state contributions and tax incentives, i.e., with signs of Pillar II according to the World Bank classification (Holzmann and Hinz, 2005). In all countries considered, Pillar III is a voluntary private pension system, which is represented by fully-funded DC schemes with individual accounts, but institutional framework differs–

professional and/or personal voluntary private plans. Furthermore, in all countries, governments provide tax incentives to encourage participation in voluntary pension provision.

In Bulgaria, Pillar III is voluntary personal schemes. Voluntary private pension funds (VPF) were introduced in 1995. Participation in VPFs is open to all those aged 16 and over; contributions are paid by the members themselves or by their employers and are not taxable up to a certain limit. As of 31 Math 2019, personal voluntary pillar encompasses 9 VPFs, offering pensions to 630 514 members; Allianz Bulgaria (34.11%) and Doverie (22.96%) occupy the largest market shares in terms of membership (Financial Supervision Commission [FSC], 2019). In addition, on January 1, 2007, voluntary occupational Pillar IV was introduced, in which the collective bargaining agreement or the collective employment contract determines the coverage.

In the Czech Republic, voluntary Pillar III was established as a supplementary pension insurance system in 1994. The system had generous government support (state contributions, tax deductibles, exemption of employers' contributions from social insurance premiums) and, as a result, in 2010, operating costs accounted for 1.4% of total assets, higher than in Bulgaria (1.2%), Hungary (1.0%), Slovenia (.9), Slovak Republic (.5%), Poland (.4%), but less than in Ukraine (5.9%) (OECD, 2011). In 2013, the supplementary pension system was reformed. Pension funds had to transform into "pension companies", the existing supplementary pension insurance plans were closed for new participants and renamed as "transformed funds", each managed by a pension company; new clients may enter one of the new "participation funds" managed by a pension company, and participants in transformed funds may switch to new participation funds (Vostatek, 2016). In 2019, 8 pension companies manage Pillar III funds. But, despite the reform, substantial state support has been preserved, so Pillar III can be characterized as a nudging system, and in fact it is the Pillar II according to the World Bank classification, which explains a very large number of participants in the system. The total number of participants in the Pillar III in the first quarter of 2019 reached 4 442 424 persons (of which 3 425 736 in transformed funds and 1 016 688 in participation funds) (Association of Pension Companies CR [APCCR], 2019).

In Romania, Pillar III is the voluntary occupational pension system introduced in 2006. Currently, 10 voluntary pension funds are active; the total number of participants is 469 532 persons; NN Optim (36.51%) and BCR Plus (28.73%) occupy the largest market shares in terms of membership (Financial Supervisory Authority [FSA], 2019). The Romanian third pillar allows both the employee and employer to contribute and each of them is entitled to a deduction of 200 Euros per fiscal year.

In Ukraine, Pillar III is the voluntary occupational-personal pension system introduced in 2004. It is based on three types of voluntary non-state pension funds (NPFs)–open, corporate and professional. Participants in open fund may be any individuals, regardless of location and nature of their activities, and citizenship; participants of corporate fund are individuals who have been in labor relations with employers-founders or payers of the fund; participants in professional fund are individuals linked by their professional activity (occupation) defined in the fund's charter. As of 31 March 2019, 61 NPFs are registered, and the total number of participants is 858 400 persons (National Commission for Regulation of Financial Services Markets [NCRFSM], 2019). The structure of the pension fund market in terms of membership is as follows: 54.58%, 43.19% and 2.23%, respectively, for open, professional and corporate NPFs. At the same time, the professional NPF Magistral (38.03%) (Administrator of the Pension Fund "Center of Personified Accounting" [APFCPA], 2019) and the open NPF Europe (15.59%) (All-Ukrainian Pension Fund Administrator [APFA] 2019) occupy the largest market shares. As in other countries, in Ukraine tax relief is given to participants and payers of NPFs. In particular, pension contributions paid by an employer to non-state pension coverage of its employees are related to the company's expenses in full, and are not included in the basis for calculating the single contribution to compulsory state social insurance; for an individual, the amount of his personal pension contributions is not included in the calculation of the total monthly (annual) taxable income.

Summing up, we note that the participation rate in voluntary pension Pillar III (the percentage of the population over 15 years old) is 10.4% in Bulgaria, 49.5% in the Czech Republic, 2.8% in Romania and 2.3% in Ukraine. Dependence on the degree of state support is obvious, given that "the overall value of state subsidies for Czech private pension plans is the highest in the world" (Vostatek, 2016). However, such a government policy distorts the essence of voluntary private pensions. The questions arise: Why does voluntary pension provision develop only with strong government funding? What hinders the diffusion of voluntary pension schemes?

2.2 Literature review

Voluntary pension provision is an innovative product in the pension markets of post-communist countries, therefore, the innovation diffusion theories are applicable and appropriate for describe and predict their diffusion. Three diffusion theories that differ in the underlying causal mechanism of diffusion can be distinguished in contemporary studies: (i) classic diffusion theory (contagion mechanism) (Rogers, 1962/1983; Bass, 1969), (ii) institutional diffusion theory (conformity mechanism) (e.g., Tingling and Parent, 2002), and (iii) cognitive-institutional diffusion theory (social or observational learning mechanism) (e.g., Strang and Soule, 1998). In reality, however, diffusion mechanisms often act simultaneously and complement each other throughout the entire diffusion process, which is manifested in the diffusion of pension innovations. Contagion implies the commonly observed S-shaped cumulative adoption curve (Strang and Soule, 1998) that established by analyzing the spread of the first retirement systems worldwide (Orenshtein, 2003), voluntary pensions in Ukraine and Romania (Yakymova 2013; 2018).

Conformity or social influence is determined by (i) imitation of peers, (ii) context or pressure (coercion of influential institutions), and (iii) compliance with accepted norms. Brooks (2005; 2007) identified institutional mechanisms in the cross-national diffusion of pension privatization (Pillar II), namely, the imitation of peers, the impact of demographic, political, and economic context. Brooks (2005) stresses that the likelihood of adopting pension privatization should be higher in nations where demographic pressures are high, and in nations where macroeconomic incentives are strong (e.g., where domestic capital markets are underdeveloped). At the same time, empirical evidence of the significant role of financial coercion by the Word Bank was not found (Brooks, 2007). In addition, researchers point to the impact of the pension context–the generosity of public pension systems. For instance, Marcinkiewicz (2019) found that in countries where mandatory pension benefits are expected to be lower, and in countries where a flatter pension benefit formula is adopted in the public system, voluntary pensions are better developed. However, our evidence above regarding voluntary private provision coverage in selected CEE countries does not confirm these findings. In Ukraine, demographic pressure is high, domestic capital markets are underdeveloped, mandatory pension payments are expected to be the least, but coverage is the least. Thus, we see that social influence, like contagion, does not provide a clear reason why people do not accept innovation, while others have already accepted it.

From an economic standpoint, the social or observational learning is the most plausible diffusion mechanism. Social learning mechanism occurs when prospective adopters obtain necessary knowledge and information from collective rationales (Bui, 2015), when the evidence is generated by the outcomes among prior adopters (Young, 2009). At the same time, the learning literature distinguishes between social learning (information is communicated directly) and observational learning (potential adopters simply observe whether or not others are adopting, and thus interpret such adoption as a signal of quality) (Gilchrist and Sands, 2016). However, with incomplete information and limited ability to process it, people make decisions using simple mental shortcuts–heuristics "which sometimes yield reasonable judgments and sometimes lead to severe and systematic errors" (Tversky and Kahneman, 1974). When analyzing the behavior of individuals in the field of voluntary pensions, heuristics and cognitive biases that arise at the stage of (i) retirement planning, (ii) joining a voluntary pension fund, and (iii) retirement savings and investing can be identified.

Accumulating sufficient retirement income requires timely retirement planning. However, people postpone retirement planning due to the perceived length and complexity of the process (Ontario Securities Commission [OSC], 2018), low expectations of success (Brucker and Leppel, 2013) especially when considering the generally unpleasant thought of aging and possible mortality (Howard and Yazdipour 2014). In addition to barriers of "overload" and emotional burdens, barriers to retirement savings are "bounded self-control" (Mitchell and Stephen, 2003) and procrastination caused by hyperbolic discounting (Knoll, 2010). The reason is that the primary benefits of retirement planning accrue in the future, but people discount long-term outcomes compared to short-term outcomes (OSC, 2018); that is, retirement savings involves a trade-off between more money in one's paycheck now and a more comfortable life in the future (Knoll 2010). It should be noted that previous studies have also revealed other factors affecting retirement planning: current income and wealth, the expected primary source of retirement income, gender, age. Brucker and Leppel (2013) found that women, people with low net wealth, and those who expect to rely primarily on social security as their retirement income, are least prone to retirement planning. Hedesstrom et al. (2007) revealed that participation in choosing a fund increases with the amount invested, but decreases with age.

