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# Investors' risk perceptions of structured financial products with worst-of payout characteristics

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ABSTRACT

We conduct an experiment to investigate how investors assess the risk of reverse convertibles that link their payouts to the worst performing stock of a pool of underlying assets. Based on theory from psychology, we conjecture that investors' risk perception can be systematically biased downwards via the strategic selection and composition of the underlying assets. We predict and find that adding relatively safe assets to a risky underlying asset *decreases* perceived investment risk despite the fact that the risk always strictly *increases*. Investment experience and expertise alleviate but do not eliminate the bias. Our findings contribute to the understanding of the puzzling success of structured products that link their payouts to the worst performing underlying asset. They also provide important implications for investor protection in a market in which financial institutions can tailor financial products to exploit behavioral biases of retail investors.



## 1. Introduction

Structured equity-linked products have become an important element of the available asset universe for institutional and retail investors. The European market is by far the largest in the world, representing a market value of $650 billion at the end of 2014 (SRP, 2015, 26). Reverse convertibles are the most popular type of structured products on the European markets (SRP, 2015, Part 2, 16). They provide a seemingly attractive, fixed interest payment in exchange for bearing considerable downside risk on the investment. Barrier reverse convertibles (BRCs) include a barrier feature in which the invested capital is protected as long as the assets that underlie the product do not breach a downside barrier. Typically, BRCs link their final payouts to the *worst* performing stock in a pool of underlying assets. The risk associated with this worst-of payout characteristic is difficult to assess for BRC investors (Lindauer and Seiz, 2008; Hens and Rieger, 2014; Rieger, 2012). Biased risk perceptions might therefore have contributed to the success of BRCs on European markets.

In this paper, we hypothesize that investors' risk perception can be systematically biased downwards via the strategic selection and composition of the assets that underlie a BRC. We derive our hypothesis from research of a misconception known in psychology as the "dieter's paradox" (Chernev, 2011, 2010; Chernev and Gal, 2010). According to this paradox, people tend to erroneously believe that adding healthy food (e.g., a salad) to an unhealthy meal (e.g., a hamburger) decreases calorie intake. Researchers explain the paradox by peoples' inclination to categorize different options according to opposing, semantically loaded categories (e.g., good–bad) and their propensity to evaluate combinations of options of opposing categories in a compensatory manner (Chernev, 2011, 2010; Chernev and Gal, 2010). As a consequence, people tend to average rather than total the calories contained in an "unhealthy" burger and a "healthy" salad (Chernev and Gal, 2010). We posit that a conceptually similar misperception can occur when retail investors assess the risk of BRCs. Due to the worst-of payout characteristic of BRCs, a larger pool of underlying assets always strictly increases investors' loss risk, similar to adding additional food to a meal always increases calories. Market participants broadly agree on coarse risk classifications (e.g., low risk, high risk) of stocks that are familiar to them (Blitz and van Vliet, 2007; Ortiz et al., 2015).[1] Anecdotal evidence suggests that BRCs based on multiple underlying stocks often include at least one stock that investors generally

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[1] Coarse risk classifications of stocks are also provided by finance portals such as www.cash.ch.

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consider as a safer investment (Wallmeier and Diethelm, 2009). Applying the dieter's paradox to BRCs, we therefore hypothesize that adding relatively safe assets to a risky underlying asset will induce investors to erroneously believe that the overall risk of the BRC decreases when the risk in fact always *increases*.

Studying this analog of the dieter's paradox in financial markets is interesting because BRCs enjoy a widespread popularity, particularly among retail investors (Wallmeier and Diethelm, 2009). The overwhelming success of BRCs is puzzling for two reasons. First, BRCs involve considerable downside risk, which appears to conflict with investors' well-documented loss aversion (Kahneman and Tversky, 1984; Breuer and Perst, 2007). Second, independent financial experts typically advise against investments in BRCs, primarily because they are seen as overly complex and largely overpriced (e.g., Leisinger, 2014; Deng et al., 2015; Swedroe, 2015).[2] However, BRCs may be popular because they may be designed to exploit behavioral biases of retail investors. In support of this claim, prior research provides evidence that investors seem to base their investment decisions too narrowly on the fixed interest that BRCs offer (Wallmeier and Diethelm, 2009) and that conjunction errors can cause investors to underestimate the loss risk of multivariate BRCs (Rieger, 2012). Further corroborating evidence comes from analytical research by Hens and Rieger (2014). They show that rational investors have no incentive to invest in structured products unless they suffer from incorrect market beliefs or are sufficiently loss-averse to engage in gambling behavior to avoid *sure* losses.

We intend to contribute to the literature by providing a novel explanation as to why investors underestimate the loss risk of BRCs. We investigate whether experienced retail investors are deceived by the dieter's paradox. More specifically, we investigate whether the strategic selection and composition of the financial assets that underlie a BRC can be used to bias investors' risk perception downwards despite the fact that the product's risk increases. Following the dieter's paradox, we hypothesize that investors engage in semantic anchoring and an averaging bias when assessing BRCs (Chernev, 2011, 2010; Chernev and Gal, 2010). We conjecture that investors will anchor on a dichotomous risk-safe categorization of stocks, and that they will evaluate the BRC's overall risk based on the average risk of its underlying stocks. We therefore predict that investors will systematically underestimate the risk of BRCs that comprise *differentially* risky stocks, while we predict no such misjudgment effect when the BRC comprises stocks that all belong to the same risk category.

