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Interfaces with Other Disciplines

Transparent structured products for retail investors

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A B S T R A C T

Structured investment products (SPs) are derivative securities whose return is contingent on the return of their underlying assets, such as a certain stock market index. SPs have been criticized for being complex and costly on the inside, while attracting retail investors with emotionally appealing promises, on the surface, to provide tempting yields and protection for the capital invested. To circumvent such criticism, we consider transparent SPs (TSPs), which simply offer a lower and upper limit on annual return (after costs and fees) as well a transparent rule defining the return based on the return of the underlying asset. We study TSPs using both empirical and theoretical approaches. An empirical survey of real investors with best-worst scaling as well as theoretical analyses based on utility theory and multi-stage stochastic programming (MSSP) show that moderately priced TSPs are competitive in comparison with other investment products, such as index funds. Furthermore, retail investors actually exhibit substantial preference for TSPs with partial capital guarantees, over and above SPs with the superficially tempting, full capital guarantees. A theoretical, MSSP-based analysis similarly confirms that including TSPs in an investment portfolio can yield substantial gains in certainty equivalent annual return. The results further indicate that perceived gains from TSPs are sensitive to costs, market imperfections, and interest rates, as well as private preferences and stock market expectations of retail investors. This demonstrates how MSSP can be applied to financial engineering for successful implementation of TSPs in future financial markets.

1. Introduction

Structured products (SPs) are *securities that have embedded forwards or options or securities, whose return is contingent on changes in the value of underlying assets, indices or interest rates* (U.S. Securities and Exchange Commission (SEC) Rule 434).[1] According to Célérier & Vallée (2017), European financial institutions alone have sold more than € 2 trillion of SPs to retail investors since 2000. More recently, the European Structured Investment Products Association reported, based on data from its eight national members, that the current, total market value of SPs issued by Europe's largest financial institutions was close to € 300 billion, with an ever-growing upward trend (Eusipa, 2021).

Despite the fact that nothing prevents financial institutions from introducing simpler SPs (like the present transparent SPs), the majority of SPs existing in markets are rather complex and non-transparent. Correspondingly, both practical investment guidebooks (e.g., Baker & Puttonen (2017)) and academic research literature (e.g., Célérier & Vallée (2017); Vokata (2021)) have directed copious criticisms towards these complex, non-transparent SPs. As a case in point, one investment advisory company criticizes providers of SPs with capital protections for "framing their marketing pitches to exploit our psychological deficiencies... without ever divulging the exceptionally high implicit costs of those protections" (Ford, 2018). At the same time, however, the literature has largely neglected to discuss the possibility that simple, transparent SPs may also exist, or be conceived. Indeed, previous literature seems to have taken it for granted that all SPs would be complex and non-transparent, in featuring, e.g., exaggerated headline rates and emotionally appealing but costly capital guarantees (e.g., Vokata (2021))[2] In the present paper, in contrast, we seek to demonstrate that this not necessarily the case, by showing that both rational and behavioral investor demand can well exist for transparent SPs, as well – SPs

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[1] Structured products should not be confused with structured finance which concerns pooling and tranching; see e.g., Coval, Jurek, & Stafford (2009).

[2] Bertrand & Prigent (2019) take another perspective by examining the significant cost of standardization in an important class of standard SPs.

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which do not feature superficially attractive headline rates or capital guarantees, nor any hidden costs.

Against this backdrop, the purpose of this article is to revisit and challenge the unilaterally negative criticism directed at SPs previously. In particular, we focus on exploring and investigating such a subset of SPs that could escape or avoid the aforementioned criticisms. Because we are not studying the entire range of SPs, for clarity, we refer to the subset of SPs which we focus on as 'transparent SPs' (TSPs). We define TSPs based on a collar options trading strategy (see e.g., Das & Statman (2013)) as follows. A simple TSP contract between the issuing bank and its client/investor offers, for a given maturity, a lower and upper limit on the return, after all bank fees, as well as a transparent rule defining the return based on the return of the underlying asset. A TSP is written on a well-known underlying asset, such as a stock index (e.g., S&P500), and offers a minimum annual net return L, promising investors a full ($L = 0$) or partial ($L < 0$) capital guarantee, partly independent of the return of the index. That is, if the return of the index is below a pre-specified lower threshold, then the return of the TSP is L. As part of the scheme, a maximum annual return U (e.g., 15%) for the TSP is also specified: if the return of the index exceeds a pre-specified upper threshold, then the annual return of the TSP is U. Between the lower and upper thresholds, the total return of the TSP will increase in the same proportion as the total return of the index; i.e., the participation rate is 100 percent.

For TSPs not to become subject to the same criticism as non-transparent SPs in general, there are two basic requirements: (1) there must be a transparent contract defining the return, net of all fees and costs, based on the return of the index, and (2) the contract must be 'pure' in the sense that it excludes any content which diverts the investor's attention from the essential parameters of the contract (thereby potentially misleading the investor). Insofar as these requirements are met, the TSPs do not suffer from complexity and hidden costs, and can avoid emotional and psychological manipulation of the investor. Yet, financial service-providers may continue to take advantage the heterogeneity in investors' preferences, in the case of TSPs as well. For instance, service-providers do not need to reveal their private assumptions on market expectations, or justify their costs. Namely, if the service-provider sets the cost charges at too high a level, then the investors simply escape and the service-provider suffers.

In the present research, we use both empirical and theoretical approaches to investigate and evaluate the TSPs. The survey-based empirical study is important, because it explores the behavior of a number of real investors; however, it allows us to investigate a limited set of relevant aspects only. Thus, as a complementary approach, the theoretical analysis enables us to examine a number of additional aspects and assumptions, such as a wider spectrum of TSPs, private preferences and expectations of retail investors, the underlying asset price dynamics, and the role of market interest rates.

For the empirical study, we surveyed a sample of retail investors (n = 301) from among the members of Finnish Shareholders' Association. Even though the sample may not be representative, the respondents' preferences can be considered universal in the sense defined in standard finance textbooks (see e.g., Ingersoll (1987); Luenberger (2013)). In the survey, we employ the *best-worst scaling* (BWS) approach (Louviere, Flynn, & Marley, 2015), which is a survey procedure involving discrete choice tasks, akin to choice-based conjoint analysis. Such methods are widely applied today in OR/MS (see e.g., Braun, Schmeiser, & Schreiber (2016); Halme & Kallio (2014) and Footnote 4 in Section 3.1.) In practice, this approach lets the investors compare TSPs (and their historical return graphs) side by side with other investment products, such as non-SP index funds. Using the BWS approach, we asked the surveyed investors to choose the most and least preferred investment product, among a set of investment products offered for evaluation.

In turn, our theoretical analysis is based on multi-stage stochastic programming (MSSP), which was first proposed by (Dantzig, 1955). Past decades have witnessed substantial advancements in stochastic programming methods, and new applications to various sub-fields have been emerging (see e.g., Birge & Louveaux (2011)). Accordingly, even for the specific application of MSSP-based financial portfolio optimization, several OR/MS articles have been published over the years (see for instance, Bertocchi, Moriggia, & Dupacova (2006); Dupacova & Bertocchi (2001); Homem-de Mello & Pagnoncelli (2016); Topaloglou, Vladimirou, & Zenios (2008); Valladao, Veiga, & Veiga (2014) and Klaassen (1998)). Presently, we employ MSSP for financial portfolio optimization to examine, in particular, the competitiveness of various TSPs in comparison with other investment products in the financial market. Specifically, we employ utility theory for studying the gains investors obtain from TSPs, and measure the gain by the increment in certainty equivalent annual return (*CER*) when TSPs enter in the optimal portfolio.

Prior to us, Hens & Rieger (2014) also used utility theory to study SPs and their *CER*s. Given the utility function of an investor, they employed variational calculus to design an optimal SP maximizing the expected utility. For example, for a power utility, they show that the optimal payoff of the SP is a strictly convex function of the payoff of the underlying asset. The *CER* of such an SP is determined assuming that the investor does not hold assets other than the SP. The *CER* gain from the SP is the improvement (difference) over the *CER* of an optimal portfolio, consisting of the risk-free asset and the market portfolio. Notably, both the analyses of Hens & Rieger (2014) and our analyses presently, consider heterogeneous preferences and market expectations of investors. However, while Hens and Rieger addressed the investor's optimal SP and assumed a complete and nearly perfect market, we presently consider a variety of TSPs, and allow market incompleteness as well as a variety of market imperfections. This constitutes the main distinction of the present model, vis-a-vis that of Hens & Rieger (2014). In fact, the market imperfections addressed presently, turn out to be important determinants of the gains of a TSP. At the same time, due to the aforementioned differences in our underlying assumptions, our results are not directly comparable with those of Hens & Rieger (2014). Still, the substantial impact of biases of individual investors, for instance, is observed in both their and our studies.

Depending on offered return limits L and U as well as cost charges, a TSP may or may not be competitive against other investment products. Thus our first research question (RQ1)is: to what extent are individual investors attracted towards TSPs, in comparison with even simpler index fund products? Both our empirical and theoretical results show that even when individual investors can compare TSPs side by side with simpler index fund products, considerable demand for moderately priced TSPs exists. Specifically, considerable demand exists even for TSPs that do not provide emotionally appealing (but costly) full guarantees of capital. Analytically, we further assess other determinants of the competitiveness of TSPs, than the cost charges. Building our portfolio analysis on the seminal work by Cox, Ross, & Rubinstein (1979), we observe that (i) given a lower level L for a TSP, an increase in the upper limit U increases the price of a TSP as well as the probability of the return hitting the lower limit L; (ii) given an upper limit U, a decrease in the lower limit L (to more negative, from zero) decreases the price of a TSP and increases the probability of hitting the return limit U; (iii) the gains in *CER* from a TSP increase with decreasing risk aversion; (iv) imperfections in terms of increasing costs or relaxing the set of feasible portfolios undermine the benefits from TSPs; (v) interest rate and private market expectations have a strong impact on the perceived value of TSPs.

Moreover, if the critique pointing to retail investors' emotionally biased preference for SPs with full capital guarantees was perfectly valid, our empirical survey should indicate that investors exhibit a disproportionate demand for TSPs offering a full capital guarantee (i.e., $L = 0\%$ loss) compared to TSPs only offering a near-full capital guarantee (e.g., $L = -5\%$ loss). Thus, as our second research question (RQ2), we ask: Is the demand for TSPs with full capital guarantee disproportionately higher than the demand for equally complex/simple TSPs with partial capital guarantees? We find, both theoretically and empirically, that individual investors do not seem to exhibit disproportionate demand for TSPs with full capital guarantees, over TSPs with partial capital guarantees only, or over other non-SP investment products. Here, we also assess whether the observed preferences for TSPs with full vs. partial capital guarantees are in harmony with value functions suggested by prospect theory (Kahneman & Tversky, 1979). As a result, the preferences based on expected utility appear to be in conflict with preferences assumed by the prospect theory. Similarly, our survey study also indicates that individual investors do not seem to be risk averse in the prospect-theory sense, when it comes to TSPs. This is because we find that our investors actually have a greater preference for higher-risk TSPs without capital guarantees than for lower-risk TSPs with capital guarantees.

The issue of hidden costs leads to our third research question (RQ3): Are individual investors able to take into account the implicit costs of the TSPs? This question is primarily empirical, and has a relatively minor role in our theoretical analyses. Especially, from the perspective of portfolio optimization, and given that all costs are embedded in the return information given to investors about our TSPs, a positive answer to RQ3 is straightforward. In any case, to address this question empirically, our survey questionnaire showed, to the investors, TSP return graphs, accompanied by a note that the graph incorporates the "cost structure" of the product. The results indicate that investors were able to take into account the implicit costs visible in return graphs in our survey questionnaire. Thus, a positive answer to RQ3 obtains some empirical support, as well.