With regard to the stage of joining the pension fund, empirical studies (Benartzi and Thaler, 2007; DiCenzo, 2007; Hedesstrom et al., 2007; Rudolph, 2016; Knoll, 2010; Mitchell and Utkus, 2003; OSC, 2018; Romanos, 2013; VanDerhei, 2010) indicate a possible default bias and framing effect– people, as a rule, are tied to the default parameters and do not make any changes. Therefore, occupational voluntary pension funds use automatic registration as a nudge mechanism, which has two effects: participants join earlier and eventually more participants join (Benartzi and Thaler, 2007). However, in open voluntary pension funds this option cannot be applied. At the same time, peers may influence the decisions of individuals to save for retirement (DiCenzo, 2007). The effect of peers is explained by the fact that individuals in essence want to conform to the behavior of others. Conformity can be achieved if early individuals explain the advantages of alternatives to later ones (Rogers, 1962/1983). Bikhchandani et al. (1992) offer "an alternative explanation for the influence of peers: that individuals, especially those with little information or experience, obtain information from the decisions of others". Sequential observation of the decisions of previous people can start the information cascade both up and down. Bikhchandani et al. (1992) show that cascades can explain not only conformity, but also the rapid spread of new behavior. In this study, we will try to verify the validity of these findings for behavior in the field of voluntary pensions, using the historical data of selected CEE countries.

Having joined the pension fund, individuals continue to use convenient rules of thumb, which can lead to negative results that will be communicated to their "peers". Empirical studies show (e.g., Mitchell and Utkus, 2003) that the default bias and framing affect both the saving choices and the investment decisions of fund participants. Participants usually agree with the default options and make easiest, rather than the best, decision. The researchers explain this behavior by other anomalies, for example, saving heuristics (e.g., "saving the max"), naive diversification strategies (e.g., "1/n rule"), loss aversion, mental accounting, anchoring, inertia and procrastination (Benartzi and Thaler, 2007; Hedesstrom et al., 2007; Mitchell and Utkus, 2003; Romanos, 2013).

Thus, people apply simple rules of thumb at all stages of their "retirement trajectory"; and one of the most important reasons for their use is often called the financial illiteracy of the population. But, for instance, the findings by Romanos (2013) suggest that financial literacy cannot significantly mitigate the effects of framing. Therefore, behaviorists advise stakeholders "to accept the behavior of participants and think more about changing their own, using the automatic functions of the plan" (DiCenzo, 2007).

Behavioral heuristics also manifest themselves in the cross-country diffusion of pension reforms. Weyland (2005; 2007) identified three heuristics that explain the nature of diffusion of the so-called Chilean pension model in Latin America countries: (i) the availability heuristic explains strong neighborhood effects in diffusion innovation (geographical clustering); (ii) the representativeness heuristic affects the assessment of innovation, giving rise to the S-shaped temporal diffusion pattern; and (iii) the heuristic of anchoring explains the spread of commonality amid diversity (Weyland, 2005). At the same time, however, cultural, political or historical similarity can overcome the effects of geographic proximity (Weyland, 2007). Our previous study (Yakymova, 2018) found that in some cases classical diffusion models are unable to describe the diffusion of voluntary pension provision. The theory of observational learning, and especially informational cascades, can help increase the explanatory abilities of diffusion models.

In this study, we use BDM as the base model because, firstly, it allows us to describe the diffusion of private pension, which is essentially a new durable product in CEE countries. Secondly, the main causal mechanism of diffusion of voluntary pensions is the imitation (or contagion) mechanism that underlies BDM. Thirdly, the contagion mechanism explains the S-shaped cumulative curve that is observed in diffusion of voluntary pensions, as we will see below. Fourth, the estimated BDM parameters help explain the nature of the diffuse process to policymakers. Finally, the BDM specification makes it possible to incorporate predictors that reflect behavioral heuristics.

3 Methodology

3.1 Special cases of the Bass Diffusion Model for the diffusion of voluntary pension provision

The Bass Diffusion Model for voluntary private pension provision (Yakymova, 2018) is based on the following assumptions: (i) pension innovation (participation in Pillar III or in a voluntary pension fund) is available in the pension market with *m* persons, in other words, *m* is the size of the pension market; (ii) the diffusion process is binary, that is, individual either joins Pillar III or does not join at time *t*; (iii) eventually, all m potential participants will join Pillar III; (iv) no repeat joining or replacement; (v) the marketing strategies supporting the voluntary pension provision are not explicitly included. Moreover, the increase in the number of participants in Pillar III is due to two effects: (i) the effect of advertising (mass-media); (ii) the effect of interpersonal communication (word-of-mouth, WoM). In this sense, the pension society with *m* persons can be divided into two categories of individuals: (i) innovators themselves learn and “try” voluntary pension provision; (ii) imitators learn from the first and join Pillar III. According to (Bass, 1969), the key difference between an innovator and an imitator is the influence of the participants, namely: innovators are not influenced in the timing of their joining by the number of people who have already joined Pillar III, while imitators are influenced by the number of actual participants. Then, the original BDM in the form of a decomposition of the number of participants joining Pillar III at time t to innovators and imitators can be represented as follows:

$$n(t) = In(t) + Im(t) = p[m - N(t)] + q\frac{N(t)}{m}\,[m - N(t)], \tag{1}$$

where $n(t)$ is noncumulative number of participants (participants’ growth) at time t, $N(t)$ is cumulative number of participants at time t, m is the size of the pension market, p is the coefficient of innovation (coefficient of external influence), q is the coefficient of imitation (coefficient of internal influence), $In(t)$ and $Im(t)$ are noncumulative number of innovators and imitators at time t.

The nature of diffusion depends on the values of the parameters p and q, as well as the relationships between them. In estimating the parameters m, p, and q from discrete time series data is used the discrete analogue of the BDM (1)

$$n_t = \beta_0 + \beta_1 N_{t-1} + \beta_2 N_{t-1}^2 + \varepsilon_t, \tag{2}$$

The OLS method is used to estimating the unknown parameters β_0, β_1, and β_2, by transforming a nonlinear form into a linear one; and the BDM parameters are calculated by the following formulas:

$$\hat{m} = \frac{-\hat{\beta}_1 \pm \sqrt{\hat{\beta}_1^2 - 4\hat{\beta}_0\hat{\beta}_2}}{2\hat{\beta}_2},\ \hat{p} = \frac{\hat{\beta}_0}{\hat{m}},\ \hat{q} = -\hat{m}\hat{\beta}_2. \tag{3}$$

It should be noted here that the OLS procedure has three shortcomings (Mahajan et al., 1990): (i) due to the likely multicollinearity between the regressors, OLS-estimates of the coefficients of model (2) may be unstable, and their standard errors may be wildly inflated; (ii) the procedure does not directly provide standard errors for the estimated parameters p, q, and m, i.e., their statistical significance cannot be estimated; (iii) there is a time-interval bias because discrete time series data are used to evaluate a continuous model. Other methods can be used, but we must consider the purpose of the BDM. As emphasized by Mahajan et al. (1990), the estimation of BDM parameters is primarily of historical interest; by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes. The estimates can be used to test models and compare new products. Considered in such a context, the methods often yield estimates that do not differ greatly.

In the original BDM, the estimates p and q are positive (for simplicity, we omit the symbols of the estimates ^ in notation); otherwise it was assumed that the model does not make sense. However, more recent studies indicate that non-positive parameters are plausible and explain the nature of this diffusion. Rafi and Akthar (2011) note that there are two special cases of the BDM: the first case occurs when $q = 0$, when the model reduces to the Exponential distribution; and the second case reduces to the logistic distribution, when $p = 0$. In other words, if ($p > 0$, $q = 0$), this is a pure innovation scenario; if ($p = 0$, $q > 0$), this is a pure imitation scenario.