Our research extends prior studies of misjudgments related to structured products. In Rieger (2012), investors misestimate the loss probability of a BRC because their context-specific experience causes them to rely on a *non-predictive* cue that triggers intuitive impressions of security and safety (i.e., Swiss investors underestimate the loss risk of a BRC based on the Swiss market index vis-à-vis a BRC based on a non-Swiss market index).[3] Extending Rieger (2012), we investigate misjudgments that occur when investors are provided with *predictive* information that is *unrelated* to their personal experience (i.e., investors assess the loss risk of BRCs based on hypothetical stocks that differ in terms of their risk profile).[4] On a construct level, our study differs from Rieger (2012) in that the conjunction fallacy and the dieter's paradox describe different psychological processes. The conjunction fallacy identifies misjudgments due to the reliance on non-predictive information that alludes to peoples' experience with similar contexts (Tversky and Kahneman, 1983). However, the dieter's paradox detects misjudgments that result from peoples' tendency to aggregate predictive information that is organized in opposing mental categories in a compensatory manner (Chernev, 2011, 2010; Chernev and Gal, 2010). Consequently, whereas the conjunction fallacy exposes the danger that investors' context-specific *experience* may cause them to overweight *non-predictive* cues, the dieter's paradox additionally identifies misjudgments that can occur when investors are provided with *predictive* information that is *unrelated* to their experience.[5]

In Hens and Rieger (2014), investors misestimate loss probabilities because they suffer from incorrect market beliefs or because they are sufficiently loss averse to engage in gambling behavior to avoid *sure* losses. Extending Hens and Rieger (2014), we provide investors with objective information concerning the volatilities of the underlying assets. In addition, we investigate only payout profiles that are common in practice. This allows us to exclude by design that misjudgment effects are driven by misestimations concerning the underlying assets' volatilities or by investors' gambling behavior to avoid *sure* losses as in Hens and Rieger (2014).

In our experiment, retail investors take the role of prospective investors who consider investing in BRCs that are either based on a single hypothetical stock (univariate BRC) or three hypothetical stocks (multivariate BRC).[6] Underlying stocks are characterized with either high or low stock price volatility. All BRCs share identical characteristics with respect to the maturity, the barrier, the interest coupon, and the currency. The BRCs differ only in terms of the number of underlying stocks (one or three) and the price volatility of the underlying stocks (high- or low-volatility). We present five BRCs to the participants in sequential order and ask them to assess each BRC for the probability of full repayment (i.e., the desired outcome for investors). Two of the five BRCs we present to the participants are univariate BRCs based on either a low-volatility or a high-volatility stock. The other three BRCs are multivariate BRCs based on one of the following: (i) three low-volatility stocks, (ii) three high-volatility stocks, or (iii) one high-volatility and two low-volatility stocks. We designed the experimental material such that the multivariate BRCs include at least one of the two stocks that underlie the univariate BRCs. As a consequence, the risk of a BRC *increases* by design when the pool of underlying assets is extended. However, in contrast to normative predictions but in accordance with the dieter's paradox, we find that the loss risk that retail investors associate with BRCs *decreases*

2 The margin between the (higher) selling price and the (lower) theoretical value of structured financial products tends to increase with the products' complexity, see, e.g., Stoimenov and Wilkens (2005), Benet et al. (2006), Szymanowska et al. (2009), Henderson and Pearson (2011), Wallmeier and Diethelm (2009), Wallmeier and Diethelm (2012), Deng et al. (2015). Entrop et al. (2016) provide evidence of weak performance of individual investors in structured financial products. The pricing of BRCs with multiple assets is studied in Marena et al. (2015), Wallmeier and Diethelm (2009, 2012).

3 Rieger (2012) reports that Swiss participants rated the probability of a barrier event for a BRC based on the three market indices SMI, S&P 500 and DAX as significantly lower than the corresponding probability for a BRC based on the DJIA. Rieger (2012, p. 115) notes that the "conjunction fallacy typically occurs when one of the conjoint events seems most 'natural' to happen. [Given that] ... it seems most natural to Swiss investors that the 'solid and safe' SMI will not hit the barrier... they fall prey of the conjunction fallacy and overestimate the safety of the three index basket".

4 On an operational level, our study differs from Rieger (2012) in two important aspects. Investors in Rieger (2012) assess BRCs that are based on entirely *different* assets (i.e., no asset underlies two distinct BRCs). In addition, participants' risk perception of the individual assets that underlie the BRCs are neither elicited nor manipulated. We control for participants' risk perception of the individual assets that underlie the BRCs by classifying assets as high- or low-volatility stocks. Moreover, to control for the incremental risk of multivariate BRCs above and beyond the univariate BRC, we use BRCs based on systematic combinations of individual stocks to ensure that the *same* stock that underlies a univariate BRC is also included in at least one multivariate BRC (we explain the experimental design in more detail in Section 3.1).

5 Due to the different psychological mechanisms, the two constructs can produce conflicting predictions for investors' assessments of BRC loss probabilities. We discuss this in more detail in Section 5, footnote 13.

6 See Section 3.1 for a detailed description of the experimental design.

when low-volatility stocks are added to a BRC based on a high-volatility stock.[7] Our findings indicate that investment experience and expertise alleviate but do not eliminate this bias. As predicted, we find no such misjudgment effects when the pool of underlying stocks is extended by assets within the *same* risk category (i.e., low-volatility stocks are added to a BRC based on a low-volatility stock or high-volatility stocks are added to a BRC based on a high-volatility stock).