In addition to literatures mentioned above, our results also contribute to general OR/MS literature related to investors' asset evaluation problems (see, e.g. Zopounidis, Galariotis, Doumpos, & Stavroula (2015)), which typically utilize multi-criteria methods. While the previous studies have mostly dealt with aggregate preferences or a single decision-maker (see e.g., Xidonas, Mavrotas, & Psarras (2009) and (Pätäri, Karell, Luukka, & Yeomans, 2018)), our study makes a contribution by examining heterogeneous preferences, as well. Furthermore, we extend the focus of the asset evaluation literature from ordinary investment products to a variety of SPs. Finally, our empirical study also makes a contribution by adding to the previous behavioral finance literature. Indeed, we apply survey-based methods to study heterogeneous investor preferences by a discrete choice method, which is rare in the literature so far (for an exception, see e.g., Clark-Murphy & Soutar (2005)).

The outline of the rest of the article is as follows. Section 2 provides a theoretical motivation and perspective on the demand of simple TSPs, thereby laying out a theoretical framework for the analysis of investor demand towards such TSPs. For the empirical study, Section 3 introduces BWS as well as describes the financial instruments addressed empirically, the survey questionnaire, and the sample of respondents. Section 4 presents the empirical results: market shares of TSPs and other investment products, and preference clusters of investors. Based on numerical analysis of TSPs employing MSSP-based portfolio optimization under expected utility and prospect theory, Section 5 presents the analytical results, as well as comparisons with empirical results on RQ1–RQ3. A concluding discussion is in Section 6. Please note that in Sections 2–5, 'SP' refers to TSPs unless stated otherwise.

2. A theoretical perspective on SPswith capital guarantees

In this theoretical section, we employ utility theory by von Neumann & Morgenstern (1947) and MSSP-basedportfolio optimization building on options valuation of Cox et al. (1979)to introduce a theoretical basis for understanding the demand of SPs with full and partial capital guarantees. Market imperfections as well as the heterogeneity of individual investors turn out to be fundamental in explaining the demand. In our empirical study, later on, we examine the demand for several SPs of this kind. After the empirical study, we return to the theoretical model, and assess the SPs, including those addressed in the empirical study, through the model presented below.

Consider three assets B, I and D for financial investment over a period $[0, T]$ of T years. Asset B is a risk free asset (e.g., a bank account) with an interest rate r such that the total return in t years is $\exp(rt)$. An investment at time $t = 0$ in asset I (an index fund) yields a random total return S_T at time T. We scale asset I to have an initial price equal to 1. Asset D (a derivative written on I) is an *SP with a certain level capital guarantee*, which pays at time T a cash flow $F_T = \min(K_1, \max(K_2, S_T))$ with threshold levels K_1 and K_2, $K_1 > K_2$. Hence, the level of cash flow F_T is between K_1 and K_2 and $F_T = S_T$ if $K_1 \geq S_T \geq K_2$. If P denotes the amount of capital invested in D at time $t = 0$, then the return at time T is $R_T = F_T/P$, and the guaranteed bounds on annual net return are $U = (K_1/P)^{1/T} - 1$ and $L = (K_2/P)^{1/T} - 1$. A relative change in S_T within (K_2, K_1) creates an equal relative change in R_T; i.e., the *participation rate* is 100%.In this setting, the investor gets a (partial) guarantee for that capital, as s/he can only lose a share $1 - K_2/P$ in T years of the capital, assuming K_2 is specified by a (small) non-positive annual net return $L \leq 0$. Note that if $P < 1$, then $R_T > S_T$ for all realizations $S_T \leq K_1$. In this case the probability of the return R_T of D exceeding the return S_T of the underlying asset is at least the cumulative distribution function (cdf) of S_T evaluated at K_1.

Fig. 1 illustrates two examples of SPs, D_a (left) and D_b (right); both with $T = 3$ years. The underlying asset is the same for both with S_T log-normal;[3] the annual return limits (L, U) are $(-4, 8)\%$ and $(-5, 12)\%$, and the prices are P_a =0.990 and P_b=1.047 for D_a and D_b, respectively. The shaded tails of the probability density function (pdf) of S_T indicate the probabilities p_1 and p_2 for hitting the upper limit U and lower limit L, respectively. For D_a and D_b, these probabilities are $p_{1a} = 0.37 > p_{2a} = 0.30$ and $p_{1b} = 0.23 < p_{2b} = 0.32$; the expected returns $E[R_T]$ are $1.078 = 1.025^T$ and $1.096 = 1.031^T$. Because $P_a < 1$, the probability of $R_T > S_T$ is at least 1–p_{1a}=0.63 for D_a. At the thresholds, $K_1^{1/T} - 1 = 7.6\% < U$ and $K_2^{1/T} - 1 = -4.3\% < L$. Instead, $P_b > 1$ and the probability of $R_T < S_T$ is at least $1 - p_{2b}$=0.68, and at the thresholds we have $K_1^{1/T} - 1 = 13.3\% > U$ and $K_2^{1/T} - 1 = -3.6\% > L$.

Let the *bank* refer to a financial institution providing an SP, denoted by D, to retail investors, the *agents*. For a simple analysis of demand for D, consider a single agent choosing a portfolio composed of the three assets B, I and D, and let indices $a = 0, 1, 2$ refer to these assets, respectively. Suppose the agent optimizes the portfolio based on expected utility maximization. Let $u(v)$ be the agent's utility function of the total annual return v over T years from a portfolio investment at time $t = 0$. Here v includes the principal and the net (annual) return, which is given by $v - 1$, and the

[3] The price of the underlying asset I follows GBM with drift $\nu = 0.027$ and volatility $\sigma = 0.238$ taken from our empirical study in Sections 3–4.

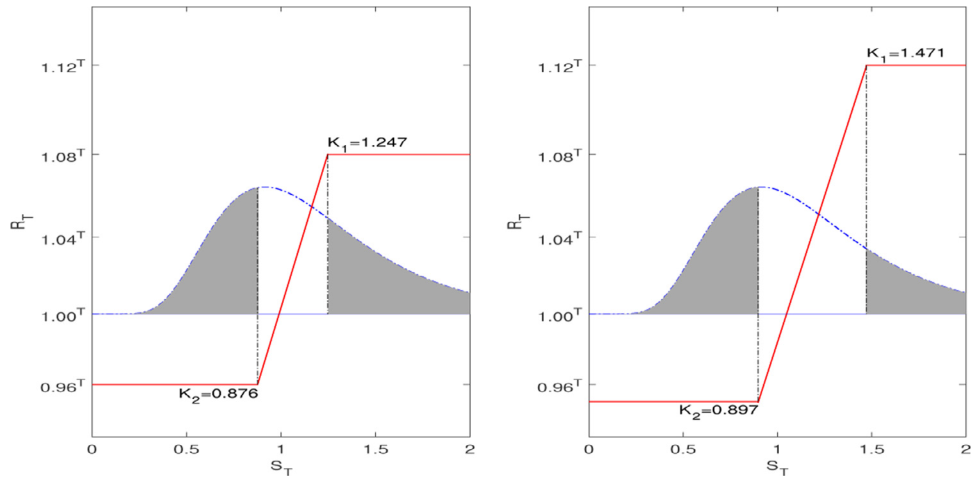

Fig. 1. Two examples of SPs, D_a with $(L, U) = (-4, 8)\%$ and D_b with $(L, U) = (-5, 12)\%$, both with maturity $T = 3$ years. S_T (horizontal axis) is T-year total return of the underlying asset; R_T (vertical axis) is T-year total return of the SP. Dotted curves show the pdf of the log-normal return S_T. .

total return over T years is v^T.We assume $u(v)$ is strictly increasing and concave defined in the domain $v \geq 0$.

For numerical analysis of demand in the product D, we set up a scenario tree Γ depicting the evolving asset prices in the financial market and formulate a MSSP model (see e.g., Birge & Louveaux (2011)) for the agent's portfolio optimization. We subdivide the T year planning horizon into m equal sub-intervals of $\delta = T/m$ years. The subdivision serves for obtaining a reasonably accurate description of the stochastic process governing the price of I, the underlying asset. Furthermore, in an MSSP framework, this allows for portfolio rebalancing in discrete time. The scenario tree Γ is composed of nodes $k = 0, 1, \ldots$ at time stages $t = \kappa\delta$ ($\kappa = 0, 1, \ldots, m$) and edges joining nodes in consequent time stages. Let node $k = 0$ be the root node at time $t = 0$. From each node k at time $t < T$ there are n edges branching from node k to n distinct nodes at time $t + \delta$. Let N be the set of all nodes in Γ, $N_T \subset N$ the set of *terminal nodes* at time $t \in T$, and p_k the probability of node $k \in N$. For $k \in N$ with $k > 0$, k_- denotes the immediate predecessor node of k; i.e., there is an edge joining nodes k_- and k. For $k > 0$, let $R_k = (R_{ak})$ be the row vector of (total) returns of the three assets $a = 0, 1, 2$ over a single period starting at node k_- and ending at node k. For all $k \in N$, let $x_k = (x_{ak})$ be the column vector of portfolio values in assets $a = 0, 1, 2$ at node k, and let $s = (1, 1, 1)$ be a sum vector. Then, the *base model* of the agent's MSSPproblem is to find x_k, for all $k \in N$, to

$$\max \textstyle\sum_{k \in N_T} p_k u(sx_k^{1/T}) \tag{1}$$

s.t.

$$sx_k \leq R_k x_{k_-} \;\; \forall \; k > 0 \tag{2}$$

$$sx_0 = 1 \tag{3}$$

Without loss of generality, we set in (3) the initial investment budget to one currency unit. Then (2) yields the total portfolio return sx_k from the root node until node k and the objective in (1) maximizes the expected utility of total annual return at time T.

To illustrate the scenario tree, Fig. 2 shows an example of a binary tree Γ with $n = 2$, and $T = 2$ years subdivided into $m = 2$ time steps $\delta = 1$ year; Γ is composed of nodes $k \in N = \{0, 1, \ldots, 6\}$ at time stages $t = 0, 1, 2$, and edges joining the nodes. The root node $k = 0$ is at time $t = 0$, and the set of terminal nodes is $N_T = \{3, 4, 5, 6\}$ are at stage $t = 2$. From each node k at time $t < T$, there are $n = 2$ equally likely edges branching from node k. For the node probabilities p_k, we have $p_0 = 1$, $p_1 = p_2 = 0.5$, and $p_3 = p_4 = p_5 = p_6 = 0.25$, and for all $k > 0$, the immediate predecessor node of k_- is given by $1_- = 2_- = 0$, $3_- = 4_- = 1$ and $5_- = 6_- = 2$. Associated with nodes, there is an exogenous return vector R_k, for $k > 0$, and an endogenous vector x_k of asset values in the portfolio, for all k.

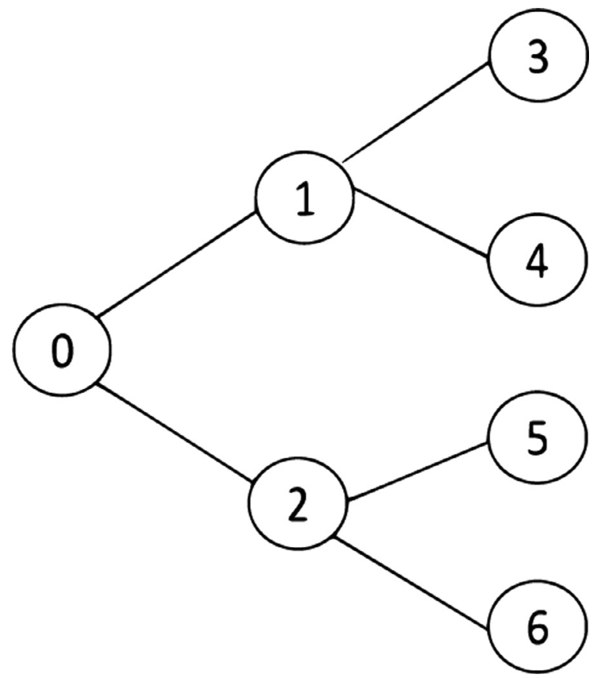

Fig. 2. A binary tree tree Γ with $T = 2$ years, $m = 2$ and n=2..