In addition, we received negative values of the imitation coefficient q, when modeling the diffusion of voluntary pension provision (Yakymova, 2018). We found that if ($p > 0$, $q < 0$), this is a negative diffusion, and the diffusion curve follows a modified logistic curve concave down. We interpreted the negative diffusion of voluntary pensions by analogy with diffusion in physical systems. In general, a negative diffusion coefficient means a process of "concentration" as opposed to diffusion.

If ($p < 0$, $q > 0$), in general, this means that there is a barrier to initial adoption and triggering diffusion. However, if $q > |p|$, the barriers to adoption can be overcome by seeding (Orbach, 2016). The nature of the diffusion of voluntary pensions for a negative innovation coefficient will be empirically established in the next section.

The fraction (q/p) determines the shape of the diffusion curve. If $(q/p) > 1$, the noncumulative number of participants $n(t)$ peaks at time $T^* > 0$, which is the point of inflection of the S-shaped curve of cumulative number of participants $N(t)$. If $(q/p) \leq 1$, $n(t)$ decreases monotonically with time t and $T^* < 0$ (negative peak). The sum $(p + q)$ determines the rate of adoption (or scale of diffusion). According to Rogers (1962/1983), "rate of adoption is a numerical indicant of the steepness of the adoption curve for an innovation". The larger the sum $(p + q)$, the steeper the diffusion curve and the larger the diffusion scale.

Thus, the following conclusions can be formulated regarding the adoption of pension innovation by the society. The larger the sum ($p + q$), the greater the diffusion rate of voluntary pension provision in society. If $q > p$, the pension innovation is successful; the influence of WoM is greater than the external influences (media). If $q \leq p$, the pension innovation is unsuccessful; the influence of WoM is less than the external influences.

Summing up, it is necessary to distinguish four special cases that can be encountered in the practical use of the BDM: (i) the negative square root error when estimating m by the formula (3); (ii) the negative peak ($q \leq p$); (iii) the negative coefficient of imitation ($q < 0$); and (iv) the negative coefficient of innovation ($p < 0$). When studying the diffusion of voluntary pensions in Romania and Ukraine (Yakymova, 2018), we found the first three cases, and this led us to the need to revise the BDM hypotheses.

3.2 A modification of Bass's hypothesis for predicting diffusion of voluntary pension provision

When analyzing the spread of voluntary pensions in CEE countries, an association with two manifestations of imitative behavior–the informational cascade and herd behavior–intuitively arises. These phenomena are considered pathological, because erroneous outcomes can occur, despite the individual rationality (Celen and Kariv, 2004). However, in the case of pension innovations that are long-term in nature, they actually become the norm of collective behavior. "An informational cascade occurs when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information" (Bikhchandani et al., 1992).

The term "herd behavior" is often used as a synonym, but Smith and Sorensen (2000), and Celen and Kariv (2004) indicate to the following difference: an informational cascade occurs "when an infinite sequence of individuals ignore their private information when making a decision, whereas herd behavior occurs when an infinite sequence of individuals make an identical decision, not necessarily ignoring their private information". Thus, an informational cascade implies a herd but a herd is not necessarily the result of an informational cascade (Celen and Kariv, 2004).

The collective behavior of individuals in the field of voluntary pensions probably has the nature of an informational cascade, as the individual (imitator) considers it optimal to follow the behavior of his predecessors, ignoring his private signal–the expediency of individual pension savings. We assume that the acts of joining and leaving voluntary pension funds are observable. Thus, innovators, as before, themselves learn and "try" voluntary pension provision, and imitators are exposed to an informational cascade, i.e., follow the behavior of the preceding individual. In other words, the diffusion of voluntary pension provision is an autoregressive process. In this study, we assume a first order autoregressive process–the AR (1) process. It is important to note that this approach to identifying the information cascade was used by Walden and Browne (2008) to explain the formation of the Internet bubble. This line of argument suggests that: H_1: The imitators' growth at time t is a function of the participants' growth at time t-1: $Im_t = f(n_{t-1})$.

Furthermore, imitators observe/study the flow of information on the growth of participants in voluntary pension provision; and the more controversial this information is, the less probability it is that they will make a positive decision on joining a voluntary pension fund. In other words, the variance of the flow of information on participants' growth is the inverse measure of the perception of pension innovations. This line of reasoning suggests that: H_2: The imitators' growth at time t is a function of the variance of the participants' growth in the previous period: $Im_t = f(Variance_{t-1})$. Note that in this study, we use the variance (σ^2) as a measure of variation. Moreover, we assume that a potential participant can monitor either the entire period of the existence of Pillar III (or voluntary pension fund), or only a certain last period, for example, a year. In the first case, we use the total variance of the time series up to the moment t-1, and in the second case, it is the 12-month rolling variance.

Finally, it is obvious that the influence of the previous participants' growth on the current imitators' growth varies depending on the variance, i.e., there is a so-called interaction effect, where variance is a moderating factor. Therefore, the third hypothesis is H_3: Variance is a moderator of the relationship between the participants' growth at time t-1 and the imitators' growth at time t: $Im_t = f(Interaction_{t-1})$. In what follows, we use the terms "interaction" and "moderation" synonymously. In our case, there is an interaction between the participants' growth in the previous period and variance, or variance moderates the relationship between the previous participants' growth and imitators' growth. Thus, summing up the hypotheses, the imitators' growth at time t is given by $Im_t = f(n_{t-1}, Variance_{t-1}, Interaction_{t-1})$.

3.3 Moderation effect test

Moderation occurs when the relationship between X and Y depends on Z (Jaccard et al., 1990), that is a moderator (Z) is a "variable that affects the direction and/or strength of the relationship between an independent or predictor variable and a dependent or criterion variable" (Baron and Kenny, 1986). In this study, moderation effect is tested using hierarchical "moderated multiple regressions" (MMR) (Saunders, 1956) as follows. The regression equation used to assess the predictive effect of two independent variables (n_{t-1} and $Variance_{t-1}$) on participants' growth n_t is:

$$n_t = b_0 + b_1 n_{t-1} + b_2 \sigma_{t-1}^2 + \varepsilon_{1t}. \tag{4}$$

To incorporate interaction in regression (4), we add the explanatory variable $Interacttion_{t-1} = n_{t-1}\sigma_{t-1}^2$

$$n_t = b_0 + b_1 n_{t-1} + b_2 \sigma_{t-1}^2 + b_3 n_{t-1}\sigma_{t-1}^2 + \varepsilon_{2t}. \tag{5}$$

Note that all predictors are centered prior to regressions estimation to reduce multicollinearity among predictor variables. Further, in accordance with Carte and Russell (2003), to identify the moderation effect, we test the null hypothesis H_0: $\Delta R^2 = R_{mult}^2 - R_{add}^2 = 0$ against the alternative hypothesis H_A: $\Delta R^2 \neq 0$, where R_{add}^2 and R_{mult}^2 are coefficients of determination for additive regression (4) and multiplicative regression (5). To do this, we use F-statistic calculated by the formula

$$F_{(df_{mult} - df_{add}, N - df_{mult} - 1)} = \frac{\Delta R^2}{df_{mult} - df_{add}} \cdot \frac{N - df_{mult} - 1}{1 - R_{mult}^2}, \tag{6}$$

where df_{add} and df_{mult} are degrees of freedom for additive regression (4) and multiplicative regression (5), N is sample size.

In the general case, if the calculated F-value is greater than F-critical value, the null hypothesis is rejected and it is concluded that either $Variance_{t-1}$ moderates the $n_{t-i} \rightarrow n_t$ relationship or n_{t-i} moderates the $Variance_{t-1} \rightarrow n_t$ relationship. But we theoretically exclude the existence of the so-called reverse interaction effect (Andersson et al., 2014), in which the independent variable n_{t-i} is actually affecting the relationship between the moderator $Variance_{t-1}$ and dependent variable n_t. In conclusion, it is important to emphasize that using b_3 instead of ΔR^2 as an indicator of moderator effect size is an error (Carte and Russell, 2003).