Our findings have important implications for the practice of investor protection. Our study provides empirical evidence that investors can systematically underestimate the risk of a multivariate BRC based on a pool of *differentially* risky assets because they tend to average rather than total the loss probabilities of the individual assets that underlie a BRC. More importantly, our results also identify the danger that issuers can design BRCs to exploit investors' behavioral biases via the strategic selection and composition of the BRCs' underlying asset pools. In particular, by supplementing a pool of high-volatility assets with low-volatility assets, issuers can strategically bias investor's risk perception *downwards*, although the loss risk of the investment in fact *increases*.

The remainder of the paper is organized as follows: Section 2 describes the payout profile of BRCs. Section 3 presents the experimental design, Section 4 the test methodology, and Section 5 discusses the findings of our study. Section 6 concludes with a discussion of the practical implications of our results.

## 2. Barrier reverse convertibles

BRCs are structured financial products that offer a fixed interest rate in exchange for bearing considerable downside risk on the investment. While the fixed interest is always paid out, the downside risk consists in the possibility that the investor might not receive the full amount of the nominal contract value. The repayment of the latter is contingent on the price movement of each underlying asset relative to its valuation on the initial fixing date (initial price) and a respective downside barrier. At maturity, the BRC investor receives a cash settlement equal to the nominal contract value if one of the following is true:

(i) during the duration of the contract, all underlying assets always traded above their respective downside barriers (no barrier event occurred), or
(ii) at maturity, all underlying assets trade above their initial prices (regardless of whether a barrier event has occurred).

However, if a barrier event has occurred *and* at least one underlying asset trades below its initial price at maturity, the repayment of the nominal contract value is settled through the physical delivery of a fixed number of units of the underlying asset that suffered the *worst* performance during the contract duration. The number of units that the BRC investor receives is determined such that the market value of the asset evaluated at its initial price is equal to the nominal contract value of the BRC. Due to the barrier feature, investments in a BRC enjoy contingent capital protection as long as no barrier event occurred (see the broken line in Fig. 1). However, once a barrier event has occurred, the BRC loses its conditional capital protection and changes into a regular reverse convertible with multiple underlying assets (see the straight and dotted lines in Fig. 1).

[7] If the assets that underlie a multivariate barrier are not perfectly correlated, the probability of a barrier event is always higher for a multivariate BRC than for a univariate BRC.

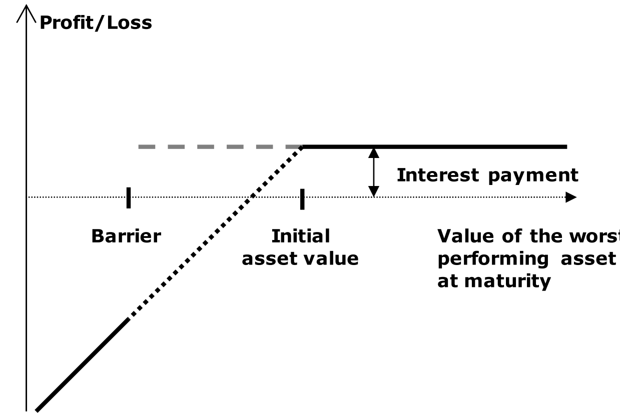


**Fig. 1.** Profit and loss diagram of multi barrier reverse convertibles. Dotted line: relevant if trigger event occurred; broken line: relevant if no trigger event occurred.

## 3. Experimental study

### 3.1. Study design

The experiment consisted of two parts. In the first introductory part, participants were informed that the study duration would be approximately ten minutes and that they could quit at any time. Participants then read general information concerning investments in BRCs and their conditional payouts. Participants with strong expertise in structured financial products had the option to skip this general information part. We illustrated the payout structure of BRCs with three underlying stocks using the examples shown in Fig. 2. In the first example, the barrier is neither reached nor breached during the product's lifetime, which implies full repayment. In the second example, the barrier is breached prior to the maturity date, but at maturity all three underlying stocks trade above their initial share prices. Again, the BRC holder receives full repayment. In the third example, the barrier is breached and one terminal stock price lies below its initial value. In this case, instead of full repayment, the BRC holder receives a fixed number of shares of the worst-performing stock.

After these illustrations, we tested comprehension of the payout structure using a specific example (see Fig. 3). It involved an investment of 1000 in a BRC based on three underlying stocks ("black", "blue", and "red").[8] All three stocks have an initial share price of 100. The barrier of 70 is breached by stock "blue", but at maturity the final stock prices are all above the barrier: 114.95 for "black", 85.88 for "red" and 92.95 for "blue". Participants were required to indicate the payout at maturity by selecting the correct answer from among five multiple-choice options. They could only continue with the survey after having provided the correct answer (i.e., physical delivery of 10 shares of stock "red", representing a value of 858.80).

In the second part, the participants took the role of prospective investors who considered investing 1000 currency units in five BRCs based on either a single fictitious stock (univariate BRC) or three fictitious stocks (multivariate BRC). We reminded participants that the probability of breaching the barrier depends on the return volatilities of the underlying stocks. We illustrated the concept of volatility with two graphs exhibiting simulated stock price evolutions for stocks with high and low volatility (Fig. 4).[9] We did not inform participants of the quantitative size of those

[8] For explanatory convenience, currency notations are omitted in the text when possible.

[9] The price paths were simulated using geometric Brownian motion with volatilities of 10% and 30%.