Suppose an optimal solution exists for (1)–(3) and let u^* denote the optimal expected utility. Then the certainty equivalent annual return (*CER*) denoted by $\hat{e}$ solves the equation $u(\hat{e}) = u^*$. To see the impact of D in $\hat{e}$, we solve (1)–(3) with the additional requirement $x_{ak} = 0$, for all $k \in N$ and $a = 2$. Thereby, excluding asset D from the portfolio, we obtain an expected utility $u \leq u^*$ and $\bar{e}$, the *CER*, satisfies $u(\bar{e}) = u$. Consequently, the gain in the *CER* due to asset D is $\Delta e = \hat{e} - \bar{e} \geq 0$.

Next, consider a complete and perfect market depicted by Γ for the three assets. Let Γ be a binary tree with $n = 2$ and assume the return vectors R_k at nodes k are such that no arbitrage opportunities exist. Then, for all $k \in N_T$, the cash flow $F_k = \min(K_1, \max(K_2, S_k))$ of asset D is identical to the cash flow of a portfolio formed by purchasing one unit of asset I (at price 1) and a put option on I with strike price K_2 as well as writing a call option on I with strike price K_1. Thus, arbitrage pricing theory implies $P = 1 + P_p - P_c$, where P_c and P_p are the prices of call and put options (with strike prices K_1 and K_2), respectively. In special instances, $P_p = P_c$ and $P = 1$.

Suppose the scenario tree is a true description of the real market and both the bank and the agents agree with this view. In an optimal portfolio, if $x_{ak} \neq 0$ for some $k \in N$ and $a = 2$, then under a perfect and complete market, there is another optimal portfolio with $x_{ak} = 0$ for all $k \in N$ and $a = 2$. Consequently, for the *CER*, $\hat{e} = \bar{e}$; i.e., $\Delta e = \hat{e} - \bar{e} = 0$ and the asset D makes no contribution to the agents' portfolio.

The above assumption of a perfect and complete market may provide some explanation to the fact that Hens & Rieger (2014, Section 3) report low incremental value for SPs in their analysis. However, the real world is somewhat different: the market is incomplete and there are imperfections such as transaction costs (including bank charges), constraints on forming portfolios (e.g., restrictions on short positions or other bounds on portfolio weights), holding costs for short positions, and interest rate gaps between borrowing and lending. Furthermore, the agents in real markets are non-homogeneous in their expectations concerning asset prices. Therefore, in the empirical study of Sections 3–4, we examine real investors' demand (implied by survey responses) for a number of SPs with capital guarantees. After the empirical study, we further analyze, in Section 5, the same SPs, using extensions of the base portfolio model (1)–(3) above. In returning to the theoretical model, we will show that the *CER* contribution Δe of the SPs can indeed be rather significant due to market imperfections and the non-homogeneous market expectations of the agents. This will be consistent with the results of our empirical study, reported next.

3. Materials and method of the empirical study

We adopt the best-worst scaling (BWS) approach in our empirical study of investors' asset evaluation problem, implemented through a survey questionnaire, which a sample of real retail investors responded to. Section 3.1 introduces the BWS approach, along with the multinomial logit choice model (McFadden, 1974). Section 3.2 defines the SPs and other investment products presented to the investors in the survey study. Section 3.3 introduces, in detail, the tasks in the survey questionnaire, and the sample of respondents are discussed in Section 3.4.

Later in Section 4, we review the Latent Class Analysis (LCA) and estimation of investor preferences. LCA assumes the multinomial logit choice model and it provides several measures to select the best clustering solution, which is an advantage compared to many approaches using standardized utilities.

3.1. Overall research design: Best-worst scaling

The BWS approach is a choice-based measurement model (Louviere et al., 2015) and has a strong resemblance with the choice-based conjoint analysis increasingly common in numerous fields. The BWS approach is a type of a discrete choice experiment (Louviere et al., 2015). Along with choice-based conjoint analyses, discrete choice studies are increasingly common in MS/OR research.[4] In BWS studies, paired comparisons of choice alternatives are presented to decision-makers in multiple choice tasks. The decision-makers repeatedly choose their most and least preferred alternatives from among a set of three or more choice alternatives.

We use the implementation of BWS by Sawtooth Software. The implementation begins from definition of a set of k choice alternatives, i.e. the SPs and other investment products, which will be presented to the investors responding to the survey. Then, the number of choice tasks to be presented to an individual respondent is determined. A common rule of thumb is that each alternative should appear at least three times among the tasks shown to an individual respondent. In turn, each choice task presents the respondent with a subset of the overall set of choice alternatives defined above. Typically, each task contains a subset of 3–5 choice alternatives. To respondents, the choice alternatives are presented with text and/or graphics. As a response to each choice task, the respondent indicates which of the choice alternatives are the most and least preferred alternatives to him/her.

In modeling the discrete choice data, we use random utility theory proposed by McFadden (1974). Hence, the total (random) utility $\tilde{u}_i$ of a given choice alternative i is the sum of a deterministic component u_i and a random error term ϵ_i,

$$\tilde{u}_i = u_i + \epsilon_i. \tag{4}$$

The error terms ϵ_i are assumed i.i.d. (across choice alternatives and individuals) with the standard Gumbel distribution, for which the pdf resembles the pdf of a normal distribution, but an analytical expression exists for the probability of item i being preferred to item j. Scaling of the utility in (4) enables the scale parameter equal to 1 to be used. This leads to the multinomial logit choice model McFadden (1974). If k items are compared by using the multinomial logit, the probability p_i that item i is chosen is

$$p_i = \frac{e^{u_i}}{\sum_{j=1}^{k} e^{u_j}}. \tag{5}$$

3.2. Investment products of the present study

Next, we introduce the investment products presented to the investor-respondents of the present survey study. Given the enormous number of investment products available globally, we relied on the opinions of three experts who are specialists in the practice and theory of financial markets. Expert 1 was chosen as a representative of retail investors, expert 2 was a strong professional in international finance, and expert 3 was chosen as a specialist in SPs.We used their judgment in selecting a small number of different types of investment products for the study, representing SPs with full and partial capital guarantees, as well relevant comparison products.

For the focal SPs, we specified six types of SPs, with different levels of capital guarantees, for the study. Based on the experts' judgment, we decided to use the MSCI Germany index as the underlying stock market index for the specification of all of the six SPs.[5] This is because this index relates to the Euro area (which also includes Finland, wherein the investor-respondents were sampled), it covers a large share of the prominent German equity market, and its historical returns data are freely available for us to construct the graph-format specifications of the SPs (see Fig. 3 below). The specifications of the six SPs are summarized in Table 1. Fig. 3 reproduces the way in which the SPs were presented to the respondents.

Reflecting the research questions, the most important dimension which the six SPs differed on, was the degree of capital guarantee: two of the six SPs featured full capital guarantee (i.e., minimum return, L %, 0%), while four featured partial capital guarantee

[4] In ISI Web of Science, 901 hits were found in Spring 2021 for "discrete choice" in title, abstract, or author keywords, in the field "operations research and management science".

[5] We use estimates $\nu = 0.027$ for the drift and $\sigma = 0.238$ for the volatility of MSCI Germany; the interest rate is set to $r = 0.01$.

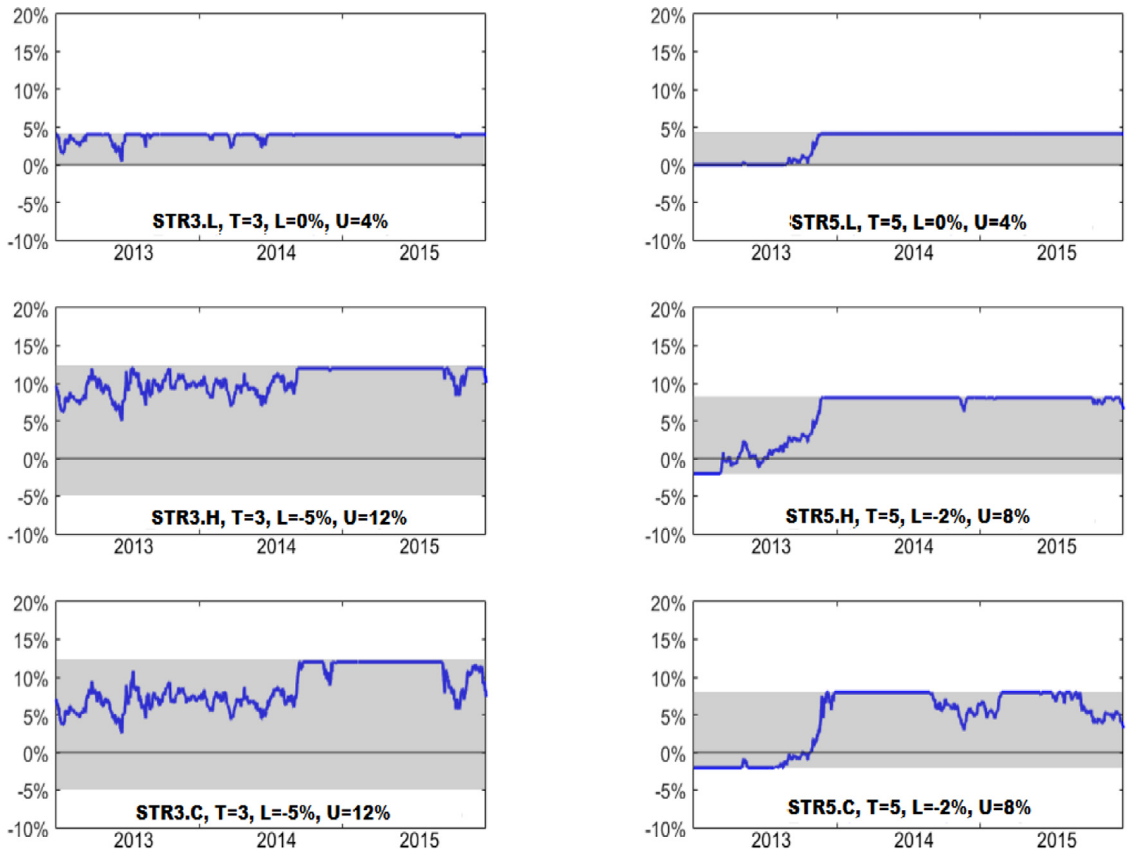

Fig. 3. Focal SPs' visualization to respondents: Time series graphs of the historical returns of the SPs. The shadowed areas in the graphs indicate possible levels of annual returns within the limits L and U; T is the maturity of the SP in years. For $T = 3$ and 5, codes **STRT.L**, **STRT.H** and **STRT.C** shown to the respondents refer to D_{TL}, D_{TH} and D_{TC}, respectively.

Table 1
Focal SPs' specified characteristics.

Item	Maturity	Return limits		Additional
	T (years)	L (% pa)	U (% pa)	cost (% pa)
D_{3L}	3	0	4	0
D_{3H}	3	-5	12	0
D_{3C}	3	-5	12	1
D_{5L}	5	0	4	0
D_{5H}	5	-2	8	0
D_{5C}	5	-2	8	1

(minimum return, L %, of -2% or -4%). In addition, the SPs differed in terms of the maximum annual return (U %), maturity and bank charges, as well as the (historical) graph of historical returns and risks. For all SPs, the return descriptions included all costs charged by the financial service-provider. If the total return of underlying index at maturity were between the specified minimum and maximum returns, K_1 and K_2, $K_1 > K_2$, the realized return of the SP was shown to be contingent on the index. Furthermore, to be able to address research question RQ3, about implicit costs, two of the SPs were characterized as including certain extra costs charged by the financial service-provider. That is, the SPs D_{3C} and D_{5C} were specified as otherwise identical to the SPs (with partial capital guarantees) D_{3H} and D_{5H}, but the former were stated to be subject to an extra 1% annual cost charge; i.e., bank charges for D_{3C} and D_{5C} are one percent point higher than for other products. For the respondents, this cost was incorporated in the graphs describing the historical returns of the SP, accompanied by a note that the lower returns level of the former SP was due to "different cost structure" charged by the financial service provider.[6]

Given our aim to assess individual investors' demand for SPs with capital guarantees in comparison with alternative investment products, we selected five types of index funds (focusing on stocks, bonds, and real estate) as comparison products to be included in the BWS choice tasks. In each choice task shown to a particular respondent, a subset of the index funds were included as comparison products. The five index funds were:

- MSCI Germany – an index measuring the overall performance of the large- and mid-cap segments of the German equity market. This index was also the underlying index of the present SPs.
- OMX Helsinki – the general index of Helsinki stock exchange in Finland. An index fund based on this index was relevant to include, as the retail investors sampled as respondents of the present study were Finnish.
- S&P 500 – a composite capitalization-weighted index of 500 stocks broadly representing different industries within the US economy.
- US Bond index – an index based on JPM US Government Bond fund, which principally invests in securities issued by the US government and its agencies.