3.4 Modified Bass Diffusion Model

According to the discrete analogue of BDM, the participants' growth at time t is equal to the sum $n_t = In_t + Im_t$, where $In_t = p(m - N_{t-1})$, $Im_t = q\dfrac{N_{t-1}}{m}(m - N_{t-1})$, and p, q, m parameters are constants. But in reality, the coefficient of imitation q is not constant, and by virtue of the accepted hypotheses, the imitators' growth at time t can be expressed as a linear regression:

$$Im_t = b_1 n_{t-1} + b_2 \sigma_{t-1}^2 + b_3 n_{t-1}\sigma_{t-1}^2 + \varepsilon_t \,. \tag{7}$$

Therefore, the number of individuals who join Pillar III at time t is defined as:

$$n_t = \beta_0 + \beta_1 N_{t-1} + \beta_2 n_{t-1} + \beta_3 \sigma_{t-1}^2 + \beta_4 n_{t-1}\sigma_{t-1}^2 + \varepsilon_t \,. \tag{8}$$

Thus, the regression equation (8) is the Modified Bass Diffusion Model (MBDM), which takes into account the effect of the informational cascade, the variance of the flow of participants and the effect of moderation. The OLS method is used to estimating the unknown parameters β_j, j = 1, 2, 3, 4, and the MBDM parameters are calculated by the following formulas:

$$\hat{m} = -\frac{\hat{\beta}_0}{\hat{\beta}_1},\; \hat{p} = -\hat{\beta}_1,\; \hat{b}_1 = \hat{\beta}_2,\; \hat{b}_2 = \hat{\beta}_3,\; \hat{b}_3 = \hat{\beta}_4,\; \hat{q}_t = \frac{\hat{Im}_t \cdot \hat{m}}{N_{t-1}(\hat{m} - N_{t-1})}. \tag{9}$$

4 Results and discussion

4.1 Data

Data on Pillar III membership have been collected from national sources. Official pension statistics provide monthly data for Bulgaria (FSC, 2019) and Romania (FSA, 2019), and quarterly data for the Czech Republic (APCCR, 2019) and Ukraine (NCRFSM, 2019). We use data for Bulgaria for the period from December 2002 to September 2018, the Czech Republic–from Q4 1994 to Q3 2018, Romania–from September 2017 to November 2018, and Ukraine–from Q1 2005 to Q3 2018. We also use data from 6 out of 9 voluntary pension funds in Bulgaria, 6 out of 10 funds in Romania, 6 out of 8 funds in the Czech Republic; other funds have a short history due to late establishment, closure or merger, so their use would violate the comparability of model results. As for Ukraine, we analyzed the membership in 61 non-NPFs from the date of their establishment, but we present the simulation results for only 6 funds (monthly statistics) (APFCPA, 2019; APFA, 2019). This choice is due to a long history of funds, the availability of comparable information, the diffusion of participants, etc. For example, the corporate non-state pension fund Poshtovyk was founded by the Ukrainian State Enterprise of Posts Ukrposhta in 2008, and by 2011 the number of participants reached 20, but in 2017 the fund was reduced to 13 people, and in April 2019 there were 3 people remained (APFCPA, 2019). It is obvious that modeling such a process is meaningless, and similar funds are subject to consolidation (merger) or rethinking of their strategy; therefore, we did not use such data series. Next, we use diffusion models to explain these processes both at the macro level (by countries) and at the micro level (by pension funds).

4.2 Empirical results and discussion

4.2.1 Discussion of simulation and hypothesis testing results

First of all, in order to confirm the need to modify the Bass model when predicting the diffusion of voluntary pension provision, we have tested the hypothesis about the moderation effect of the variation of participants on the relationship between the previous and current participants' growth. We have tested the moderation effect of the total variance ($\sigma^2(n)$), as well as the rolling variance with a 12-month windows ($\sigma^2(12)$) for Bulgaria and Romania and with a 4-quarter windows ($\sigma^2(4)$) for the Czech Republic and Ukraine. Table 1 shows the calculated *F*-statistics values by (9) and the significance of *F*. As we can see, the null hypothesis of the absence of moderation was categorically rejected for all data, with the exception of the Bulgarian VPF CCB-Sila, the Ukrainian Pillar III, and the NPF Magistral. For these data, there is no convincing evidence of the interaction (*p*-value > .1 for the effect test), so a model without interaction should be used. As for CCB-Sila, the unsatisfactory result can be explained by a technical reason: in January 2010 there was a merger with Lukoil Garant-Bulgaria-VPF, which ceased its activity, so we used the total number of participants over the entire simulation period. For all other data, the interaction model adopted for analysis is appropriate and valid.

Table 1

Testing moderation effects of total and rolling variance (*F*-statistics)

Pillar III, voluntary pension funds	Total variance	Rolling variance	Pillar III, voluntary pension funds	Total variance	Rolling variance
Bulgaria			The Czech Republic		
Pillar III, total	1.15	12.97****	Pillar III, total	.19	9.91***
Allianz Bulgaria	1.85	19.52****	Allianz PS	.23	13.28****
CCB-Sila	1.40	.12	CS PS	5.64**	19.17****
Doverie	29.41****	25.96****	CSOB PS	32.64	43.91****
DSK-Rodina	15.94****	12.05****	KB PS	18.18****	19.98****
NN VPF	3.16*	4.11**	NN PS	4.86**	40.78****
Saglasie	158.14****	131.50****	PS CP	1.17	5.88**
Romania			Ukraine		
Pillar III, total	13.92****	.08	Pillar III, total	0.50	0.002
AZT Moderato	32.73****	.60	Europe	15.04****	19.57****
AZT Vivance	.003	11.59****	Magistral	0.99	.25
BCR Plus	1.97	42.77****	OTP Pension	3.50*	2.20
NN Activ	15.26****	.14	Pension Capital	6.06**	.0006
NN Optim	2.36*	.05	Social Standard	6.27**	11.63****
Pensia Mea	.17	15.28****	Vzaemodopomoga	9.93***	18.34****

$*p < .10$, $**p < .05$, $***p < .01$, $****p < .001$

The test results also show some significant differences between countries in the moderation effect of the variance of participants' growth for the entire period or only for the last year. Bulgaria and the Czech Republic show a significant moderation effect of the variance of the last year, despite the differences in the aggregation of data (monthly and quarterly, respectively); whereas in Romania (monthly aggregation) and in Ukraine (quarterly aggregation) such homogeneity is absent.

Table 2 shows the values of the correlation matrix (R) determinant and the variance inflation factors (VIF) for testing multicollinearity among MBDM predictors, taking into account the findings of

Table 1. VIF is computed as $VIF_j = \left(1 - R_j^2\right)^{-1}$ for each of the j–1 independent variable of the MBDM. *VIF*-values greater than 10 indicate a problematic amount of multicollinearity only for AZT Vivance and Europe; for the same funds, the values of det R tend to zero (.04 and .06, respectively). This result indicates the absence of systemic multicollinearity among the independent variables of the model (8). In addition, Kutner et al. (2005, p. 283) note "the fact that some or all predictor variables are correlated among themselves does not, in general, inhibit our ability to obtain a good fit nor does it tend to affect inferences about mean responses or predictions of new observations". Based on this, we will not try to reduce the detected multicollinearity.

Table 2

Testing multicollinearity among independent variables, autocorrelation and heteroskedasticity in the MBDM residuals