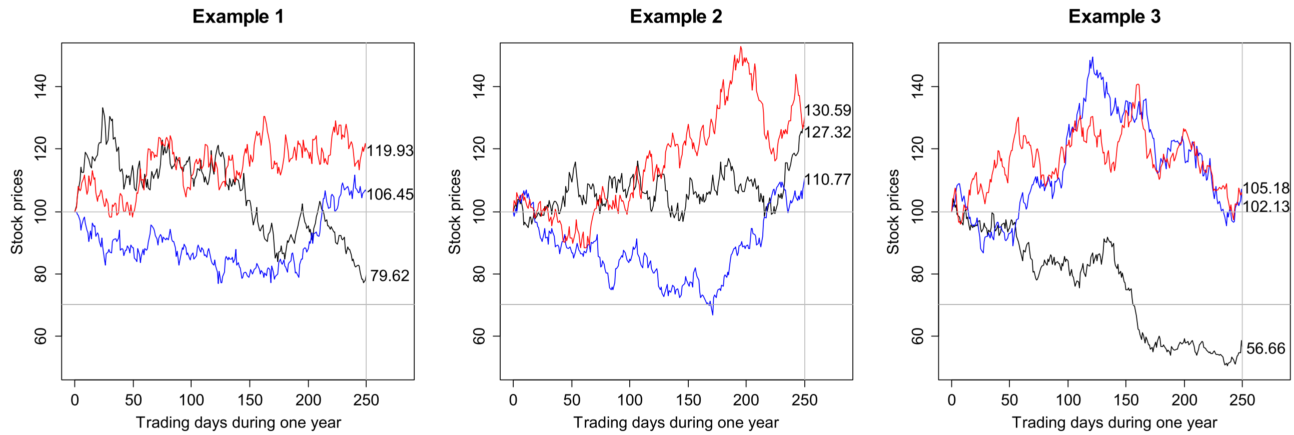


**Fig. 2.** Examples for the conditional payoff at maturity of BRCs. The three graphs show the stock price evolutions of the three underlying assets of a BRC with a barrier of 70. The initial stock prices are all 100. The initial time to maturity is 1 year, corresponding to 250 trading days. The initial investment is 1000. In Example 1, the barrier has not been breached, which implies full repayment of 1000. In Example 2, the barrier has been breached by stock "blue", but at maturity all three underlying stocks trade above their initial share prices. Again, the BRC holder receives full repayment of 1000. In Example 3, the barrier has been breached and one terminal stock price lies below its initial value. In this case, the BRC holder receives 10 shares of the worst-performing stock ("black") with a value of 566.60. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

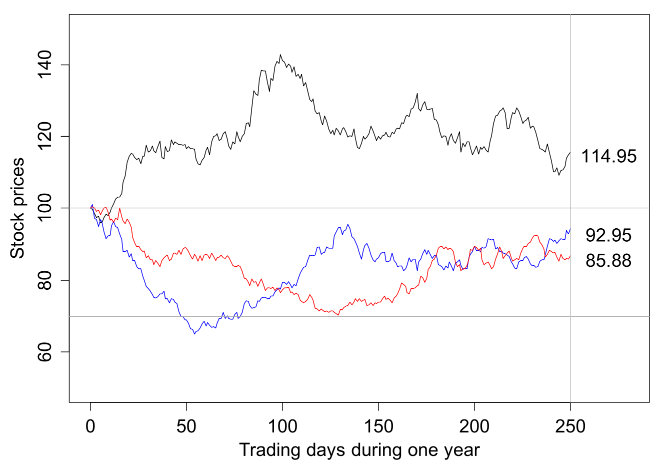


**Fig. 3.** Example to test understanding of the conditional payoff of BRCs. The graph shows the stock price evolutions of the three underlying assets of a BRC with a barrier of 70. The initial stock prices are all 100. The initial time to maturity is 1 year, corresponding to 250 trading days. The BRC holder receives at maturity 10 shares of the worst-performing stock ("red") with a value of 858.80. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

volatilities. We informed participants that during the experiment six different stocks could be used as underlying assets for the BRCs. To eliminate confounds due to personal experience with underlying assets, we neutralized the context of the experiment. We referred to the volatility of stocks as a categorical variable without providing any further details of the stocks' characteristics. More specifically, we informed participants that the stocks differ in terms of their volatility and that low- and high-volatility stocks can be distinguished. To avoid confusion with high/low barrier levels, we introduced the label "Safe" for low-volatility stocks and "Unsafe" for high-volatility stocks, and we labeled stocks from "Safe" I to III and from "Unsafe" IV to VI. We further informed participants that the returns of all six stocks were uncorrelated so that the prices of the six stocks would develop independently of each other. To test participants' understanding of the experimental material, we asked them to indicate for each of the six stocks whether they exhibit a high or low volatility. Participants could only continue with the study after having provided the correct answers.

We then presented the five BRCs shown in Table 1 to the participants. All BRCs shared the same maturity (one year), the same barrier (69%), the same interest coupon (6%), and the same currency (CHF). In each case, the participants were asked to estimate the probability of full repayment (the desired outcome for investors) and to indicate their estimate on a scale ranging from 0 to 100 (with one decimal place).

Two BRCs were univariate; one was based on a low-volatility stock (S), and the other was based on a high-volatility stock (U). The remaining three BRCs were multivariate with three underlying

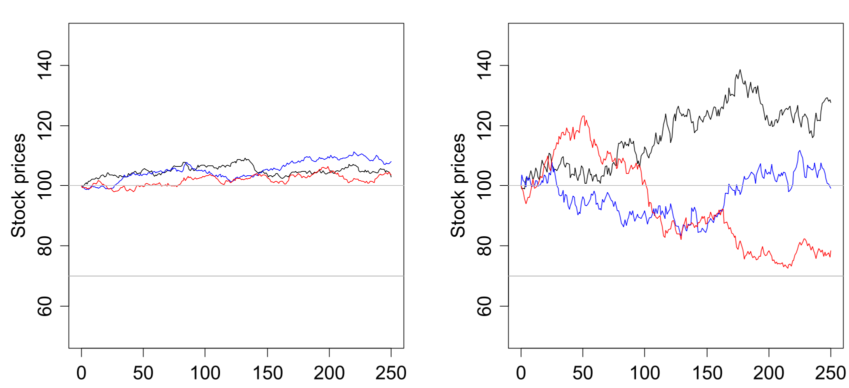


**Fig. 4.** Illustration of stock return volatility. The left (right) graph shows exemplary stock price evolutions of three stocks with a low (high) stock return volatility.