[6] Note, if D_{TH} and D_{TC} appear simultaneously in a single BWS task, then we can expect D_{TH} to be preferredover D_{TC} with an increased cost. However, such a pair of products never appeared side by side in a single task for a respondent. Therefore, it is plausible that a significant positive probability for D_{TC} in (5) is observed for many respondents.

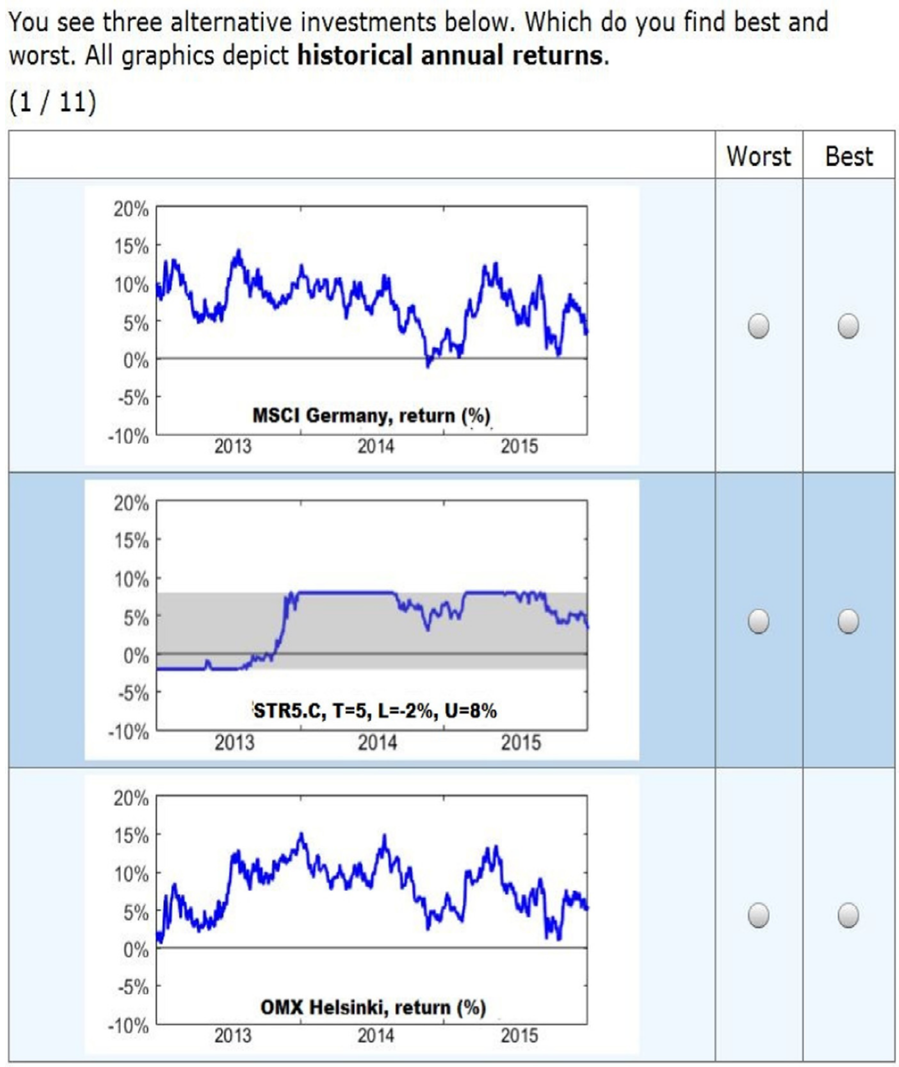

Fig. 4. Example of a choice task in the BWS questionnaire. In each task, there were three alternatives for the respondent to choose their most and least preferred one.

- Real Estate inded – the FTSE EPRA/NAREIT Developed, Europe index designed to track the performance of publicly listed real estate companies in developed European countries.

To allow maximum comparability between the focal SPs and the index fund comparison products, we showed the respondents time series graphs of the historical returns of the index funds, in the same way as we did for the SPs. The USD based returns are adjusted by changes EUR/USD exchange rate (please see Figures A.1-B.2 in the supplementary material.)

3.3. BWS Choice tasks

Eleven choice tasks were presented to each respondent. Following the BWS approach, the respondent was asked to indicate their most and least preferred among the choice alternatives.To keep the choice tasks straightforward and simple, a single choice task included no more than three choice alternatives. Fig. 4 illustrates one choice task, as presented to respondents. A balanced incomplete block design (BIBD) is typically used in designing which choice alternatives to use in the consecutive tasks. The Sawtooth Software SSI/Web 8.4.8, which we utilized, allows to employ near-perfect BIBDs (The Maxdiff System, 2020, 8). Each of the individual choice alternatives appeared three times (the minimum recommended) to each respondent. In total, there were 150 different questionnaires (i.e., combinations of sets of choice tasks). Thus, with our 301 participants (see below), only two respondents, on average, responded to exactly the same set of choice tasks.

At the beginning of the questionnaire, the respondents were asked to imagine a hypothetical scenario wherein they unexpectedly received extra income or funds of an amount that corresponded to 10 per cent of the value of their current investment portfolio. We selected 10 per cent of current investment portfolio as the reference amount because it would be a large enough amount in the sense of calling for serious assessment of the investment product's logic and specifications (and not being frivolously gambled away), yet small enough in the sense of not requiring the respondent to focus on pondering how it would affect the diversification profile of their overall investment portfolio.

After the introduction of the overall scenario, the respondents were presented with a brief overview of the five comparison products and the six focal SPs, with the help of the graphs depicted in Figure B.2 and Fig. 3, visualizing the historical returns of the respective products. Before moving to the choice tasks of the kind presented in Fig. 4, it was stressed to the respondents that besides the graphical information about the historical returns, the respondent should use whatever private information they possessed, in evaluating the choice alternatives and making the choice of the

Table 2
Descriptive statistics of the sample of respondents.

Attribute	Level	number	%
Gender	Male	272	90
	Female	29	10
Age	above 50 years	226	75
	below 50 years	75	25
Region	Helsinki metropolitan	104	35
	Other southern Finland	63	21
	Other	134	44
Wealth	below 100,000€	86	30
	above 100,000€	215	70
Trades at least monthly		162	54
Trades less often than monthly		139	46
Trades in internet		274	91
Does not trade in internet		27	9

Table 3
Market shares (%) of the focal SPs and index fund comparison products. The market shares of D_{3H} & D_{3C} and D_{5H} & D_{5C} are those of D_{3H} and D_{5H} in the left column (without cost featured) and those of D_{3C} and D_{5C} in the right column (with cost). L and U are annual return limits (%) and T is the maturity of the investment product in years. SPs with full capital guarantee have $L = 0\%$, while SPs with partial capital guarantee have $L = -2\%$ or $L = -5\%$.

		A. Without cost	B. With cost
MSCI Germany		3	3
Real Estate		17	25
OMX Helsinki		10	10
US Bond		4	5
S&P 500		20	27
D_{3L}	T=3, $L =$ 0%, $U =$ 4%	1	2
D_{3H}&D_{3C}	T=3, $L = -5\%$, $U =$ 12%	38	23
D_{5L}	T=5, $L =$ 0%, $U =$ 4%	2	3
D_{5H}&D_{5C}	T=5, $L = -2\%$, $U =$ 8%	5	3
total (%)		100	100

most preferred and least preferred alternatives. As an example of such private information, the instructions mentioned the respondent's own anticipations about the development of stock markets or exchange rates in near future. Finally, we advised the respondents that they could assume that both the SPs and the index funds are publicly traded in efficient markets until maturity (i.e., their liquidity could be assumed to be the same), as well as that there was no default risk associated with the financial institution issuing any of the SPs or index funds.

3.4. Sample of respondents

The survey was carried out in collaboration with Finnish Shareholders' Association (FSA), an association of individual investors in Finland. We sent an invitation to respond to the survey by email to a sampling frame of such 8713 members of the association, who had given permission to be sent this kind of survey invitations. Altogether 301 members completed the survey (response rate 3.5%). When we compared the descriptive statistics of our sample with known statistics of the members of FAS, no substantial differences were detected.[7] Thus, non-response or self-selection bias should not be a severe concern.

Before the BWS choice tasks, the respondents were asked about background variables, which included gender, age, area of residence, and investment wealth, as well as frequency of trading and trading over the Internet. Descriptive statistics regarding these variables are summarized in Table 2.

4. Empirical results

In this section, we present the results of the empirical survey, focusing on our research questions. First, in Section 4.1, we present the results at the aggregate level for all respondents, focusing on the demand for SPs in general (RQ1) and on the question (RQ2) of whether the demand for SPs with full capital guarantee is disproportionately higher than the demand for equally complex SPs with partial capital guarantees. At the same time, we observe (RQ3) whether individual investors were able to take into account the implicit costs of the SPs when incorporated into an empirical returns graph. In the following Section 4.2, we further analyze whether preference classes of investors can be identified with respect to their preferences towards the SPs.

[7] FSA does not possess personal information of its members, for instance, concerning age or wealth. However, FSA provided us with respondent statistics of other surveys sent to FSA members previously. The statistics related to the respondents' background variables were highly similar in the other surveys as in our present survey.

4.1. Demand and market shares of SPs

First, we analyze the demand for the different investment products presented as choice alternatives to the respondents. The results of surveyed BWS choice tasks are frequently presented as market shares or relative demand. It is assumed that all the five comparison products (i.e. index funds) and the six SPs would be available to the individual, and the individual's choice among them is determined by the multinomial logit choice model (5). Thus,given maximum likelihood estimates of the deterministic utility components v_i in (4), if p_{ir} is the probability in (5) for respondent r choosing the choice alternative i, then the market share m_i of the alternative i is

$$m_i = \sum_r p_{ir} / \sum_{jr} p_{jr}. \quad (6)$$

Table 3 shows the market shares of all the investment products on the aggregate level. Column 'without cost' on the left concerns all the SPs excluding D_{3C} and D_{5C}. The right-hand column, 'with cost', shows the market shares of the products assuming that the market only featured the cost-including versions D_{3C} and D_{5C} of the SPs characterized by partial (non-full) capital guarantee, D_{3H} and D_{5H}.

From Table 3, with regard to RQ1, we see that the aggregate demand for SPs is strong. The market share of the most preferred SP only is 38% in column A and 23% in column B. The maturity of 3 years is preferred to 5 years. Importantly, with regard to RQ2, the results reveal that SPs with only partial capital guarantee ($L = -2\%$ or $L = -5\%$) are in fact at least equally preferred as the SPs with full capital guarantee. The SP that has by far the highest demand and market share is the one with 95% capital guarantee ($L = -5\%$), rather than the one with full capital guarantee ($L = 0\%$) or even the one with near-full capital guarantee of 98% ($L = -2\%$). This suggests, regarding RQ2, that individual investors do not exhibit disproportionately higher demand for SPs with (emotionally appealing) full capital guarantees. Quite the contrary, individual investors seem to be, in fact, substantially more attracted to SPs without full capital guarantees, which also feature higher upside return potential. An additional finding consistent with this, is that the investors generally prefer the SPs with shorter maturities and higher upside returns potential over SPs with longer maturities and smaller downside risks.

With regard to implicit costs (RQ3), the results reveal that individual investors' demand for the SPs is substantially decreased in case an additional cost is implied and incorporated into the historical returns graph of the SP. That is, the demand for the SP of 3 years' maturity with partial capital guarantee decreases from 38% to 23% when the cost charge is featured (see D_{3H} in the left column

Table 4
Investor segments in terms of market shares (%) of focal SPs and comparison index funds.