Country	Pillar III / Fund	Multicollinearity tests					Autocorrelation tests			White test for hetero-skedasticity, F-statistic
		det R	*VIF*				DW^{a}-statistic	h-statistic	$LM^{\bullet}$-statistic	
			$N_{t\text{-}1}$	$n_{t\text{-}1}$	$Var_{t\text{-}1}$	$Int_{t\text{-}1}$				
Bulgaria	Pillar III	.42	1.38	1.66	1.30	1.68	1.31	n.a.[b]	.38*	2.74*
	Allianz Bulgaria	.39	1.05	1.51	1.72	2.10	.57	-1.71*		6.25***
	Doverie	.28	1.26	2.11	1.62	2.32	1.54	n.a.	8.33***	11.78
	DSK-Rodina	.34	1.91	2.15	1.58	2.05	1.65(.23*)[c]	n.a.	13.84	1.42*
	NN VPF	.23	1.16	4.10	1.06	3.93	1.75**	n.a.	.68*	0.49*
	Saglasie	.12	1.04	7.23	1.15	7.19	1.25	n.a.	5.29**	46.90
The Czech Republic	Pillar III	.25	2.17	1.53	2.49	1.72	1.70*	n.a.	12.96	2.06*
	Allianz PS	.11	1.22	7.03	1.41	6.59	1.54**	n.a.	2.05*	3.91**
	CS PS	.44	1.26	1.93	1.19	1.84	1.66*	n.a.	.53*	.62*
	CSOB PS	.75	1.13	1.25	1.07	1.20	.97	.39*		.28*
	KB PS	.42	1.29	2.21	1.12	2.03	1.75*	n	.41*	1.24*
	NN PS	.69	1.13	1.30	1.11	1.26	.90	-.86*		6.22***
Romania	Pillar III	.13	2.86	1.84	4.12	2.91	1.99*	n.a.	8.38***	35.27
	AZT Moderato	.15	3.24	2.23	3.14	2.24	1.90*	-1.33*		2.30*
	AZT Vivance	.04	2.76	1.77	14.84	12.70	2.48	-1.50*		7.32***
	BCR Plus	.24	1.23	1.36	3.50	2.77	2.53	1.18*		4.90**
	NN Activ	.12	2.69	2.03	3.96	2.94	1.56(.74*)	3.63		6.92***
	NN Optim	.33	1.43	1.91	1.68	2.21	1.80*	n.a.	.40*	4.03**
Ukraine	Pillar III	.21	1.32	3.97	1.32	3.69	2.05*	n.a.	.15*	.57*
	Europe	.06	10.2	1.73	10.03	1.62	2.40*	-4.57		9.25
	OTP Pension	.23	1.99	2.23	1.99	2.23	2.12*	n.a.	.002*	42.80
	Pension Capital	.18	1.41	2.30	2.05	3.17	1.60**	n.a.	1.77*	.43*
	Social Standard	.17	1.15	5.69	1.03	5.43	1.37	n.a.	.41*	2.65*
	Vzaemodopomoga	.17	1.38	5.49	1.32	4.60	1.41	n.a.	13.05	1.30*

[a]The Durbin–Watson statistic value for BDM; [b]n.a. = not available (a negative square root error); [c]in parentheses is the $LM^{\bullet}$-statistic for cases where the DW-statistic falls in the inconclusive region; *significance at .05 level; **significance at .01 level; ***significance at .001 level.

The next step is to estimate (OLS) the parameters of the modified Bass diffusion models to test the hypotheses put forward and the performance of these models. In estimating the parameters, the type of variance was used, which showed convincing evidence of the interaction. In addition, we estimated the parameters of the Bass models in order to compare the explanatory and predictive capabilities of BDMs and MBDMs for all funds and countries. Table 3 and Table 4 show the results of the estimation.

Table 3

Bass Diffusion Model (BDM) and Modified Bass Diffusion Model (MBDM) OLS estimates: Bulgaria and the Czech Republic

	BDM	MBDM	BDM	MBDM	BDM	MBDM
Bulgaria						
Pillar III		Allianz Bulgaria		Doverie		
Intercept	43396.6	9837.04****	79762.5****	68.883	74669.2***	775.95
N_{t-1}	-.1339	-.0160****	-.6763****	-.0004	-.9608***	-.0052
$(N_{t-1})^2$	1.0E-07		1.4E-06****		3.1E-06**	
n_{t-1}		.5118****		.8940****		.4100****
Variance		-5.6E-05		-.0003**		.0001****
Interaction		-8E-08****		-7E-07****		-1E-07****
Adj. $R^2(n_t)$	.0696	.2476	.2249	.6448	.0519	.2356
Adj. $R^2(N_t)$	.6716	.9140	.8173	.9918	.3082	.4250
Observations	177	177	177	177	177	177
DSK-Rodina		NN VPF		Saglasie		
Intercept	390.31**	-118.65	1687.41	632.06***	-15763.1****	139.23
N_{t-1}	-.0101	.0069****	-.0797	-.0158***	.7866****	-.0027
$(N_{t-1})^2$	2E-07***		9.6E-07		-9.3E-06****	
n_{t-1}		.3050***		.2809*		1.8985****
Variance		.0002		-6.4E-05		-2.1E-05
Interaction		-6E-07*		-1.4E-07		-3E-07****
Adj. $R^2(n_t)$	.1980	.2200	.0576	.0696	.0605	.5106
Adj. $R^2(N_t)$	.9763	.9871	.9320	.9441	.9158	.9114
Observations	186	186	177	177	177	177
The Czech Republic						
Pillar III		Allianz PS		CS PS		
Intercept	231305****	341499****	-8233.7	2007.5	-70130****	9911,7
N_{t-1}	-.0995***	-.0561****	.1795	-.0036	.2942****	-.0093
$(N_{t-1})^2$	1.1E-08**		-3.4E-07		-2E-07****	
n_{t-1}		.1626*		1.1579****		.6433****
Variance		-9E-06****		-1.4E-06		4.3E-06
Interaction		1.2E-11*		-5E-10****		-4E-10****
Adj. $R^2(n_t)$	.2093	.3542	.0075	.1515	.2806	.2878
Adj. $R^2(N_t)$	.8652	.9668	.7859	.9143	.9314	.9729
Observations	96	96	71	66	70	66
CSOB PS		KB PS		NN PS		
Intercept	-95133****	7277*	-76548****	7435	34218*	8996**
N_{t-1}	.4372****	-.0106	.4644****	-.0130	-.1361	-.0238**
$(N_{t-1})^2$	-4E-07****		-6E-07****		1.3E-07	
n_{t-1}		.7819****		.6408****		.7155****
Variance		-1.3E-06		5E-06		3.3E-05**
Interaction		-2E-09****		-2E-09****		-7E-09****
Adj. $R^2(n_t)$	.2685	.6123	.3320	.2929	.1869	.6278
Adj. $R^2(N_t)$	.4829	.9844	.9676	.9773	0	.8527
Observations	70	66	70	66	70	66

Table 4

Bass Diffusion Model (BDM) and Modified Bass Diffusion Model (MBDM) OLS estimates: Romania and Ukraine

	BDM	MBDM	BDM	MBDM	BDM	MBDM
Romania						
Pillar III			AZT Moderato		AZT Vivance	
Intercept	16661.3****	7013.0****	6707.56****	5276.01****	5564.86****	355.82****
N_{t-1}	-.0913****	-.0149****	-.4138****	-.1360****	-.5234****	-.0172****
$(N_{t-1})^2$	1.4E-07****		6.4E-06****		1.2E-05****	
n_{t-1}		.3596****		.3198****		.4538****
Variance		-5.4E-06		-.0003****		-.0003
Interaction		-4.7E-09*		-1.6E-08		-2.6E-06
Adj. $R^2(n_t)$	.4836	.3040	.7250	.7441	.5899	.5548
Adj. $R^2(N_t)$	.9759	.9188	.8015	.9368	.8104	.9149
Observations	133	133	133	133	133	119
BCR Plus			NN Activ		NN Optim	
Intercept	3266.45****	333,73***	3647.64****	1364.4****	2712.04****	2204.9****
Intercept	-.0531****	-.0005	-.2213****	-.0311****	-.0337***	-.0085***
N_{t-1}	2.6E-07****		3.4E-06****		1.6E-07***	
$(N_{t-1})^2$		.4621****		.7432****		.3034***
n_{t-1}		.0019****		-.0004****		-.0001**
Variance		-2E-06****		-7.3E-08		9.2E-08**
Interaction	.2543	.5094	.7955	.5924	.0723	.1023
Adj. $R^2(n_t)$	.9793	.9973	.9020	.8234	.9931	.9777
Observations	133	119	133	133	133	133
Ukraine						
Pillar III			Europe		OTP Pension	
Intercept	20825.67	45815.3***	503.06	2169.85	.6590*	.7564**
N_{t-1}	.0478	-.0497*	.4536****	-.0184	.0293	-.0411***
$(N_{t-1})^2$	-8.7E-08		-3E-06****		-.0012	
n_{t-1}		-.1815		.7969****		-.2772**
Variance		-5.3E-07		1.9E-06		.6883**
Interaction		2.3E-11		-3E-08****		.4696*
Adj. $R^2(n_t)$	.0439	.0069	.7667	.6186	.0373	.0771
Adj. $R^2(N_t)$	.9138	.8813	.9696	.9872	.7944	.8902
Observations	56	52	52	52	116	116
Pension Capital			Social Standard		Vzaemodopomoga	
Intercept	37.24****	34.30****	75.46***	60.86**	30.39****	23.36***
N_{t-1}	-.0192	-.058****	.0043	-.0120**	.0008	-.0217***
$(N_{t-1})^2$	-7.3E-05		-3.7E-06		-2.4E-05	
n_{t-1}		.0532		.7391****		.7010****
Variance		.0023		-.0002		.0098*
Interaction		.0006*		-2E-05***		-.0007***
Adj. $R^2(n_t)$	.3930	.4358	.0852	.1936	.2104	.3781
Adj. $R^2(N_t)$	.9294	.9461	.4592	.8263	0	.5831
Observations	92	92	165	153	162	150

*$p < .10$, **$p < .05$, ***$p < .01$, ****$p < .001$

However, before analyzing the quality of fitting models and the diffuse process, it is necessary to check the fulfillment of the conditions of the Gauss-Markov theorem. Table 2 reports the results of testing the null hypotheses of the absence of residual autocorrelation and homoskedasticity of residues.