**Table 1**
BRCs evaluated by the participants.

| Type | Underlying stock(s) | Label in paper |
|---|---|---|
| Univariate | Safe I | S |
| Univariate | Unsafe IV | U |
| Multivariate | Safe I, Safe II, Safe III | SSS |
| Multivariate | Unsafe IV, Unsafe V, Unsafe VI | UUU |
| Multivariate | Unsafe IV, Safe I, Safe II | USS |

stocks; one was based only on low-volatility stocks (SSS), another was based only on high-volatility stocks (UUU), and the third was a combination of one high-volatility stock and two low-volatility stocks (USS). We designed the experimental material such that the multivariate BRCs include at least one of the two stocks that underlie the univariate BRCs.[10] We counterbalanced the order of appearance of the BRCs such that half of the participants first evaluated the two univariate BRCs followed by the three multivariate BRCs, and vice versa. At the end of the survey, participants assessed their expertise in BRCs, provided demographic details and were asked to indicate the asset classes in which they were currently invested. Finally, they had the option to enter a lottery to win a cash prize of CHF 2000, were debriefed, and had the opportunity to read background material concerning the study. The questionnaire is available in the Web-Appendix.

### 3.2. Participants

Switzerland represents one of the largest markets for structured products in the world, with investments totaling CHF 184 bn in September 2016 (SNB, 2016). We therefore recruited participants via links placed in the most popular websites and blogs of financial products in Switzerland (cash.ch, finanzprodukt.ch, blicklog.ch and trader-forum.ch). We incentivized subjects to participate in the study via an option to enter a lottery to win a cash prize of CHF 2000.[11] The link to the study was opened 460 times. In total, 249 people read all the instructions and 244 participated in the study (221 males, mean age = 49.15 years, *SD* = 19.16). All participants were active capital market investors. The majority (55.6%) had purchased structured products at least once during the previous five years. Of all the participants, 50.4% evaluated their expertise in structured financial products as strong or very strong, 33.1% as average, and 16.5% as limited or very limited. Table 2 provides an overview of the asset classes the participants were invested in at the time of the experiment.

## 4. Test methodology

We conduct a regression analysis of the estimated repayment probabilities to test for the significance of differences between the five BRCs. Let $i = 1, \ldots, N$ be an identifier for the participants and let $\boldsymbol{P}_i = \left(P_{U,i}, P_{S,i}, P_{SSS,i}, P_{UUU,i}, P_{USS,i}\right)'$ denote the products' repayment probabilities as assigned by participant $i$. Our regression model defines U as the base product and includes dummy variables for the additional repayment probabilities of other products. More specifically, we define the regression coefficients as $\boldsymbol{\beta} = (\beta_U, \beta_{S-U}, \beta_{SSS-S}, \beta_{UUU-U}, \beta_{USS-U})'$, where $\beta_U$ measures the repayment probability of the baseline BRC U, while the elements $\beta_{SSS-S}$, $\beta_{UUU-U}$ and $\beta_{USS-U}$ capture the additional repayment probability of the BRC indexed first compared to the BRC indexed second in the subscript. This leads to the following system of equations:

$$\begin{pmatrix} P_{U,i} & = \beta_U & & & & & + & \varepsilon_{U,i} \\ P_{S,i} & = \beta_U & + \beta_{S-U} & & & & + & \varepsilon_{S,i} \\ P_{SSS,i} & = \beta_U & + \beta_{S-U} & + \beta_{SSS-S} & & & + & \varepsilon_{SSS,i} \\ P_{UUU,i} & = \beta_U & + & & \beta_{UUU-U} & & + & \varepsilon_{UUU,i} \\ P_{USS,i} & = \beta_U & + & & & \beta_{USS-U} & + & \varepsilon_{USS,i} \end{pmatrix}. \quad (1)$$

For example, the third equation of system (1) explains the repayment probability of product SSS as the repayment probability of the base product U plus the differential effect of S compared to U plus the differential effect of SSS compared to S.

In matrix notation, equation system (1) can be written as the following:

$$\boldsymbol{P}_i = \boldsymbol{D}_i\boldsymbol{\beta}' + \boldsymbol{\varepsilon}_i \quad (i = 1, \ldots, N), \quad (2)$$

where $\boldsymbol{\varepsilon}_i = \left(\varepsilon_{U,i}, \varepsilon_{S,i}, \varepsilon_{SSS,i}, \varepsilon_{UUU,i}, \varepsilon_{USS,i}\right)'$ and

$$\boldsymbol{D}_i = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \end{pmatrix}.$$

Eq. (2) can be viewed as a special case of the generalized least squares (GLS) model (Zellner, 1962). In our particular case with dummy variable regressors, the standard implementation of Feasible GLS (FGLS) provides the same results as OLS when robust standard errors are used.[12] We use clustered-robust standard errors with clustering by participants. Robust standard errors in the sense of heteroscedasticity-consistent (HC) estimators provide similar results.