	Cl. 1	Cl. 2	Cl. 3	Cl. 4
Size (% of respondents)	22.8	25.8	14.5	36.9
MSCI Germany	6	5	3	1
Real Estate	21	16	8	10
OMX Helsinki	15	11	8	2
US Bond	7	0	8	1
S&P 500	35	31	4	5
D_{3L}	2	0	10	1
D_{3H}	4	26	8	55
D_{3C}	4	8	8	18
D_{5L}	2	0	11	0
D_{5H}	2	2	19	6
D_{5C}	1	1	13	2

vs. D_{3C} in the right column). Likewise, the demand for the SP of 5 years' maturity with partial capital guarantee decreases from 5% to 3% (D_{5H} in the left column vs. D_{5C} in the right column) when introducing the cost charge. This result suggests, regarding RQ3, that individual investors are generally able to take into account the implicit costs of SPs when such costs are incorporated into an historical returns graph and when the investors are informed that the graph includes the "cost structure" of the product. This seems to be true even if the information provided to investors does not explicitly indicate the cost component in % or € terms.

4.2. Investor segments

As an additional analysis of market demand for the SPs with full vs. partial capital guarantees, we applied LCA to the choice data to gain insight into heterogeneous preferences among the investors. In LCA, both the utilities across classes and the class sizes are determined simultaneously (DeSarbo, Ramaswamy, & Cohen, 1995). Each individual is assigned with membership scores in each class, which represent the probabilities of the individual belonging to each class. *Consistent Akaike Information Criterion* (*CAIC*) is recommended as the main measure of the goodness of the solution. In addition, the solution needs to provide decision support for managerial decision making. The segmentation is carried out for different numbers of classes with several repetitions to avoid local minima of *CAIC*. Thus, repetitive runs have to be made with a pre-set number of classes. Each run produces the *CAIC* measure

$$CAIC = -2\rho + (kc + c - 1)(\log(N) + 1) \tag{7}$$

where ρ is the log-likelihood, c is the number of classes, k is the number of independent parameters estimated per group.

For 2, 3, 4, 5, and 6 clusters, the *CAIC* was 11055, 10569, 10342, 10226, and 10212, respectively. We choose the 4-cluster solution. This is because even if *CAIC* was not at its smallest for the 4-cluster solution, it was clearly leveling off starting from this solution (i.e. the drop in CAIC from the 4-cluster solution to the 5-cluster solution was rather marginal, compared to the drop from the 3- to 4-cluster solution). Another advantage of the 4-cluster solution was that the size of the smallest cluster was still almost 15% of respondents, whereas in the 5- and 6-cluster solutions, the smallest clusters remained very small, below 10% of the respondents. Also, the classes in the 4-cluster solutions were relatively easier to interpret and characterize. The 4-cluster solution is shown in Table 4.

In Table 4, Cluster 1 stands out as the only one in which the investors have very little demand for SPs in general. The size of the cluster is 22.8% of the respondents, and the market share of none of the SPs exceeds the market share of any of the index fund comparison products, in this segment. Yet, in all the other clusters, representing the vast majority (77.2%) of respondents, there is substantial demand for at least some of the SPs. At the extreme cluster 4, representing 36.9% of the respondents, the investors would mostly prefer to invest in SPs only, especially the ones with partial capital guarantees and shorter maturity of 3 years (D_{3H}: 55% and D_{3C}: 18%)

In summary, the four clusters of Table 4 can be characterized as follows:

- Cluster 1. This cluster is not interested in SPs, as there is no substantial demand for either SPs with full or SPs with partial capital guarantees.
- Cluster 2. This cluster prefers SPs that have partial capital guarantees only, but feature higher upside returns potential and 3-year maturity (D_{3H} and D_{3C}). Among index funds, this cluster is attracted to all alternatives, except bonds and MSCI Germany.
- Cluster 3. This cluster prefers especially the SPs that have a longer-term maturity of 5 years, whether with full or partial capital guarantee.
- Cluster 4. Among the SPs, this cluster prefers especially the ones with shorter maturity of 3 years and partial capital guarantee (D_{3H}), even if the cost charge is included (D_{3C})

5. Theoretical analysis of TSPs

Next, we return to the portfolio optimization framework introduced in Section 2. Note that for finding optimal dynamic portfolio strategies, the multi-stage stochastic programming (MSSP) allows us to rebalance the portfolio at each time stage, and in fact, in each node of the scenario tree Γ.We start in Section 5.1 by theoretically analyzing the same SPs (with full and partial capital guarantees) considered in the empirical study and reflect the analytical results on those obtained in the empirical study. The market rate of interest and asset price processes underlying the survey are assumed to be the same as in Section 5.1. Given the heterogeneity of respondents in our survey, in the theoretical study, we also consider a variety of preferences toward risk and return, subjective portfolio restrictions, and individual market expectations.In Section 5.2, we further extend the theoretical analysis beyond the SPs discussed above by considering the impact of changes in the rate of interest and in the price processes of the underlying assets as well as considering a wide set of lower and upper limits on the annual return of the SPs. As an alarming example, we also discuss a yield enhancement product (YEP); see Vokata (2021). Finally, in Section 5.3, we make suggestions about the practical implementation of TSPs. Especially, we explore how transparency of TSPs can be assured and how retail investors could be supported in their choice of preferred SPs.

For the portfolio optimization framework, consider portfolio optimization with three or more assets: B (bank account), I (index fund), and one or more SPs D written on I. For m-stage stochastic programming, we adopt the binary tree Γ of Section 2 with $m = 10$ steps and step size $\delta = T/m$. The base model (1)–(3) is used with the following specifications and modifications:

- **Utility function.** Specifically, given a risk aversion parameter $\gamma \le 1$, let $u(v) = \frac{1}{\gamma} v^{\gamma}$ for $\gamma \neq 0$, and $u(v) = \log(v)$ for $\gamma = 0$; $r_R = 1 - \gamma$ is the Arrow–Pratt measure of relative risk aversion (RRA). As Luenberger (2013) suggests the risk aversion parameter γ for power utility to be in the neighborhood of zero, we let γ vary in the interval $[-1, 1]$.
- **Risk free return.** To start with, we set the rate of risk-free return at $r = 0.01$ from Section 3. Later, we test the impact of $r = 0.03$. The total risk-free annual return is $\exp(r)$.
- **Price process.** The MSCI Germany stock market index is the underlying asset I. For this, similarly as in Section 3.2, we use the estimates $\nu = 0.027$ for the drift and $\sigma = 0.238$ for the volatility of the price process following Geometric Brownian Motion

(GBM). Given node $k \notin N_T$ (k is not a terminal node), let p denote the conditional probability of a price increase for the index fund I and let $1 - p$ denote the probability of a price decrease. In the base model, the logarithmic increase in the price of I in a single time step of δ becomes $u = \nu\delta + \sigma\sqrt{\delta}$ and the decrease is $d = \nu\delta - \sigma\sqrt{\delta}$. For $p = .5$, the expected logarithmic change in price is $\nu\delta$ and the variance is $\sigma^2\delta$, so that the binary process fits the estimated data. In contrast, a choice $p > .5$ ($p < .5$) reflects excessively optimistic (pessimistic) expectations on future market developments.

- **Arbitrage pricing.** Given the logarithmic price increments u and d for the index I, the respective risk neutral probabilities are $q_u = [\exp(r\delta) - \exp(d)]/[\exp(u) - \exp(d)]$ and $q_d = 1 - q_u$; see Cox et al. (1979). For our data, $q_u > 0$ and $q_d > 0$, and they are used in backward recursion to determine the value of the cash flow of D in each node of Γ.
- **Self-imposed imperfections.**The portfolio weights have lower limits $\bar{w}_a$ and upper limits $\hat{w}_a$ for the assets $a = 0, 1, \ldots$ referring to risk free asset B, index fund I, and SP D, respectively. For all nodes k of the tree Γ, x_{ak} is the value in asset a and sx_k is the portfolio value, with a column vector $x_k = (x_{ak})$ and sum vector $s = (1, 1, \ldots)$. Thus we have the following additional constraints:

$$\bar{w}_a s x_k \le x_{ak} \le \hat{w}_a s x_k \quad \forall\ a,\ \forall\ k \notin N_T \tag{8}$$

- **Holding assets.** We assume an investment in D is held until maturity; hence, for $a > 1$ we require

$$x_{ak} = R_{ak} x_{ak_-} \quad \forall\ k > 0 \tag{9}$$

where k_- is the immediate predecessor node of node k and R_{ak} is the total return of D from node k_- to k. Note that the investment in D can only be purchased at time 0 and can only be sold at time T. Hence, any rebalancing activities involve only the holdings in B and I.
- **Bank charges.** A proportional bank charge $c \ge 0$ applies to buying products D. That is, if the theoretical price of D is P (under perfect market), then the agent pays a price $(1 + c)P$. However, product D with maturity T must yield the annual return after bank charges within limits L and U as promised. Hence, the strike prices satisfy $\frac{K_1}{(1+c)P} = (1 + U)^T$ and $\frac{K_2}{(1+c)P} = (1 + L)^T$. Given the random total return S_T of I, the price of D is given by $P = e^{-rT} E[F_T]$ where $E[F_T]$ is the risk neutral expectation of the random cash flow $F_T = \min(K_1, \max(K_2, S_T))$ of D at T. Because F_T depends on strike prices K_1 and K_2, we solve for K_1, K_2, and P from the equations above. For simplicity, bank charges for assets B and I are set to zero.
- **Market expectations.** We assume the bank issuing the SPs relies on a perfect and complete market while retail customers (agents) may perceive a different market as specified below.

5.1. Comparing empirical and theoretical results

In this section, we address research questions RQ1-RQ3 by analytically studying four of the SPs, D_{3L}, D_{3H}, D_{5L} and D_{5H}, of the empirical study, summarized in Table 1. Using Mosek software (ApS, 2021), we solve numerically a series of multi-stage stochastic programming problemsto find an optimal portfolio strategy both with and without SPs. This enables us to determine the gain Δe in the certainty equivalent annual return (*CER*) due to the SPs.

To start with, consider portfolio optimization with assets B, I, and one or two SP derivatives among D_{TL} and D_{TH} in Table 1 written on I. In case of two derivatives, both an SP with full capital guarantee and an SP with partial capital guarantee (of the same maturity) are included. We assume that the financial institution providing the products considers a complete and perfect market. Instead, retail investors (agents) are subject to several market imperfections and other assumptions about the market, as follows:

- Investments in *SPs* are held until maturity of T years.
- Short positions are prohibited and weight upper limits $\hat{w}_I$ are considered for asset I.
- Relative cost charges c apply to prices of products D.
- Two variants of the agent's market expectations are investigated:
  - *aligned*: the agent shares the view with the bank
  - *optimistic*: the agent expects the annual return of asset I to be 5% above the bank's estimate.[8]

Furthermore, in the analyses below, we assume (unless otherwise stated) that the risk-free rate of return is $r = 0.01$, the risk aversion parameter γ is in $[-1, 1]$, the drift ν is 0.027, and the volatility σ is 0.238. The analysis is divided into the four sub-tasks T1,…,T4 concerning variations in underlying assumptions.

T1. Some specific instances. First, we study the gain Δe as a function of the risk aversion parameter γ in some specific instances involving certain assumptions about the market. We consider portfolio optimization with three assets only: B, I, and a single derivative SP, D. A few instances of results are shown Fig. 5 with $\hat{w}_I = 0.3$. Two cases are presented, specifically: (a) a case wherein cost charge $c = 0$ and market expectations are aligned ($p = .5$), and (b) a case wherein c=1% and investors' market expectations are optimistic ($p > .5$). Fig. 5 shows (for both cases and separately for the four products D) the contribution Δe in *CER* due to SP D in the optimal portfolio of assets B, I, and D. The annual return contribution Δe in case (a) ranges from 11 to 82 basis points and in case (b) from 17 to 224 basis points.[9] The optimal portfolio weight of SP D at the root node ranges from 0.62 to 0.70 for both cases, all products D, and $-1 \le \gamma \le 1$. Hence, in the general case, strong demand for an SP D seems to exist, when it is an alternative investment in a portfolio with I and B. This is in line with empirical findings concerning RQ1.