Durbin-Watson test results for 14 Bass models (2) indicate that the null hypothesis is not rejected and no significant residual autocorrelation is assumed at the .05 level of significance. Since MBDM (8) includes a lagged dependent variable, we used Durbin h-test as a test for autocorrelated residuals. In case of a negative square root error of the h-test (i.e., $Tvar(\beta_2) > 1$), we applied the F-test version of the Breush-Godfrey test that uses a modified version of the Lagrange multiplier statistics: $LM^{\bullet} = \frac{R^2}{1-R^2} \cdot \frac{T-p-k-1}{p} \approx F(p, T-p-k-1)$, where R^2 is the value calculated for regression $e_t = \beta_0 + \beta_1 N_{t-1} + \beta_2 n_{t-1} + \beta_3 \sigma_{t-1}^2 + \beta_4 n_{t-1}\sigma_{t-1}^2 + \rho_1 e_{t-1} + ...\rho_p e_{t-p} + \delta_t$, T is the original sample size, k is the number of independent variables of (8). Recall that if $p = 1$, the BG test checks first-order autoregression and is also called the Durbin M-test. The test results indicate the rejection of null hypothesis (no autocorrelation) for only 5 MBDMs. To test the null hypothesis of homoskedasticity, we used the White test. Test results indicate rejection of the null hypothesis for only 5 MBDMs. It should be noted that multicollinearity, autocorrelation, and heteroskedasticity were found only for the Ukrainian fund Europe. A typical strategy followed by econometrics with residual autocorrelation and heteroskedasticity is the use of generalized (GLS) or weighted least squares (WLS) methods, respectively. However, Safi and White (2006) proved that if the disturbance structure is autoregressive and the dependent variable is nonstochastic and linear or quadratic, the OLS performs nearly as well as GLS in terms of efficiency of the estimates. In this sense, our models allow the use of OLS estimates, but we will bear in mind that standard errors can be underestimated.

We use adjusted coefficient of multiple determination Adj. R^2 as a measure of goodness-of-fit for comparing models fitted to different data sets, with different numbers of observations and explanatory variables. For all types of models, Adj. R^2 is calculated by the formula $R_{adj}^2 = 1 - (1 - R^2) \cdot \frac{T-1}{T-k-1}$, where R^2 is the value calculated for model, T is the sample size, k is the number of independent variables. Conclusions that we can draw include the following. First, as expected, the Adj. $R^2(N_t)$ for cumulative curves are significantly higher than for noncumulative curves Adj. $R^2(n_t)$ due to high volatility of time series of the participants' growth.

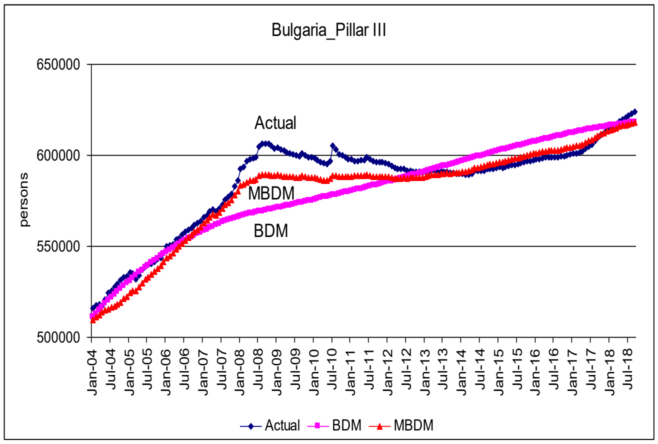
Secondly, the adjusted R^2 values indicate that the Bass models are definitely better fitted only in three cases (12.5%), namely: Romanian and Ukrainian Pillar III, and the Romanian NN Activ. Moreover, in two other cases (the Bulgarian VPF Saglasie and the Romanian NN Optim) the goodness of fit of the cumulative curve is better, but noncumulative is worse. Thirdly, we did not manage to avoid the negative Adj. R^2 value when evaluating the cumulative Bass model for the Czech fund NN PS and the Ukrainian fund Vzaemodopomoga. We apply the proposed Cohen and Cohen (1975) convention of reporting Adj. $R^2 = 0$ when the value becomes negative. Generally speaking, a negative value of Adj. R^2 appears when the residual mean of squares is greater than the total mean of squares, and means the insignificance of the explanatory variables. Theoretically, the results can be improved by increasing the sample size. But in our case, the ratios of sample size to independent variables are 70/2 and 162/2, that is, significantly exceed the requirement to have 20 times more observations than independent variables (Tabachnick and Fidell, 1989). At the same time, these funds have one thing in common: a significant and long-lasting reduction in the number of participants (concentration of funds): in the Vzaemodopomoga since July 2009 and in the NN PS since the first quarter of 2009. As a result, the cumulative diffusion curve is not S-curve, but a bell-shaped curve. Thus, the Bass model is not able to adequately describe the substantial and long-lasting concentration of funds; and the only strategy in this case is to modify the model.

Figure 1 and Figure 2 visualize the goodness-of-fit of the models to the data. In all cases, with the exception of Ukrainian Pillar III, the MBDMs are better fitting than the BDMs (even for the Romanian Pillar III). In this sense, the results of modeling by VPF Allianz Bulgaria and the Czech fund CSOB PS are especially indicative. As for the Ukrainian Pillar III, none of the models capture a Q4-13 jump (participants' growth of 42.64 %). However, after the jump, the BDM is a well-fitting model; probably it should be used in forecasting.