To test for a moderating effect of investors' experience on the repayment difference USS–U, we extend the last equation of system (1) to the following:

$$P_{USS,i} = \beta_U + \beta_{USS-U} + D_{Unexp,i}\beta_{(USS-U)xUnexp} + \varepsilon_{USS,i}$$

where $D_{Unexp,i}$ is equal to 1 for inexperienced investors and 0 for experienced investors. Thus, $\beta_{(USS-U)xUnexp}$ captures the differential effect of (USS–U) for inexperienced investors compared to experienced investors. Analogously, we can introduce the moderating effects of experience on the other regressors.

It is important to note that, due to the structure of regression (2), the $\boldsymbol{\beta}$ estimates correspond to the mean values of the participants' stated probabilities, e.g., $\hat{\beta}_U = 1/N\sum_i P_{U,i}$ and $\hat{\beta}_{USS-U} = 1/N\sum_i \left(P_{USS,i} - P_{U,i}\right)$. Thus, the purpose of the regression is not primarily to estimate $\boldsymbol{\beta}$, but to allow $t$-tests with robust standard errors.

## 5. Results

Table 3 shows descriptive statistics of the participants' estimates of the probability of full repayment. Data columns (1) through (5) contain estimates for the five BRCs (two univariate and three multivariate) and columns (6) through (9) show the differences in pairwise comparisons. Panel A includes all participants, while Panels B and C focus on experienced versus inexperienced investors. Our main interest is in the last column, which compares the estimates of USS with U.

10 As shown in Table 1, the stock Safe I underlies the three BRCs S, SSS, and USS and the stock Unsafe IV underlies the three BRCs U, UUU, and USS.

11 At the time of the experiment, CHF and USD traded near parity (1 CHF = 1.03 USD).

12 FGLS in the standard form, as presented in Wooldridge (2015, 259–262), uses the explanatory variables of the original regression to additionally explain the structure of the variance–covariance matrix of the error terms. In our dummy variables approach, this means that the coefficient estimates of regression (2) are the same for FGLS and OLS. The standard errors, however, are different because FGLS considers heteroscedasticity across regressions $j = 1, \ldots, 4$. As we also must consider heteroscedasticity across participants, robust standard errors are still needed. With robust standard errors, however, OLS and FGLS provide identical results, due to the particular structure of regression model (2).

**Table 2**
Participants' investments in different asset classes.

| Asset class | Share of participants with investments in a specific asset class |
|---|---|
| Saving accounts | 83.7% |
| Company stock | 89.5% |
| Equity funds | 63.9% |
| Real estate | 60.5% |
| Derivatives | 40.6% |
| Precious metal, precious wood, precious stones | 40.0% |
| Government or corporate bonds | 22.0% |
| Real estate funds | 20.2% |

**Table 3**
Descriptive statistics: estimates of the probability of full repayment for different BRCs.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| BRC | S | U | USS | SSS | UUU | S–U | SSS–S | UUU–U | USS–U |
| Panel A: All participants | | | | | | | | | |
| Mean | 78.19 | 46.40 | 55.82 | 75.43 | 39.92 | 31.79*** | −2.76*** | −6.48*** | 9.42*** |
| SD | 22.21 | 23.85 | 23.10 | 21.08 | 23.59 | 28.97 | 14.69 | 19.75 | 24.41 |
| Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | −99.10 | −50.80 | −98.60 | −99.10 |
| Perc25 | 70.20 | 29.70 | 39.78 | 64.88 | 20.38 | 18.78 | −9.90 | −16.03 | −0.60 |
| Median | 85.10 | 49.30 | 60.05 | 80.70 | 39.15 | 31.05 | −2.30 | −5.20 | 5.50 |
| Perc75 | 93.23 | 64.70 | 71.55 | 90.63 | 55.85 | 48.18 | 0.75 | 0.70 | 21.03 |
| Max | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 97.80 | 67.90 | 89.10 |
| *N* | 244 | 244 | 244 | 244 | 244 | 244 | 244 | 244 | 244 |
| Panel B: Experienced investors | | | | | | | | | |
| Mean | 77.36 | 46.88 | 52.52 | 74.59 | 41.21 | 30.47*** | −2.77*** | −5.68*** | 5.64*** |
| SD | 22.33 | 24.09 | 23.71 | 21.32 | 24.78 | 28.54 | 15.48 | 18.36 | 22.99 |
| Min | 0.20 | 0.00 | 0.20 | 0.20 | 0.00 | −99.10 | −50.80 | −98.60 | −99.10 |
| Perc25 | 70.00 | 29.70 | 34.30 | 64.20 | 19.80 | 17.30 | −9.90 | −15.00 | −1.00 |
| Median | 84.70 | 49.20 | 52.50 | 80.70 | 39.70 | 31.00 | −2.70 | −3.50 | 1.80 |
| Perc75 | 92.10 | 62.50 | 70.00 | 89.90 | 56.90 | 45.10 | 0.50 | 0.90 | 14.90 |
| Max | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 97.80 | 55.00 | 71.90 |
| *N* | 137 | 137 | 137 | 137 | 137 | 137 | 137 | 137 | 137 |
| Panel C: Inexperienced participants | | | | | | | | | |
| Mean | 79.26 | 45.78 | 60.04 | 76.52 | 38.27 | 33.47*** | −2.74*** | −7.52*** | 14.26*** |
| SD | 22.12 | 23.63 | 21.67 | 20.82 | 21.98 | 29.56 | 13.68 | 21.45 | 25.41 |
| Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | −71.90 | −50.00 | −66.00 | −60.00 |
| Perc25 | 73.75 | 29.95 | 46.35 | 65.80 | 22.65 | 19.65 | −9.80 | −19.85 | −0.35 |
| Median | 87.20 | 49.30 | 63.30 | 80.90 | 34.00 | 31.20 | −2.00 | −6.40 | 10.10 |
| Perc75 | 94.75 | 64.85 | 75.30 | 91.80 | 51.40 | 49.90 | 1.20 | 0.30 | 30.30 |
| Max | 100.00 | 100.00 | 100.00 | 100.00 | 90.10 | 100.00 | 40.50 | 67.90 | 89.10 |
| *N* | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 |