Second, to focus on RQ2,related to the relative demand for SPs with full vs. partial capital guarantees, we let SPs with full and partial capital guarantees compete in an optimal portfolio. We compare the demand for D_{TL} and D_{TH} in the cases $T = 3$ and $T = 5$. As above, with $\hat{w}_I = 0.3$, we consider the same two cases (a) and (b). In all instances, the optimal portfolio weight of the SP with partial capital guarantee, D_{TH}, at the root node is in the interval [0.63,0.70], while the weight of the SP with full capital guarantee, D_{TL}, is zero. Hence, the graphs of Δe as a function of γ are those shown in Fig. 5a for products D_{TH}. With regard to RQ2, all cases indicate a strong demand for the SP with partial capital guarantee only, D_{TH}, and no demand for the SP with full capital guarantee. These results are highly consistent with our empirical results, suggesting that no disproportionate demand exists for the SPs with full capital guarantees; on the contrary, the demand for SPs with partial capital guarantees results much higher than that for SPs with full capital guarantees.

Third, we now assume that the agent perceives the volatility σ of the underlying asset differently from the bank. Consider two cases: assume that $\sigma = 0.238$ (seen by the financial institution providing the products) is as above but the investor-agent perceives a volatility that is either 5% points higher or lower. This changes the agent's return prospects of products I and D. Adopting the terminology of Hens & Rieger (2014), in case the investor perceives the higher volatility, the investor is *under-confident* about the market and the range of the gain Δe over $-1 \le \gamma \le 1$ for the four products D_{3L}, D_{3H}, D_{5L}, and D_{5H} decreases by 2–12 basis points

[8] The 5% excess return is approximately achieved by setting the probability for price increase to $p = .56$ for T=3 and $p = .58$ for T=5.

[9] In case (b), if we set $c = 0$, then Δe increases further by 20 to 30 basis points.

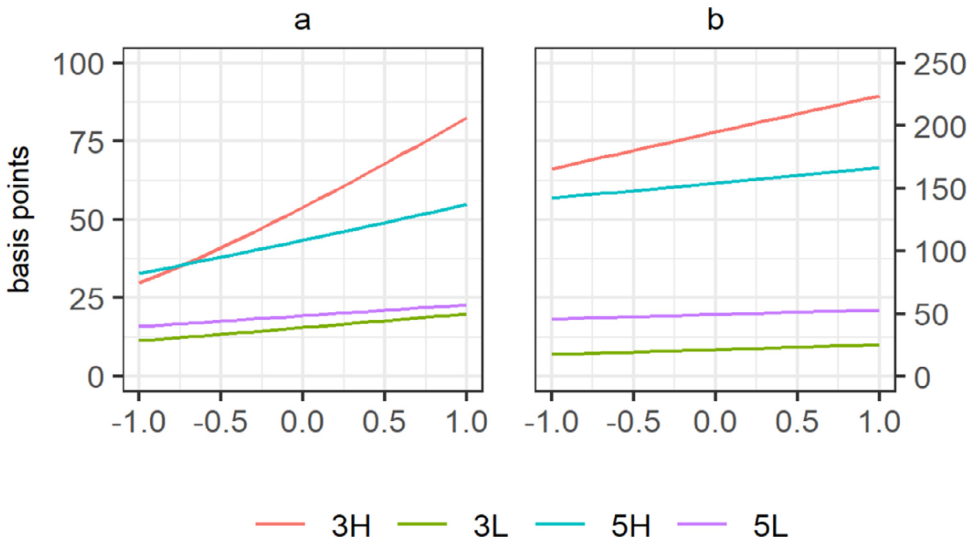

Fig. 5. Portfolios of *B*, *I*, and *D*. The gain Δe (basis points) in *CER* due to structured product *D* with risk aversion parameter $\gamma \in [-1, 1]$, with weight limit $\hat{w}_I = 0.3$, and with $c = 0$, $p = .5$ (left) or $c = 0.01$, $p > .5$ (right). The four lines in each sub-figure refer to the four products D_{3L}, D_{3H}, D_{5L} and D_{5H}. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Portfolios of *B*, *I*, and *D*. The contribution Δe (basis points) in *CER*, due to four assets *D* (D_{3L}, D_{3H}, D_{5L}, D_{5H}). γ = risk aversion parameter; *c* = cost charge; $\hat{w}_I$ = weight limit for the underlying asset.

		$\hat{w}_I = 0.3$				$\hat{w}_I = 0.4$				$\hat{w}_I = 0.5$			
c (%)	γ	3*L*	3*H*	5*L*	5*H*	3*L*	3*H*	5*L*	5*H*	3*L*	3*H*	5*L*	5*H*
		aligned market expectations											
0	-1	11	30	16	33	6	13	9	18	2	3	4	8
0	0	16	54	19	43	10	35	12	28	6	20	7	16
0	1	20	82	23	55	14	63	16	39	10	46	10	26
1	-1	0	12	2	19	0	3	0	8	0	0	-0	1
1	0	0	31	5	29	0	16	1	16	0	6	0	7
1	1	0	57	8	40	0	41	4	26	0	28	1	16
		optimistic market expectations											
0	-1	48	192	64	159	35	148	48	123	25	110	35	92
0	0	53	222	68	171	40	178	52	135	30	138	38	103
0	1	57	251	72	184	45	207	56	148	35	165	42	115
1	-1	17	165	45	141	10	125	32	108	5	91	22	79
1	0	21	194	48	154	14	154	36	120	9	118	25	90
1	1	25	223	52	166	19	182	39	132	13	144	28	102

from [11,20], [30,82], [16,23], and [33,55] (from case (a) in Fig. 5), respectively, to [8,18], [18,74], [12,19], and [23,47]. In case the investor perceives the lower volatility, her *over-confidence* leads to increased ranges of the gain Δe, to [15,22], [43,90], [20,26], and [43,63], respectively. This constitutes an improvement of 2–13 basis points only. Thus, the sensitivity of the gain Δe is rather minor with respect to the volatility σ.

T2. A broader set of instances. For a broader picture, beyond task **T1**, more instances of portfolio optimization results on the incremental value Δe are shown in Table 5 for the four variants D_{TL} with full and partial capital guarantees (and with maturity *T* of 3 or 5 years). Here, we consider levels 0.3, 0.4, and 0.5 for the limit $\hat{w}_I$, levels 0% and 1% for the cost charge *c*, and three levels -1, 0, and 1 for the risk aversion parameter γ. Both aligned and optimistic market expectations are studied. Consider the case with aligned expectations first. For $c = 0$ and $\hat{w}_I = 0.3$, the contribution Δe due to product *D* clearly implies a demand for each product D_{3L}, D_{3H}, D_{5L} and D_{5H}. However, the SPs with partial capital guarantees only are again more favorable than the ones with full capital guarantees. The same applies to $c = 0$ and when $\hat{w}_I$ increases to levels 0.4 and 0.5. Letting the cost charge increase to 1%, the SPs with partial capital guarantee remain favorable while the SPs with full capital guarantee do not. Letting $\hat{w}_I$ increase beyond the level 0.5, in turn, leads to vanishing incremental value for all four SPs. In the case of optimistic market expectations, similar phenomena are observed; however, the contributions Δe due to SPs *D* remain much higher in that case.

T3. Incomplete markets. Concerning the impact of market incompleteness, we study a case similar to the one in Fig. 5a, with $c = 0$ and aligned market expectations ($p = .5$). However, we now assume the investor faces an incomplete market (with $n = 4$ edges branching from each non-terminal node *k* of the scenario tree Γ) while the financial institution providing the products relies on a complete and perfect market. Incompleteness of the market implies that there are unhedgeable assets. In our complete market model, there are two equally likely edges branching from nodes in the scenario tree, and the logarithmic increment in the price of *I* in a single time step of δ is $u = \nu\delta \pm \sigma\sqrt{\delta}$, as explained above. In the incomplete market model with four equally likely edges branching from each non-terminal node, the logarithmic price increment for two branches is $\nu\delta \pm f\sigma\sqrt{\delta}$, and for the other two branches, $\nu\delta \pm 3f\sigma\sqrt{\delta}$, where $f = 1/\sqrt{5}$. These choices result in the same drift and volatility of *I* as in the complete market model. Thus,we assume that both agree on the estimates of the drift $\nu = 0.027$ and the volatility $\sigma = 0.238$ of the underlying asset *I*. In this analysis, the *CER* contributions Δe as well as initial portfolio weights for the

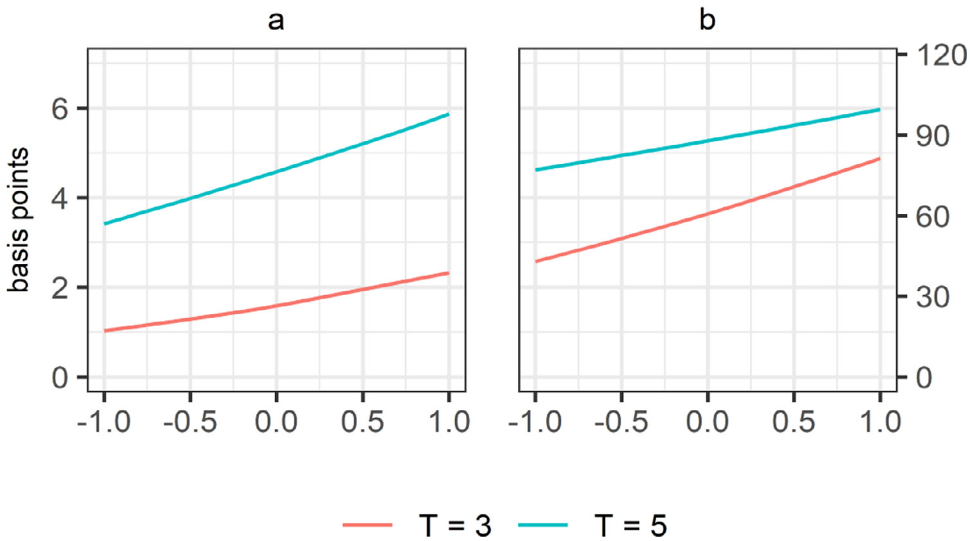

Fig. 6. Prospect Theory. The gain Δe (basis points) due to structured product D with risk aversion parameter $\gamma \in [-1, 1]$, with weight limit $\hat{w}_I = 0.3$, and with $c = 0$, $p = .5$ (left) or $c = 0.01$, $p > .5$ (right). The two lines in each sub-figure refer to the structured products with maturity $T = 3$ and $T = 5$ years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

four SP products D become quite similar with the respective values in Fig. 5a (for brevity, we omit displaying these results). Hence, in this case, market incompleteness alone does not play a major role in shaping the attractiveness of the capital-guaranteeing SPs.

T4. Prospect theory. Finally, we again let the SPs with full capital guarantee, D_{TL}, and with partial capital guarantee, D_{TH}, compete in the same portfolio – but now the S-shaped utility utility function $u(v)$ is adopted from the prospect theory (Kahneman & Tversky, 1979), with the reference level $v = 1$ referring to total annual return; i.e., $v = 1$ is equivalent to a zero annual net return. The value function $u(v)$ is strictly increasing and continuous for all $v \geq 0$,it is strictly convex for $v < 1$, strictly concave for $v > 1$, and the marginal value decreases at the reference level $v = 1$ by factor λ.[10] We use $\lambda = 2.25$, as reported in Hastie & Dewes (2001), although significant cross-country differences in risk attitude exist; see Rieger, Wang, & Hens (2015).

Fig. 6 again depicts two specific cases: (a) a case with cost charge $c = 0$ and aligned expectations ($p = .5$) and (b) a case with $c = 0.01$ and optimistic expectations ($p > .5$), both with $\hat{w}_I = 0.3$. Fig. 6 shows the joint contribution Δe due to both structured products D_{TL} and D_{TH}. In case (a), for $T = 3$, the optimal initial portfolio weight on the SP with full capital guarantee, D_{3L}, is in the range [0.51,0.60] while the weight on the SP with partial capital guarantee, D_{3H}, is zero. For $T = 5$, the optimal portfolio weight for the former, D_{5L}, is in the range [0.45,0.52] and for latter, D_{5H}, in [0.06,0.12]. With regard to RQ2,case (a) would indicate a strong demand for the SP with full capital guarantee and no or small demand for the SP with partial capital guarantee. This is in conflict with our empirical results, as well as those based on expected utility analysis. At the same time, however, this constitutes further evidence with respect to RQ2:individual investors do not seem to be risk averse in the prospect-theory sense (which would imply that they had greater preference for the SPs with full capital guarantees, than those with partial capital guarantees only). At any rate, even when assuming prospect-theoretical utility function, in case (b) (and both for $T = 3$ and $T = 5$), the roles of the two SPs are inverted, again, and investments in the SP with full capital guarantee again become zero.