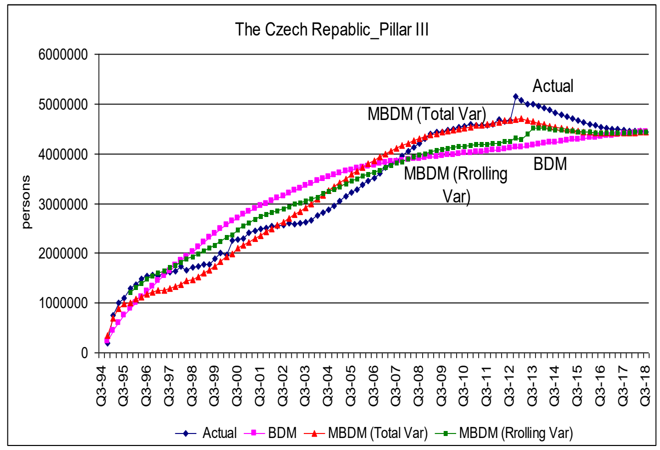
Figure 1

Actual and predicted cumulative number of participants in national Pillars III

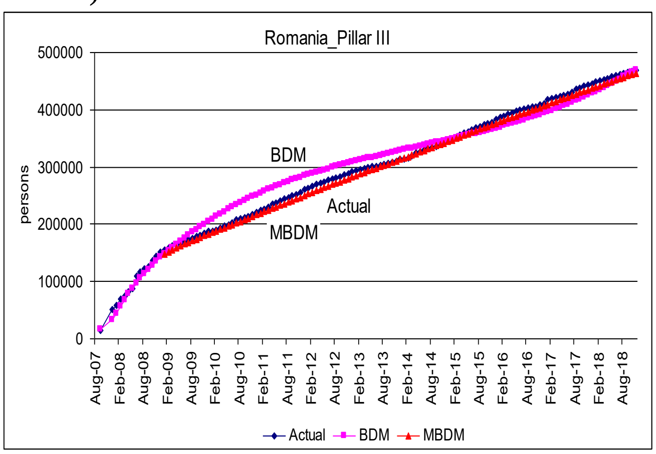
a) Bulgarian Pillar III



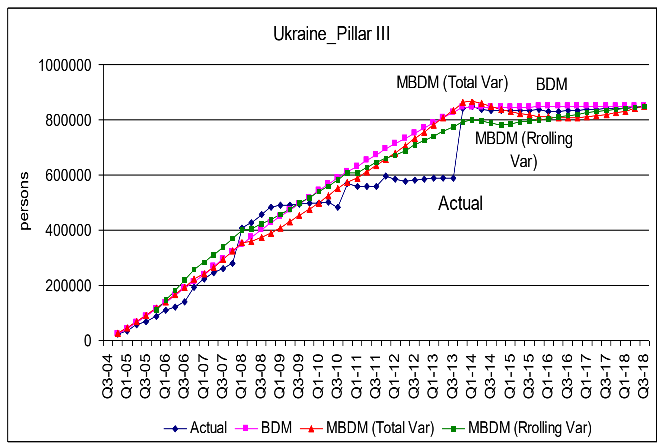
b) Czech Pillar III



c) Romanian Pillar III



d) Ukrainian Pillar III

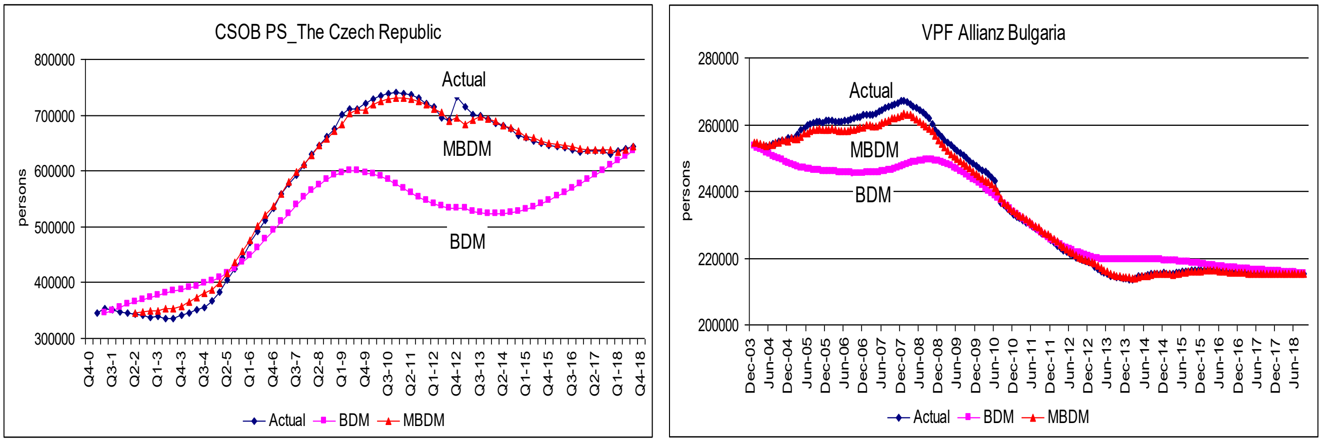


The following remark applies to Czech Pillar III. For these data, the rolling variance showed significant moderation (see Table 1), but the model with the total variance is better fitted. We obtained for the model with a rolling variance Adj. $R^2(n_t) = .1425$ and Adj. $R^2(N_t) = .9310$, and for the model with a total variance, these coefficients are .3542 and .9668, respectively. In addition, Figure 1 shows the best fitting for this model. Therefore, we recommend using a model with a total variance (see Table 3), i.e., a better fit of one model over another to a given data set is a reason to prefer that better fitting model, and there is no difference in the complexity variables (Schunn and Wallach, 2005). This approach should be used in the practice of funds.

Figure 2

Multiple cascading S-curves in the evolution of voluntary pension funds

a) CSOB PS (The Czech Republic) b) Allianz Bulgaria



As for the hypotheses about the existence of informational cascade, the effect of variance in the flow of participants and its moderation, the decision on their acceptance / rejection is made based on the significance of the estimated parameters β_2, β_3 and β_4 of MBDM (8). As Table 3 and Table 4 show, the empirical testing supported the hypothesis H_1 about the existence of informational cascades for Pillar III in all countries, except for Ukraine, and for all funds, except for Ukrainian Pension Capital. Moreover, only for Ukrainian data, we obtained a negative β_2 values. These are Pillar III, OTP Pension, and Magistral. The reasons for the results that are different from other countries are obvious. Ukraine differs from other countries, firstly, by significant political and, as a result, financial and economic turbulence. Secondly, in corporate pension funds employers use the nudging mechanism, but this process is also uneven both in time and in space due to the political and economic instability. Therefore, individuals at the collective level make pension decisions in the conditions of current instability ignoring both their own signals (about the need for additional voluntary pensions) and the actions of earlier participants. Most likely, in the whole country, we observe "herd behavior on the contrary"–the collective unwillingness to think about financing future retirement benefits, including employers.

With regard to the second hypothesis, for all national Pillars III, the variance of the participants' growth in the previous period is the inverse measure of the level of joining in the current period. However, we received strong evidence of this hypothesis (p-value < .001) only in the Czech Pillar III. For pension funds, the results are different, and there is no dependence on the level of a country's development or pension reforms. Romania demonstrates the most stable results; only BCR Plus shows the positive effect of rolling variance on the participants' growth that has become quite stable since 2013–the value of the correlation coefficient is .5992.

Finally, on the third hypothesis, the interaction effect is negative in the Bulgarian and Romanian Pillars III, but positive in the Czech and Ukrainian (in Ukraine, as expected, moderation is not significant, see Table 1). In addition, in all pension funds, except for the Romanian NN Optim and the Ukrainian OTP Pension and Pension Capital, the interaction effect is negative. For 13 out of 20 pension funds, empirical evidence confirms the significant negative impact of the interaction between the participants' growth and its variance in the previous period on the participants' growth in the current period; and variance is a moderator of the interaction effect. The controversial result obtained from Czech data should also be noted, namely: the positive impact of the interaction in Pillar III (p-value < .1) and the statistically highly significant negative impact of interaction in all funds (p-value < .001).

4.2.2 Parametric analysis of diffusion patterns

This part of the discussion focuses on analyzing the estimated diffusion parameters for the Bass model and the modified model that are shown in Table 5. First of all, it should be noted that when using the Bass model, we received a negative root error in 9 cases, and the modified model allowed us to avoid this error and find the diffusion parameters. MBDM identified 4 types of diffusion: (i) a successful product ($q > p$); (ii) unsuccessful product ($q < p$); (iii) negative diffusion ($q < 0$); (iv) multiple cascading S-curve ($p < 0$). Diffuse processes with negative q or p parameters require detailed analysis.

Table 5

Estimated diffusion parameters

Model	Pillar III, VPFs	*p*	*q*	Comments	Pillar III, VPFs	*p*	*q*	Comments
	Bulgaria				The Czech Republic			
BDM	Pillar III	n.a.[a]	n.a.	n.a.	Pillar III	n.a.	n.a.	n.a.
MBDM		.0160	-.0068	concentration		.0561	-.0921	concentration
BDM	Allianz Bulgaria	.3720	-.3043	concentration	Allianz PS	-.0172	.1623	multiple S
MBDM		.0004	.0030	successful		.0036	.0154	successful
BDM	Doverie	.4970	-.4638	concentration	CS PS	-.0724	.2218	multiple S
MBDM		.0052	.0305	successful		.0093	.0303	successful
BDM	DSK-Rodina	n.a.	n.a.	n.a.	CSOB PS	-.1366	.3006	multiple S
MBDM		.0069	-.0051	concentration		.0106	.0498	successful
BDM	NN VPF	n.a.	n.a.	n.a.	KB PS	-.1428	.3216	multiple S
MBDM		.0158	.0033	unsuccessful		.0130	.0281	successful
BDM	Saglasie	-.3078	.4788	multiple S	NN PS	.0858	-.0503	concentration
MBDM		.0027	.0358	successful		.0238	-.4043	concentration
BDM	CCB-Sila	-.3024	.3546	multiple S	PS CP	-.0277	.1874	multiple S
MBDM		.0195	.1093	successful		.0310	.0896	successful
	Romania				Ukraine			
BDM	Pillar III	n.a.	n.a.	n.a.	Pillar III	.0248	.0726	successful
MBDM		.0149	.0179	successful		.0497	-.0168	concentration
BDM	AZT Moderato	.2201	-.1937	concentration	Europe	.0037	.4573	successful
MBDM		.1360	-.2298	concentration		.0184	-.1321	concentration
BDM	AZT Vivance	.2783	-.2451	concentration	Magistral	n.a.	n.a.	n.a.
MBDM		.0172	.0095	unsuccessful		.0574	-.0774	concentration
BDM	BCR Plus	n.a.	n.a.	n.a.	OTP Pension	.0166	.0459	successful
MBDM		.0005	.0084	successful		.0411	-.0194	concentration
BDM	NN Activ	n.a.	n.a.	n.a.	Pension Capital	.0624	.0433	unsuccessful
MBDM		.0311	-.0182	concentration		.0576	-.0226	concentration
BDM	NN Optim	n.a.	n.a.	n.a.	Social Standard	.0147	.0190	successful
MBDM		.0085	.0008	unsuccessful		.0120	.0047	unsuccessful
BDM	Pensia Mea	.1987	-.1166	concentration	Vzaemodopomoga	.0264	.0272	successful
MBDM		.0560	.0084	unsuccessful		.0217	.0119	unsuccessful