S and U stand for univariate BRCs with low volatility (label S for "safe") and high volatility (label U for "unsafe"). USS, SSS and UUU are multivariate BRCs, where the label indicates the combination of underlying stocks with low and high volatility. The last three columns are based on the difference between a participant's estimates for two different BRCs. SD is standard deviation, Perc25 and Perc75 are quartiles. Experienced investors are defined as participants who declare to have purchased structured financial products in the last five years.
* Significance level for the mean difference: 10%; test based on regression presented in Table 4.
** Significance level for the mean difference: 5%; test based on regression presented in Table 4.
*** Significance level for the mean difference: 1%; test based on regression presented in Table 4.

Table 4 shows the results of our regression analysis without the moderating effects of experience (column 1), with moderating effects for USS–U (column 2) and with moderating effects for all regressors (column 3). The $t$-statistics based on clustered-robust standard errors are reported in parentheses.

In accordance with our main hypothesis, the participants incorrectly estimated the probability of full repayment as *higher* for the multivariate BRC based on one unsafe and two safe stocks (USS) ($M = 55.82$) compared to the univariate BRC based on one unsafe stock (U) ($M = 46.4$). The difference of 9.42 is significant at the 1% level ($t = 6.02$; see column (1) in Table 4). Furthermore, also in accordance with our prediction, participants correctly estimated the probability of full repayment as higher for the univariate BRC based on a single unsafe stock (U) ($M = 46.4$) compared to the multivariate BRC based on three unsafe stocks (UUU) ($M = 39.92$). The difference of 6.48 ($t = 5.12$) is again strongly significant. Similarly, participants correctly rated the probability of full repayment as higher for the univariate BRC based on a single safe stock (S) ($M = 78.19$) compared to the multivariate BRC based on three safe stocks (SSS) ($M = 75.43$; difference 2.76, $t = 2.92$).[13]

From the SSS–S and UUU–U comparisons, we conclude that investors generally understand that more underlying assets imply a higher loss risk. Our results are therefore neither driven by a general difficulty to combine loss probabilities nor by a naive notion of

[13] Note that the dieter's paradox and the conjunction fallacy lead to different predictions for this comparison. Our data shows that investors correctly assess the loss probability of a univariate BRC based on one low-volatility stock (S) as lower than the corresponding probability for a multivariate BRC based on the same low-volatility stock plus two more low-volatility stocks (SSS). This finding is in accordance with the dieter's paradox that predicts no misjudgment when cues are categorized within the same mental category (e.g., all assets are low-volatility, i.e., S). However, this finding is not explicable in terms of the conjunction fallacy. Since representativeness and cue frequency tend to co-vary (Tversky and Kahneman, 1983), conjunction fallacy-based explanations would predict that a 'triple safe' BRC (SSS) is more representative of a safe investment than a 'single safe' BRC (S). Therefore, in contrast to our findings, conjunction-based explanations expect investors to provide lower loss probability ratings for the multivariate BRC than for the univariate BRC.

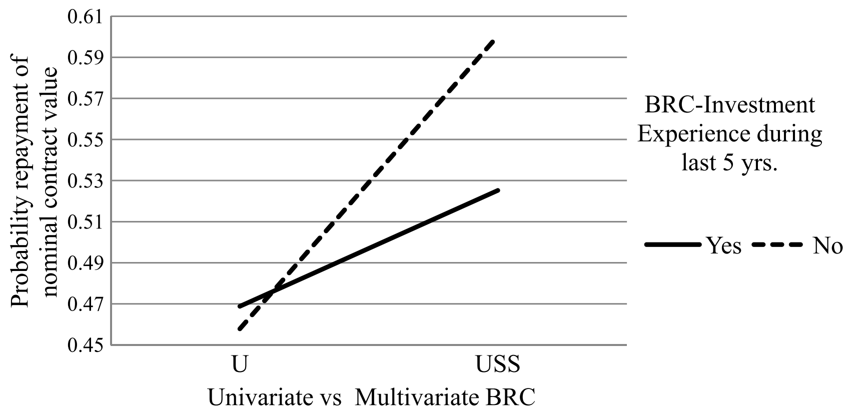


**Fig. 5.** Investment experience and misjudgment effect. Fig. 5 exhibits the interaction of BRC-investment experience and BRC-loss risk judgments for a univariate BRC based on an unsafe stock (U) and for a multivariate BRC based on two safe and the same unsafe stock (USS). Qualitatively correct estimates of the relative BRC-loss risk would be indicated by strictly decreasing lines from U to USS.