To summarize, comparing our empirical and theoretical results, we observe remarkable consistency. Firstly, both studies show that individual investors exhibit strong attraction towards SPs in general, as an alternative to investing in index funds directly (underlying asset). Secondly, considering both SPs with full capital guarantees and those with partial capital guarantees only, the former SPs are not favored over the latter. In fact, both studies suggest that the SPs with partial capital guarantees are clearly favored over SPs with full capital guarantees. In this sense, the final analysis above showed that that preferences for SPs with full vs. partial capital guarantees are also in disharmony with value functions suggested by prospect theory. Thirdly, because all costs embedded in the return figures of TSPs enter logically in portfolio optimization, a positive answer to RQ3 is also consistent with empirical findings.

5.2. Extensions of theoretical analysis

To broaden our understanding of TSPs, we analyze four more test extensions **E1**–**E4** concerning interest rates, underlying assets, and return limits, as well as a cautionary example. The numerical results in this section are based on the same theoretical framework which is used in Section 5.1. Hence, all relevant formulae are as above and only some of the data parameters change.

E1. Changing interest rate. To see the sensitivity of the results with respect to risk-free interest rate, we ran the case (a) of task **T1**, shown in Fig. 5a, with the risk-free interest rate r increased from 0.01 to 0.03. For products D_{3L}, D_{3H}, D_{5L}, and D_{5H}, the ranges of the gain Δe (basis points) in *CER* with $-1 \leq \gamma \leq 1$ decreased substantially from [11,20], [30,82], [16,23], and [33,55], respectively, to $[0, 6]$, $[0, 23]$, $[1,6]$, and $[2,13]$. A simple explanation for the decrease in Δe is an intensified competition due to the increased return on the risk-free asset B. However, the full story is more complicated because an increase in r affects risk neutral probabilities and the prices P of the SPs, as well as the strike prices K_1 and K_2. For example, for D_{3L} with $(L, U) = (0, 4)$ (percent), the interval $[K_2, K_1]$ shifts down from [1.26,1.42] for $r = 0.01$ to [0.75,0.84] for $r = 0.03$. Consequently, the expected annual return for D_{3L} is 1.2% for $r = 0.01$ and 2.9% for $r = 0.03$. Yet, in the latter case, D_{3L} is less valuable under the increased interest rate r.

[10] For $v \geq 1$, our value function is a CRRA utility function as before: for $\gamma \neq 0$, $u(v) = \frac{1}{\gamma}(v^\gamma - 1)$, and for $\gamma = 0$, $u(v) = \log(v)$. Thus, in both cases, we have $u(1) = 0$ and $u'(1) = 1$. For $v \leq 1$ and $v \geq 0$, u is the mirror image (of $u(v)$ for $1 \leq v \leq 2$) with respect to $v = 1$ multiplied by $-\lambda$ where $\lambda > 1$; i.e., for $v \in [0, 1]$, $u(v) = -\frac{\lambda}{\gamma}[(2 - v)^\gamma - 1]$ if $\gamma \neq 0$ and $u(v) = -\lambda \log(2 - v)$ if $\gamma = 0$.

Table 6
Portfolios of B, I, and D. The gain Δe (basis points) due to structured product D as a function of annual return limits L (%) and U (%) for maturities $T = 3,\ 5$ years, risk aversion parameter $\gamma = -1,\ 0,\ 1$, aligned market expectations ($p = .5$), weight limit $\hat{w}_I = 0.3$, interest rate $r = 0.01$ and cost charge $c = 0$.

	$\gamma=-1$					$\gamma=0$					$\gamma=1$				
$U\backslash L$	0	-2	-4	-6	-8	0	-2	-4	-6	-8	0	-2	-4	-6	-8
	$T=3$														
4	11	18	21	22	22	16	26	31	33	34	20	34	40	44	47
8	13	23	27	29	29	19	36	45	50	52	26	51	64	72	78
12	14	24	29	30	31	21	40	51	56	60	29	59	76	88	96
16	14	24	29	31	32	21	42	53	60	63	30	63	83	96	105
20	14	24	29	31	32	22	43	54	61	64	31	65	86	102	112
	$T=5$														
4	16	25	29	30	30	19	31	37	39	39	23	38	44	47	49
8	19	33	38	40	40	24	43	52	57	58	30	55	68	74	78
12	20	34	40	42	43	26	47	58	63	65	32	62	78	87	92
16	19	34	40	43	44	26	49	59	64	67	33	65	83	93	99
20	19	34	40	43	44	26	49	60	65	68	34	67	85	95	102

E2. Alternative underlying assets. Instead of the drift ν and the volatility σ used in Subsection 5.1, we may consider other underlying assets which deviate from MSCI Germany only in these two parameters. In Section 5.1, task **T1**, we discussed the cases concerning an increase and decrease of volatility σ by 5 percentage points; otherwise, the assumptions were as in task **T1**. The impact in the gain Δe was rather minor, 13 basis points at the maximum. Next, we test similarly an increase and decrease in the drift ν by 2 percentage points. In case of decreasing the drift to $\nu = 0.007$, the ranges of the gain Δe (basis points) in $-1 \le \gamma \le 1$ for the four products D_{3L} D_{3H}, D_{5L}, and D_{5H} decrease from [11,20], [30,82], [16,23], and [33,55], respectively, to [0,7], [0,22], [1,7], and [2,12]. Similarly, an increase to $\nu = 0.047$ yields the ranges [24,33], [87,149], [32,39], and [78,103]. Thus, in both cases the impact of changing ν is rather significant, in particular, for products D_{TH}.

E3. A wide spectrum of return limits. Next, starting from the case (a) of task **T1**, we study the impact on the gain Δe due to varying limits L and U on the annual return of the SP. Table 6 shows the cases with aligned market expectations ($p = .5$), cost charge factor $c = 0$, risk-free interest rate $r = 0.01$, three levels of risk aversion parameter γ = -1, 0, 1, and weight limit $\hat{w}_I = 0.3$.

Certain result figures in Table 6 may seem surprising. For example, for $T = 3$ and $\gamma = -1$, both cases D_a with $(L, U) = (-4, 16)$ and D_b with $(L, U) = (-8, 8)$ provide $\Delta e = 29$ basis points; i.e., D_a and D_b are equally good. To interpret this, it is helpful to notice that for D_a and $\gamma = -1$, the price $P_a = 1.12$ as well as the strike prices $K_1 = 1.75$ and $K_2 = 0.99$ are much higher than the respective figures $P_b = 0.91$, $K_1 = 1.15$, and $K_2 = 0.71$ for D_b. Please see Fig. 7, where the 3-year total return R_T for D_a is shown in green and for D_b in red, both as a function of the 3-year total return S_T of the underlying asset. For D_a, the strike prices are $K_1 = 1.75 \approx 1.20^T$ and $K_2 = 0.99 \approx 0.997^T$, showing an annual return 20% and -0.3%, respectively, for the underlying asset. Because $P_a > 1$, both of these are well above the limits 16% and -4% of D_a. For D_b instead, $K_1 = 1.15 \approx 1.05^T$ and $K_2 = 0.71 \approx 0.89^T$; in this case, both annual returns of S_T (5% and -11%) are below the respective limits 8% and -8%, because $P_b < 1$.

By definition of the strike prices, if P denotes the price P_a or P_b, then $K_1/P = (1+U)^T$ and $K_2/P = (1+L)^T$, so that the slope of R_T in the interval $[K_2, K_1]$ is $[(1+U)^T - (1+L)^T]/(K_1 - K_2) = 1/P$. Thus, the slopes of the green and red increasing line segments in Fig. 7 are $1/P_a < 1$ and $1/P_b > 1$, respectively. On the lower tail (with $S_T < 0.82$ and annual returns -4%) and on the upper tail (with $S_T > 1.45$ and annual return ranging fron 8% to 16%) of the return distribution,D_a is favorable over D_b. However, in the wide middle range ($0.82 < S_T < 1.45$), the preference order is reversed and the probability for this event is quite high as shown by dotted line of the log-normal pdf of S_T. For $\gamma = -1, 0, 1$, similar arguments are helpful in seeing why both D_a and D_b are preferred

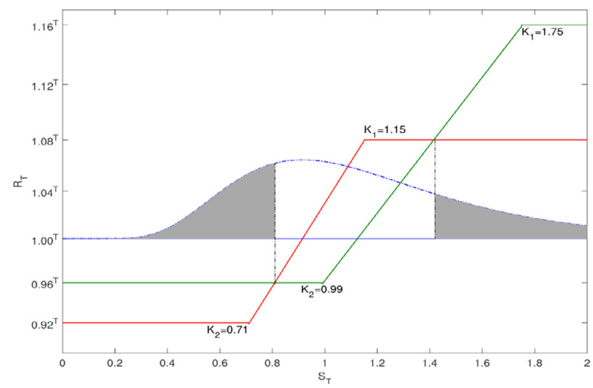

Fig. 7. Comparison of two SPs, D_a with $(L, U) = (-4, 16)$ and D_b with $(L, U) = (-8, 8)$ (% p.a.), both with maturity $T = 3$ years and $\gamma = -1$. S_T (horizontal axis) is T-year total return of the underlying asset; R_T (vertical axis) is T-year total return for D_a (in green) and D_b (in red); dotted line shows the pdf of the log-normal return S_T and the shaded tails refer to levels of S_T where D_a is superior to D_b. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

to the case $(L, U) = (-4, 8)$, and why both are inferior to the case $(L, U) = (-8, 16)$.

In the cases of Table 6 the increments Δe are significant in general: however, this is based on zero (or small) cost charges c. For $T = 3$ years and $c = 1\%$, the increments Δe vanish for all cases (L, U) in Table 6 with $L = 0$. The same occurs for $T = 5$ years and $c = 2\%$.

E4. Cautionary cases: yield enhancement products (YEP). Vokata (2021) studies the performance of a sample 28,000 YEPs from 2006–2015 which advocate attractive yields; yet, offering benefits incompatible with investor's preferences. To illustrate one type of YEP, we set the thresholds of an SP to $K_1 = 1$ and $K_2 = 0$; if the price for the SP is P, then the annual return limits are $L = 0$ and $U = (1/P)^{1/T} - 1$. To see the idea of such a YEP, let us consider the case (a) of task **T1** of Section 5.1 with $T = 3$ years but increasing the volatility of I to $\sigma = 0.4$, a typical choice for YEPs in practice. For the cost factor c, we consider two alternatives. First, if $c = 0$, then $U = 11.7\%$ and the increment Δe ranges from 22 to 132 basis points for $-1 \le \gamma \le 1$. However, according to Vokata (2021), on the average YEPs charge 6–7% annually. For example, cost factor $c = 0.15$ means about 5% annual charge. In this case we have $U = 6.6\%$ which still may seem abnormally lucrative; however, the gain Δe falls to zero even for a risk neutral investor.