[a]n.a. = not available (a negative square root error when estimating *m*)

A negative q does not necessarily mean a negative WoM effect, due to the fact that most of the previous participants are dissatisfied with a new pension product or fund. There are several reasons that inhibit imitation and, therefore, cause the concentration of voluntary pension provision. First, the negative effect of word of mouth can be caused by the rejection of the new product due to premature introduction (Kalish and Lilien, 1986). In post-communist countries, breaking established behavioral pattern–an orientation toward state paternalism in welfare provision–is a long process; and the early introduction of voluntary pension provision is the reason why society does not accept it. The most significant in this sense is Ukraine, where the impact of socialism was the longest: the innovators accepted voluntary pensions, but there were not enough imitators to start diffusion. In addition, the paternalism of employers replaced the state paternalism and the nudge mechanism explains the spasmodic nature of the cumulative curve of the Ukrainian Pillar III; and individual entry into voluntary pension funds has not acquired the nature of a mass process.

Secondly, "negative information tends to be more diagnostic or informative than positive or neutral information" (Herr et al., 1991), it spreads faster (especially in combination with the previous aspect) and the overall effect becomes negative. Third, the negative WoM disseminated by resistance leaders significantly undermines market growth; the more prolific and influential these resistance leaders are, the smaller the eventual market (Moldovan and Goldenberg, 2004). For example, in Ukraine, such influential resistance leaders are life insurance companies. Fourth, negative q may correspond to the case when the benefit from a product declines as more people adopt (Orbach, 2016). For instance, for some corporate funds, the local market has reached its potential. Finally, the savings behavior of people is subject to the negative impact of political and economic crises; and the poorer the country, the stronger and more prolonged such influence. Figure 1 shows that in all 4 countries the diffusion of voluntary pensions (Pillar III) slowed down in 2008–2009, especially in Bulgaria and Ukraine. During this period, the imitation coefficient is negative in all countries, including Romania, where the average value is positive.

The following concerns diffusion with a negative innovation coefficient. The interpretation of a negative p value does not necessarily mean that the product is useless (Orbach, 2016). In the case of long-term dynamics of voluntary pension provision, diffusion graphs with negative p show multiple cascading S-curves (see, e.g., the BDM trajectory for SCOB PS). S-curves are known to cascade with a new one beginning where the last one leaves off (Modis, 2007); new pension schemes (products) replace old schemes just as new technologies replace old technologies. In this sense, we obtained the expected results in the Czech Republic. Table 5 shows that in 5 of 6 founds, the BDM-estimates of innovation coefficients are negative, while $q > |p|$, i.e., these are cases where sowing (reform 2013) overcomes the barriers to adoption, expressed by a negative p. Notably, MBDM-estimates identify a successful product, since $q > p$, p and q are positive. Figure 2 demonstrates which diffusion identification is more accurate for the CSOB PS. On the BDM graph, a pronounced new growing wave (since 2013) doesn't fit the actual pattern. At the same time, the MBDM resulted in a well-fitted curve that shows the growth in participants since the fourth quarter of 2017. However, for the Czech Pillar III and NN PS estimates indicate negative diffusion. In particular, Figure 1 illustrates that, both actual and predicted by the modified model, the total number of participants in Pillar III continues to decline. Probably, an additional fall in the number of participants reflects the natural difficulties associated with structural changes in voluntary pension provision. In addition, the introduction of a new product (pension reform) should take place in a timely manner so that there is no decline during the transition period.

In the terms of multiple cascade S-curves, we obtained similar findings for the Bulgarian VPFs Saglasie and CCB-Sila explained by the transformations. For example, the merger of CCB-Sila and Lukoil Garant-Bulgaria-VPF caused a downswing wave in the trajectory of the total number of participants, which was later replaced by a upswing wave. In addition, the Allianz Bulgaria diffuse curve should be noted. For this fund, BDM estimates ($p > 0$, $q < 0$) identify negative diffusion; and the MBDM estimates ($p > 0$, $q > 0$, $q > p$) identify a successful product, but $p \to 0$. Figure 2 shows that (i) the MBDM-curve is better fitted, and (ii) since 2014, a new growing wave of the fund's life cycle has been observed. Thus, $p \to 0$, as well as $p < 0$, recognizes the case of multiple cascading S-curves.

5 Conclusions and perspectives

When modeling the diffusion of pension innovations–voluntary pension schemes–the original Bass Diffusion Model does not always provide interpretable results. Therefore, our study consisted of two aspects: (i) the modification of hypotheses and the BDM specification in terms of observational learning, and (ii) hypothesis testing and analysis of the diffusion of voluntary pension coverage using estimated models based on data from 4 CEE countries: Bulgaria, the Czech Republic, Romania and Ukraine. The first hypothesis about the informational cascade in joining the voluntary pension provision has been convincingly confirmed in all countries, except Ukraine. This result is explained as follows: (i) in the Czech Republic, the influence of the behavior of previous participants is enhanced by strong state financial support; (ii) in Romania, voluntary pension funds are occupational and this also supports the information cascade; (iii) Bulgaria has a real interest in voluntary private pensions, perhaps because the old-age dependency ratio is the highest (32.02%); (iv) in Ukraine, high political turbulence causes unstable behavior in the field of voluntary pension savings. Regarding the second hypothesis, the variance of the flow of information about the growth of participants is indeed the inverse measure of the level of perception of a new pension product in all national Pillars III. However, this conclusion is statistically significant only for the Czech Pillar 3. At the same time, the hypothesis for the Czech pension companies is rejected; this once again confirms that the decision to join is mainly dependent on state subsidies for private pensions. We confirmed the third hypothesis about the negative moderation effect of variance on the information cascade in all Bulgarian and Czech funds, in three Ukrainian NPFs and in one Romanian fund.

As for the goodness-of-fit of the models, the modified models were unambiguously (that is, both non-cumulative and cumulative diffuse curves) better fitted for 87.5% of time series. In addition, the modified models allowed us to avoid the error of the negative root, which was obtained by the Bass model, and therefore we were able to identify diffuse processes. We obtained an interesting result when the BDM-estimate of the innovation coefficient is negative, but the MBDM-estimate is positive. We argue that this diffusion of voluntary pensions is described by a multiple cascade curve, and the pension product (scheme or fund) is successful. We identified such diffusion in 5 of 6 pension companies in the Czech Republic, where a structural reform of Pillar 3 was carried out in 2013, as well as in 2 Bulgarian funds, where funds merged and new organizations joined. Thus, we conclude that the modified model allows us to correctly describe the wave-like nature of the evolution of voluntary pension provision, which is caused by pension reforms and fund transformations.

Our findings will be useful to policymakers and actuaries in both transition economies and high-income countries, since the issue of the development of voluntary pensions is on the agenda in all countries. Future empirical research may examine the effects of observational learning on joining voluntary funds in age and gender contexts. Future theoretical research may assess the impact of the financial indicators of the performance of voluntary funds in combination with the income of the population.

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