**Table 4**
Regression-based test of differences of BRCs with respect to the participants' estimated probabilities of full repayment.

| | (1) | (2) | (3) |
|---|---|---|---|
| U | 46.40*** (30.35) | 46.40*** (30.33) | 46.88*** (22.73) |
| U × Inexperienced | | | −1.10 (−0.36) |
| S–U | 31.79*** (17.11) | 31.79*** (17.11) | 30.47*** (12.47) |
| (S–U) × Inexperienced | | | 3.00 (0.80) |
| SSS–S | −2.76*** (−2.92) | −2.76*** (−2.93) | −2.77** (−2.09) |
| (SSS–S) × Inexperienced | | | 0.04 (0.02) |
| UUU–U | −6.48*** (−5.12) | −6.48*** (−5.12) | −5.68*** (−3.61) |
| (UUU–U) × Inexperienced | | | −1.84 (−0.71) |
| USS–U | 9.42*** (6.02) | 6.12*** (3.09) | 5.64*** (2.86) |
| (USS–U) × Inexperienced | | 7.52*** (2.58) | 8.62*** (2.74) |

The table shows regression results for regression model (2). The $t$-statistics in parentheses are based on heteroscedasticity-consistent standard errors. S and U stand for univariate BRCs with low volatility (label S for "safe") and high volatility (label U for "unsafe"). (S–U), (SSS–S), (UUU–U), and (USS–U) indicate the differences in the estimated probabilities of full repayment for the respective pair of BRCs. "Inexperienced" is a dummy variable with value one for participants who declare not to have purchased structured financial products in the last five years. The interaction effect of a BRC pair with inexperienced participants ("× Inexperienced") indicates the additional difference in the estimated repayment probability of inexperienced participants compared to experienced investors. The coefficient estimates in column (1) are equal to the means in Table 3, Panel A, columns (2) and (6)–(9). The new coefficient estimates in column (2) are equal to the difference between the mean of Table 3, Panel B, column (3) and the mean of column (2) in Panel A ($52.52 - 46.40 = 6.12$) and analogously for Panel C ($60.04 - 46.40 = 6.12 + 7.52$). The coefficient estimates in column (3) correspond to the mean values in Table 3, Panels B and C (e.g., for USS–U: 5.64 is the mean in Table 3, Panel B, column (9); $5.64 + 8.62 = 14.26$ is the mean in Table 3, Panel C, column (9)).
* Significance level: 10%.
** Significance level: 5%.
*** Significance level: 1%.

diversification (i.e., an erroneous assumption that pooling multiple assets in a portfolio by itself reduces loss risk). Participants tend to ignore the risk-enhancing effect of more underlying assets only when safe stocks are added to a risky underlying stock, which is in accordance with the hypothesized processes of anchoring on and averaging the dichotomous risky vs. safe classifications of the underlying assets.

To investigate whether investment experience alleviates misjudgment effects, we include experience as a moderator variable in columns (2) and (3) in Table 4. Our findings reveal that experienced investors still show significant misjudgment effects ($t = 3.09$ and $t = 2.86$ for USS–U). However, inexperienced investors show a significantly stronger bias than experienced investors ($t = 2.58$ and $t = 2.74$ for the interaction (USS–U) × Inexperienced) (see also Fig. 5). Simple correlation analyses are in accordance with potential moderating effects of different measures of investor experience on investors' misjudgments, although no causation can be inferred. The more frequently participants had invested in BRCs during the previous five years, the less pronounced the dieter's paradox tends to be (U–USS, $r = -.19$, $p = .003$) (untabulated). Similarly, the difference in repayment probabilities U–USS was negatively associated with the participants' expertise in structured products ($r = -.30$, $p < .001$) (untabulated).

## 6. Discussion

Our study provides strong evidence that experienced retail investors are deceived by an analog of the dieter's paradox when assessing the risk of structured products with a worst-of payout characteristic. Due to this feature, the *absolute* loss risk of BRC investments *increases* when the pool of underlying stocks is extended. We show that investors' *perceived* risk, however, tends to *decrease* when safe stocks are added to a risky underlying stock. Our findings thus imply that the selection and composition of the financial assets that underlie a BRC are an adequate means to strategically bias investors' risk perception *downwards* despite the fact that the absolute loss risk of the investment in fact *increases*.

Our study has important implications for the research and practice of investor financial protection. First, our findings corroborate suspicions that BRCs can be tailored to exploit investors' behavioral biases. By supplementing a pool of high-volatility assets with low-volatility assets, issuers can *decrease* the risk that investors associate with the BRC although the risk actually *increases*. Our study thus provides a novel explanation as to why investors underestimate the risk of BRCs. Prior studies have hypothesized that investors underestimate the loss risk of BRCs because they fixate on seemingly attractive interest coupons (Wallmeier and Diethelm, 2009), are deceived by conjunction errors (Rieger, 2012), suffer from incorrect market beliefs or engage in gambling to avoid sure losses (Hens and Rieger, 2014). Extending these findings, we provide evidence that issuers can attenuate investors' risk assessments via the strategic selection and composition of the assets that underlie a BRC because investors tend to average instead of totaling loss probabilities of differentially risky assets.

Our study also generalizes prior research findings by testing boundary conditions of the dieter's paradox. Prior studies have demonstrated misjudgment effects by using experiments based on between-subject-designs (Chernev, 2011, 2010; Chernev and Gal, 2010). An important limitation of between-subject-designs with respect to external validity is that participants can neither observe nor compare alternative choices. We employ a within-subject-design that explicitly allows for the comparison of alternative choice options. Our study therefore generalizes prior findings by showing that misjudgments due to semantic anchoring and the averaging bias are robust to sequential comparisons between alternative choice options.

Finally, our findings reveal that investors' experience with investments in BRCs mitigates but fails to eliminate the dieter's paradox. Learning by trial-and-error is costly in financial decision making, particularly for investors who systematically underestimate the risk of their investments. In light of the multi-billion-dollar volume currently traded in BRCs worldwide and the repercussions of investors' misjudgments for individual and societal welfare, our findings may alert investors and regulators for potential improvements to investor protection in a market in which professional institutions can exploit behavioral biases of retail investors.

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