For comparison, we consider the YEP with $c = 0.15$ and the TSP with $L = -5\%$, $U = 12\%$ and $c = 0.01$, both written on the same index fund with volatility $\sigma = 0.4$ and $T = 3$ years. In a binary tree with T subdivided into $m = 10$ time steps, there are $2^{10} = 1024$

Table 7
Comparison of a YEP and a TSP. n_i = number of scenarios for different levels s_I of index return; s_I = annual return (%) of the idex I; s_{YEP} = annual return (%) of the YEP; s_{TSP} = annual return (%) of the TSP; the last column shows the sum of scenarios n_i, and the expected values of s_I, s_{YEP} and s_{TSP}.

n_i	1	10	45	120	210	252	210	120	45	10	1	1024
s_I	-50.5	-42.7	-33.7	-23.3	-11.2	2.7	18.9	37.6	59.2	84.3	113.2	5.5
r_{YEP}	-47.2	-38.9	-29.3	-18.2	-5.3	6.6	6.6	6.6	6.6	6.6	6.6	-0.8
r_{TSP}	-5.0	-5.0	-5.0	-5.0	-5.0	0.8	12.0	12.0	12.0	12.0	12.0	2.8

scenarios. As stated at the beginning of Section 5, in m time steps, the logarithmic change in the index value of I is $iu + (m-i)d$, where i, for $i = 0, 1, \ldots, m$, is the number of price changes up and $m - i$ is the number of changes down. Hence there are $m + 1$ distinct price levels of I at the end of the 1024 scenarios. Table 7 shows the net annual return (%) s_I of the index I, r_{YEP} of the YEP, and r_{TSP} of the TSP. The number of scenarios n_i, $i = 0, 1, \ldots, m$, at each price level is shown in the table and they are used to determine expected annual returns in the last column: -0.8% for the YEP and 2.8% for the TSP; this and the return distributions show the advantage of the TSP over the YEP.

Why someone still might be interested in investing in YEPs, such financial engineering 'lemons'? Some of the reasons may be as follows. The issuer bank targets YEPs to unsophisticated investors and appealingly frames the coupon rates, with the intention to exploit the investors' potential biases. Due to a salient presentation of attractive coupon rates U (paid semi-annually), and less salient description of loss likelihoods, the investor may overweight the chances of favorable returns and under-weight the possibility of losses. The probability of loss depends on the volatility σ. In our example, the loss probability is 38%. Furthermore, the increase of σ from the initial level 0.238 to 0.4 contributes an increase of about 5% points in the annual return U.

From these extensions of the theoretical analysis, we learn that *CER* of a SP (with partial capital guarantees) D is sensitive to changes in the interest rate r and in the drift of the underlying asset. Obviously, *CER* is sensitive to the annual return limits L and U of the derivative D. Within the range of values shown in Table 6 for the limits, we notice that the *CER* increases with U, given a fixed level of L. Yet, more surprising may be the observation that for any given U, *CER* increases with a decreasing, more negative L. An intuitive explanation may lie in the observation that the expected return of the SP increases with increasing U as well as with decreasing L. The true explanation is rooted in the fact that the price P as well as the strike prices K_1 and K_2 are jointly determined by the limits L and U. At the end, the cautionary example about YEPs demonstrates how an issuer bank may be tempted to framing manipulation.

5.3. Supporting retail investors' decisions when choosing SPs

In Table 6, the increments in *CER* are significant in general. However, based on our analysis, *CER* may not be helpful for a retail investor to choose the most preferred SPs because of monotone improvements with respect to limits L and U. In fact, for power utility and for any risk aversion parameter γ, $-1 \le \gamma \le 1$, the expected utility of the SP is also similarly monotone in L and U. Yet, it seems plausible that a retail investor prefers an SP with limits (L, U) where the lower limit L is not a large negative percentage figure.

To assist the retail investor in comparing alternative return limits (L, U) and cost charges, Fig. 8 shows examples how this might be arranged. For given levels of capital protection L, the graphs show the annual net return r_D of SPs as a function of annual net returns s_I of the underlying asset I. For each L, there are alternative choices for U. The dotted line in Fig. 8 shows the pdf of s_I, assuming GBM for the price process of I (with drift $\nu = 0.027$

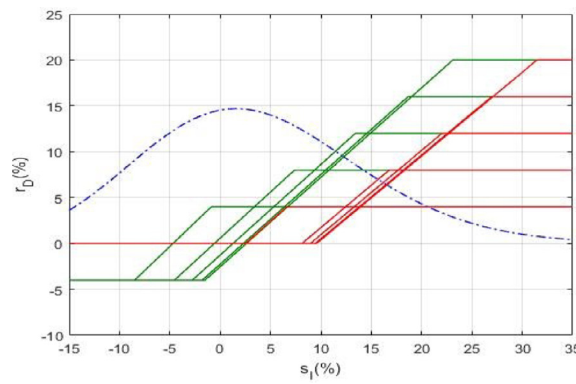

Fig. 8. Annual return comparison of SPs with $L = 0\%$ (red) and $L = -4\%$ (green); i.e., SPs with full and partial capital guarantee. For both cases, alternative levels U = 4, 8, 12, 16, 20% are considered. The horizontal axis shows the annual net return s_I of the underlying asset I and the vertical axis the annual net return r_D of the SPs. The dotted line shows the pdf of s_I. Maturity is $T = 5$ years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and volatility $\sigma = 0.238$ as in Section 5.1). For the total return S_T over T years, $S_T \sim \log - N(T\nu, T\sigma^2)$, and the annual total return is $1 + s_I = S_T^{1/T}$ which is also log-normal,[11] $1 + s_I \sim \log - N(\nu, \sigma^2/T)$.

For cases with $L = 0\%$, Fig. 8 reveals that the probability of return $r_D = 0$ is about 50–70% (depending on the upper limit U) and r_D rises above zero only after the return s_I of the underlying exceeds 8 to 10% for $U \ge 8\%$; yet, in such events the SPs with $L = -4\%$ can yield 8% return already. This demonstrates why SPs with full capital protection may not be highly desirable. Both cases $L = 0\%$ and $L = -4\%$ show that relaxation in upper limit U leads to an increased probability of r_D hitting the lower limit L. Similarly, for all U, a decrease of L from 0% to -4% increases the probability of r_D hitting the upper limit U.

These illustrative diagrams in Fig. 8 are produced assuming GBM for the price process of I, and setting the bank charge c to zero. However, in practice, similar figures based on moderate bank charges and on the banks' view of the price process of the underlying asset can be helpful to state clearly all commitments of the issuing bank and to provide a transparent basis for a retail investor to identify preferred investments in SPs. In such a real situation, it is not necessary for the bank to reveal the assumed price process nor even the cost charges; similarly as for any other investment products, it is left to the investors to use private judgement without fear of being manipulated.

6. Discussion and conclusions

A wide variety of structured products (SPs) exist, especially in the European and US markets. A growing body of literature discusses SPs from diverse perspectives (e.g., Célérier and Vallée,

[11] Note that $S_T = \Pi_{t=1}^T R_t$ where $R_t \sim \log - N(\nu, \sigma^2)$ is the return of year t. Because returns R_t are i.i.d. random variables, $\log(1 + s_I) = (1/T)\log(S_T) = (1/T)\sum_t \log(R_t)$ is normally distributed, the expected value is $E[\log(1 + s_I)] = \nu$ and the variance is $\mathrm{var}[\log(1 + s_I)] = \sigma^2/T$.

2017; Baker and Puttonen, 2017). A highly critical stance towards SPs is common to many literature sources. Most notably, the SPs have been criticized for the fact that their logic is too complex to understand in-depth, while at the same time they allegedly exploit risk-averse individual investors' emotionally biased attraction towards the surface elements of these products: the tempting headline return and the ostensible protection they offer for the invested capital. Another stark critique is targeted to the fact that the cost structure of SPs is often not very clear. That is, financial service-providers seem to have an incentive to conceal various cost charges within the relatively complex structure of SPs, in order to profit on investors' inability to notice or fully take the cost charges into account.

Against this backdrop, we embarked to investigate TSPs, transparent SPs, which could be immune to, or at least less subject to, the above criticisms. For a given maturity, a TSP contract among the issuing bank and a retail investor simply offer a lower and upper limit on annual return after all bank's charges as well as a transparent rule defining the annual return of the TSP based on the annual return of the underlying asset, such as a well-known stock market index. While the lower limit provides full or partial capital protection, the upper limit serves for reducing the cost of the TSP and for increasing the chances of the return exceeding the lower limit.

We investigate three research questions. First, we studied investors' attraction towards TSPs in competition with alternative non-SP investments. Second, we addressed the alleged tendency of SPs to exploit investors' psychological bias towards SPs with full capital guarantees, versus ones with partial capital guarantees only. In turn, the third question addressed the implicit cost charges: are individual investors able to take into account the implicit costs of the SPs?

Regarding all three questions, both our empirical results and theoretical analyses provide consistent answers. Moderately priced TSPs appear in high demand among retail investors. Both studies consistently indicate considerably greater investor demand for SPs with partial capital guarantees only, as opposed to SPs with full capital guarantees. Hence, investors do not seem to be behaviorally biased, much at all, towards only favoring SPs with full capital guarantees (in the prospect theoretical sense, or otherwise). Finally, regarding the issue of hidden costs, in theoretical analysis, of course, all embedded costs are logically incorporated. However, our empirical results also indicate that individuals are generally able to take into account the costs of TSPs even though they were presented to them rather implicitly, within historical return graphs.

Our theoretical analyses based on MSSP allowed further examination of the important roles that private market expectations, market imperfections, and market rates of interest have in shaping the demand for SPs. As a final culmination, we suggested how TSPs might be implemented in practice. Here, the key issue is to simply depict the return graph of the TSP, in terms of how the annual net return (after bank charges) depends on the annual net return of the underlying asset. This was demonstrated by examples in Fig. 8. In such a real situation, banks need not reveal their assumptions on underlying price processes (for instance, by omitting any pdf as shown in Fig. 8) nor even their charges; it is left to the customer to use the return graphs and private judgement, free of manipulation.

Besides for their optimal (rational) return-risk profile for future, we assume that the real investors in our empirical study may have preferred the presented TSPs due to the following, 'behavioral' reasons. (1) The historical return graphs, presented side by side for the TSP and the underlying index product, vividly illustrated the return-risk profile of the TSPs, and made them easy to grasp for the investors as well as easy to compare with the index products. In real markets, the return-risk profiles of SPs are rarely presented in this illustrative, or comparative, way, as the marketing materials for the SPs often focus on text and numbers about the key parameters of the product. (2) The cost of the TSP was also relatively clearly illustrated in the aforementioned graphs. This may have elicited confidence among the investors, in the fact that they are not requested to invest in a product whose cost components they do not quite understand. (3) The fact we illustrated the return-risk profile of the product with historical return graphs, instead of hypothetical future return levels of the underlying index fund, is likely to have further eased up the investors' decision-making. Paradoxically enough, even if it might be claimed that historical return graphs are questionable to present (as historical returns are no guarantee of future), for retail investors, the historical return graphs may be the most illustrative and informative way of convincing the investors about the potentially favorable return-risk profile of the TSPs.

When it comes to limitations of the present research, firstly, our empirical survey study suffered from a relatively low response rate.[12] Nevertheless, the final sample of 301 investors was adequate for the BWS approach employed in the analysis. Another advantage of our sample was that the respondents were real retail investors of the Finnish Shareholder Association. Even though the sample is not representative for retail investors, the respondents' preferences can be considered universal in the sense defined by standard textbooks on financial investments (e.g., Luenberger (2013)). Secondly, even if the survey respondents were reminded that the historical returns shown to them did not ensure similar returns in the future for any of the products presented, it is unclear whether the respondents' trust in the historical (vs. expected future) returns differed for the SPs versus the index fund products. This could be studied in more detail in future empirical research. Thirdly, our theoretical analysis relies on GBM for the asset price processes. Although GBM has been for decades a standard in finance research, other approaches to price processes exist, as well.

We conclude that there is room on the market for moderately priced simple TSPs. We end up suggesting a basis to successful implementation of SPs in future financial markets. Thus, our findings may help financial service providers to improve customer service by designing SPs with genuine benefits for both retail investors and financial institutions. Our suggestion to the financial supervisory agencies on SPs is three-fold: first, to request an easily understandable definition of the SP's return, net of all costs, based on the return of the underlying asset; second, not to allow the marketing material include statements which aim to divert the customer's attention from the core features (defining the benefits to the customer) of the SP; third, to prevent the issuer also from other marketing communication which is potentially misleading to the customers.

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[12] When no rewards nor other incentives are offered and the voluntary respondents see the first time this kind of choice questionnaire, the response rates typically are low and it is difficult to estimate an attrition bias.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2022.01.014.

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